Swin Transformer: Hierarchical Vision Transformer using Shifted Windows

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Zheng Zhang[1] Stephen Lin[1] Baining Guo[1]
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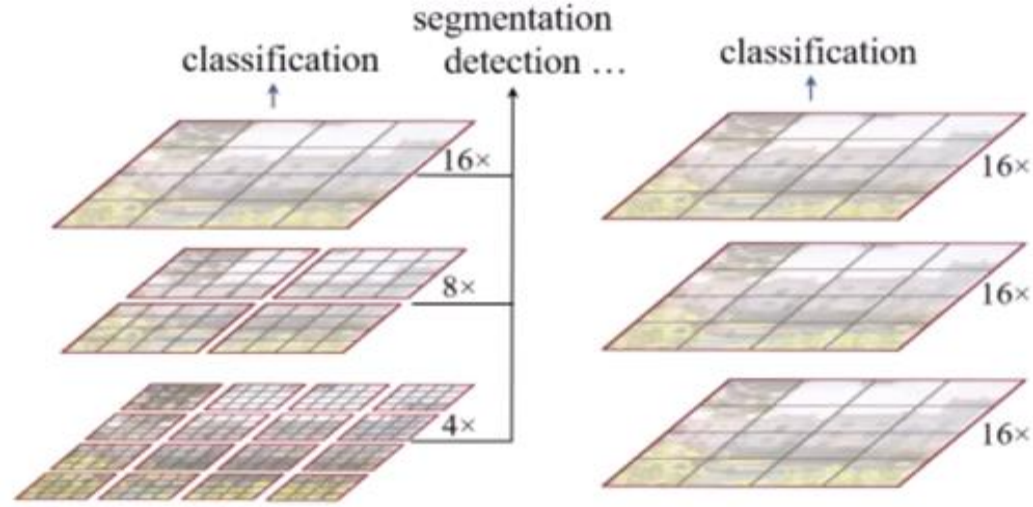
{v-zeliu1,v-yutlin,yuecao,hanhu,v-yixwe,zhez,stevelin,bainguo}@microsoft.com

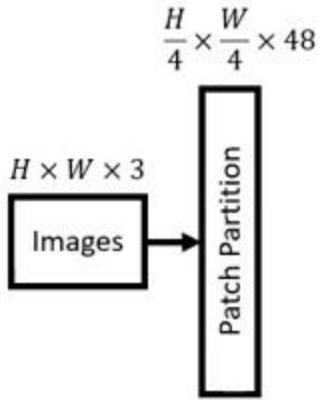
Abstract

*This paper presents a new vision Transformer, called Swin Transformer, that capably serves as a general-purpose backbone for computer vision. Challenges in adapting Transformer from language to vision arise from differences between the two domains, such as large variations in the scale of visual entities and the high resolution of pixels in images compared to words in text. To address these differences, we propose a hierarchical Transformer whose representation is computed with **S**hifted **win**dows. The shifted windowing scheme brings greater efficiency by limiting self-attention computation to non-overlapping local windows while also allowing for cross-window connection. This hierarchical architecture has the flexibility to model at various scales and has linear computational complexity with respect to image size. These qualities of Swin Trans-*



(a) Swin Transformer (ours) (b) ViT

Figure 1. (a) The proposed Swin Transformer builds hierarchical feature maps by merging image patches (shown in gray) in deeper layers and has linear computation complexity to input image size due to computation of self-attention only within each local window (shown in red). It can thus serve as a general-purpose back-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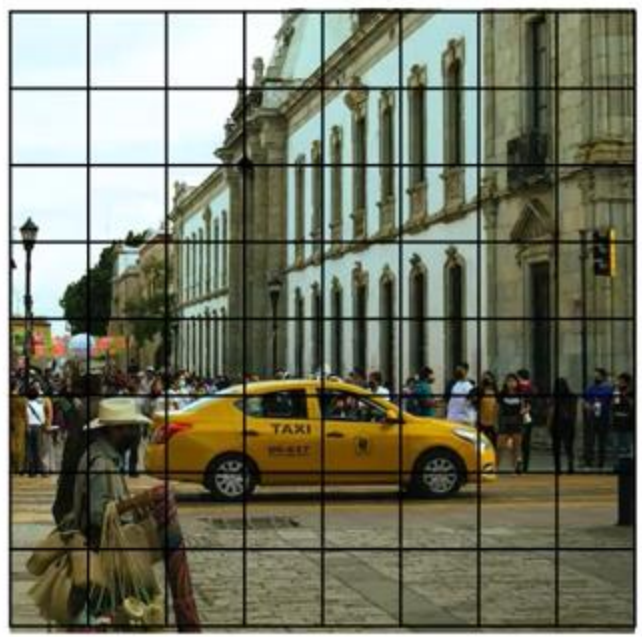
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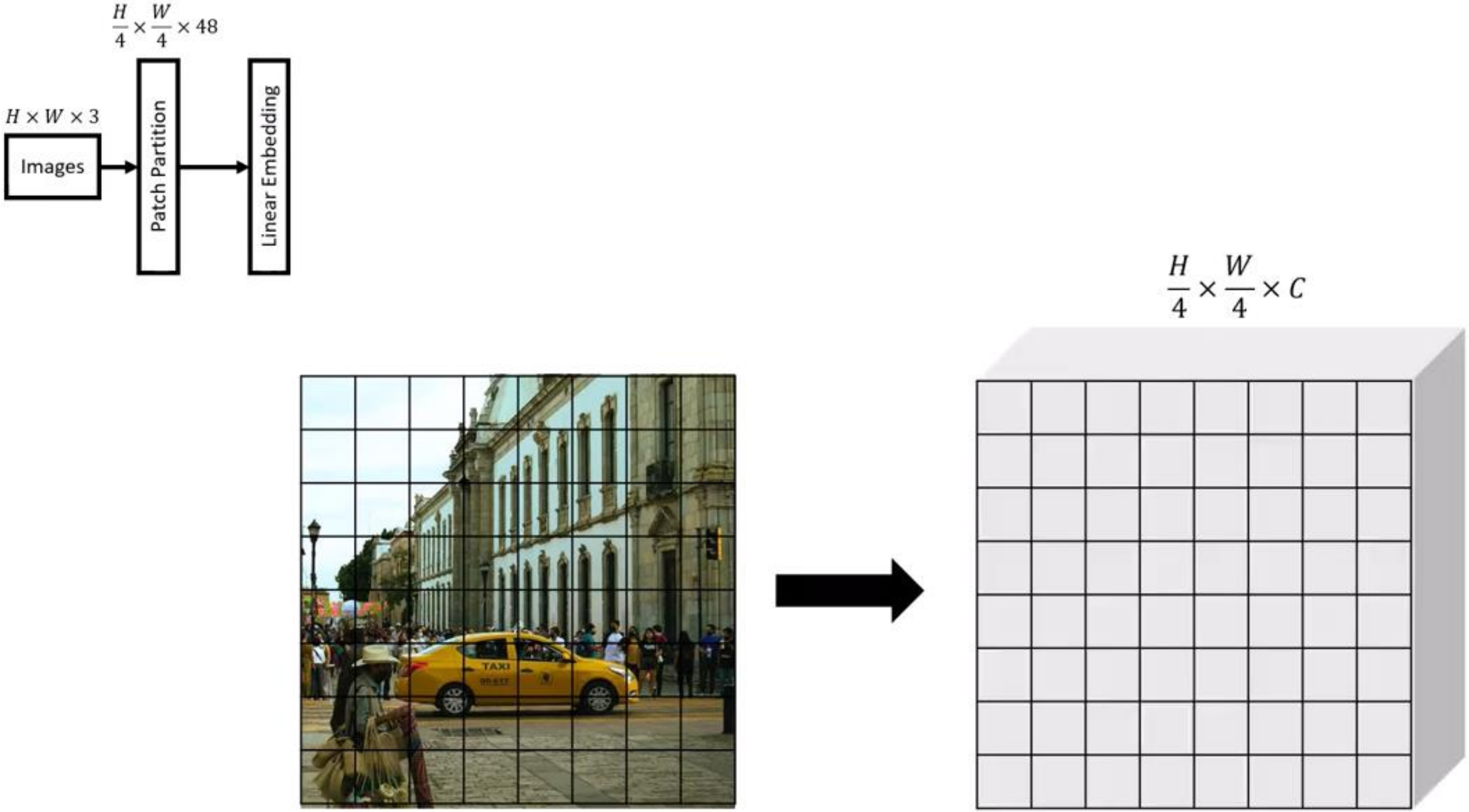
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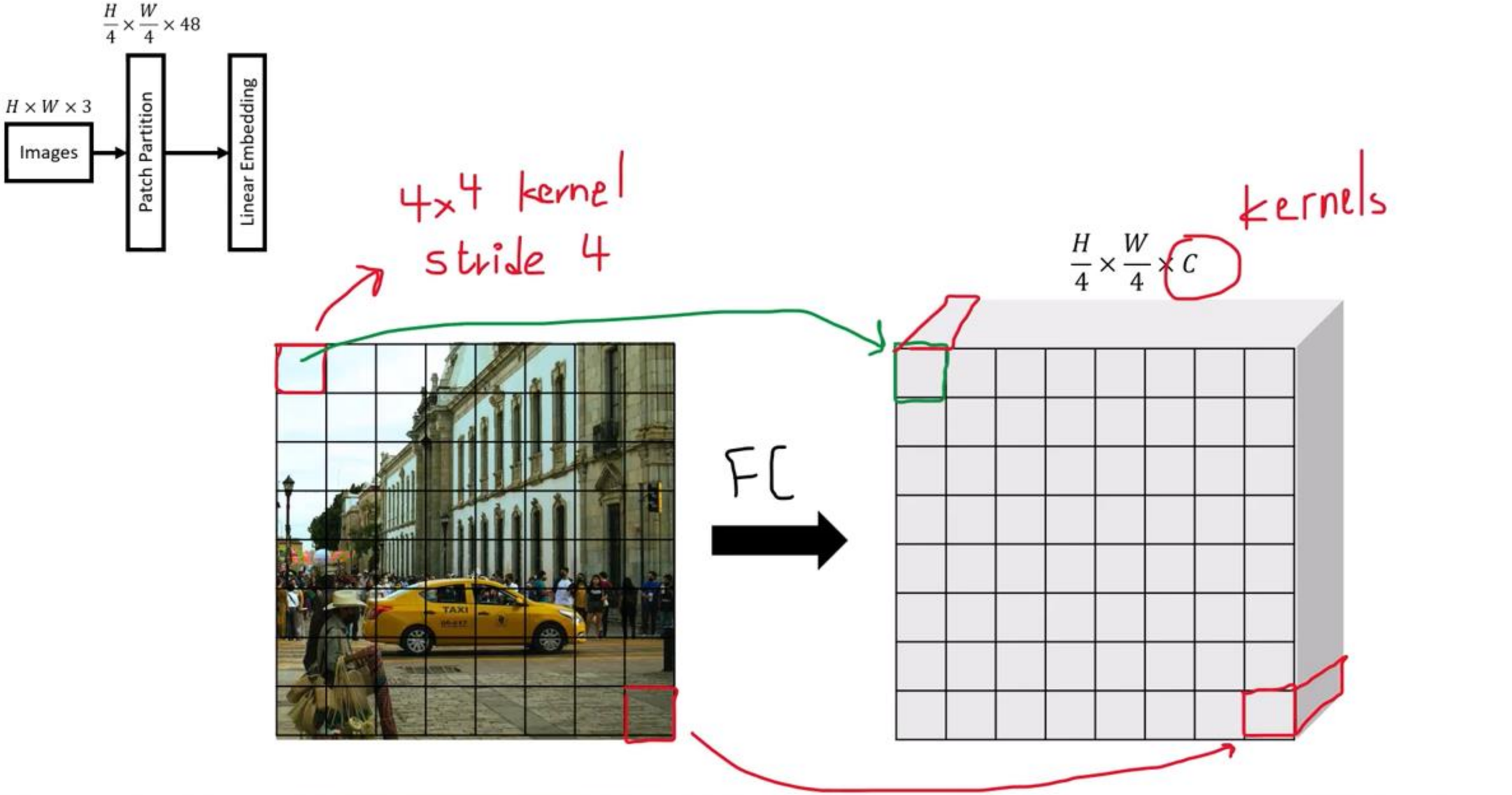
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
$\frac{H}{4} \times \frac{W}{4} \times C$
TAXI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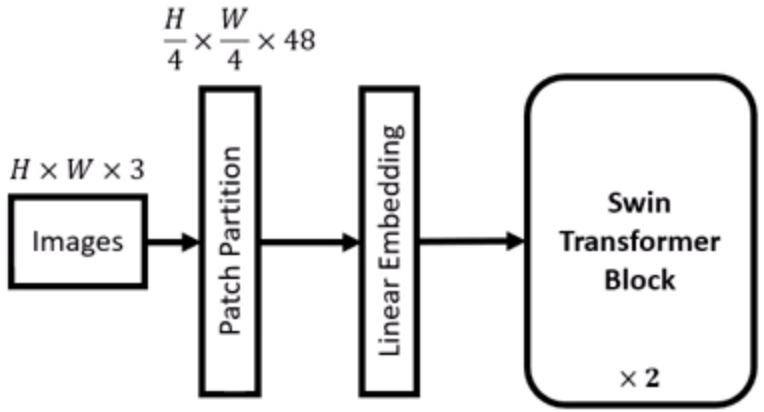
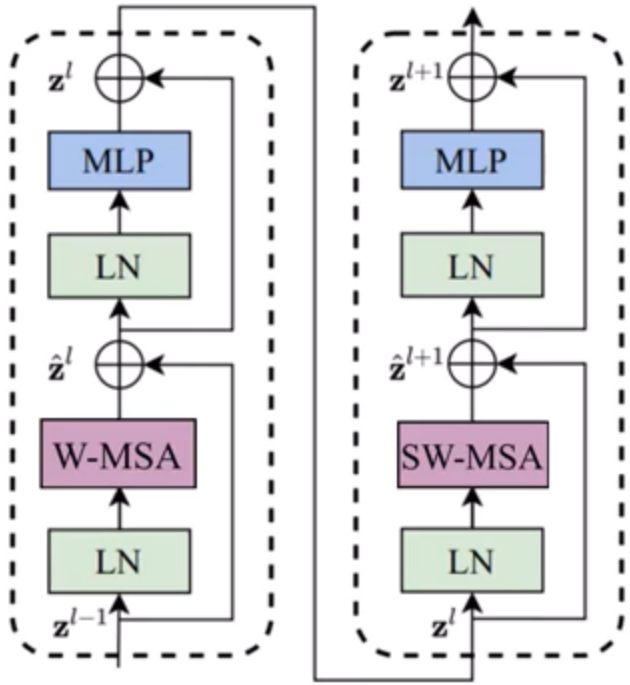
Images
Patch Partition
Linear Embedding
4x4 kernel
stride 4
kernels
$\frac{H}{4} \times \frac{W}{4} \times C$
FC
TAXI





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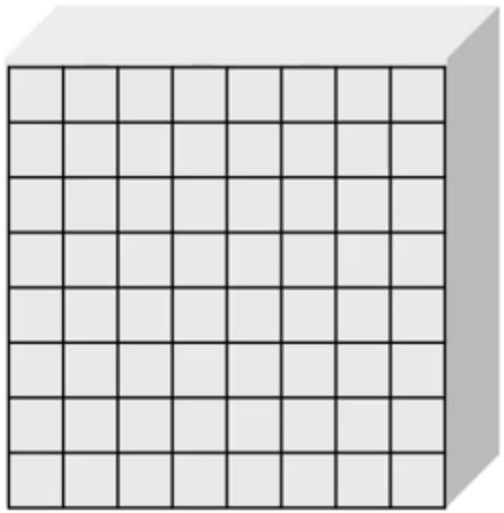

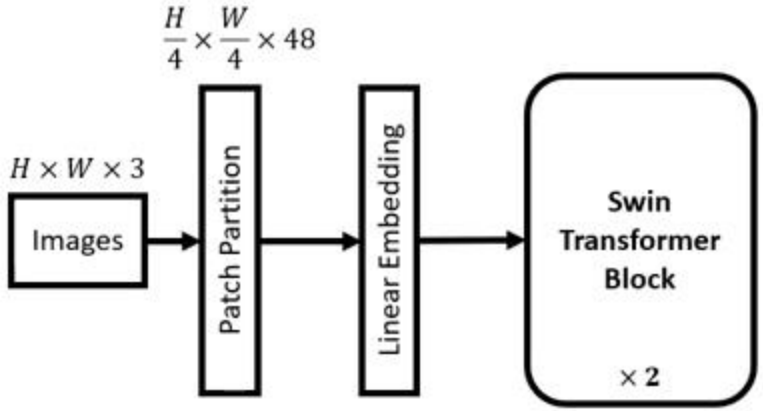
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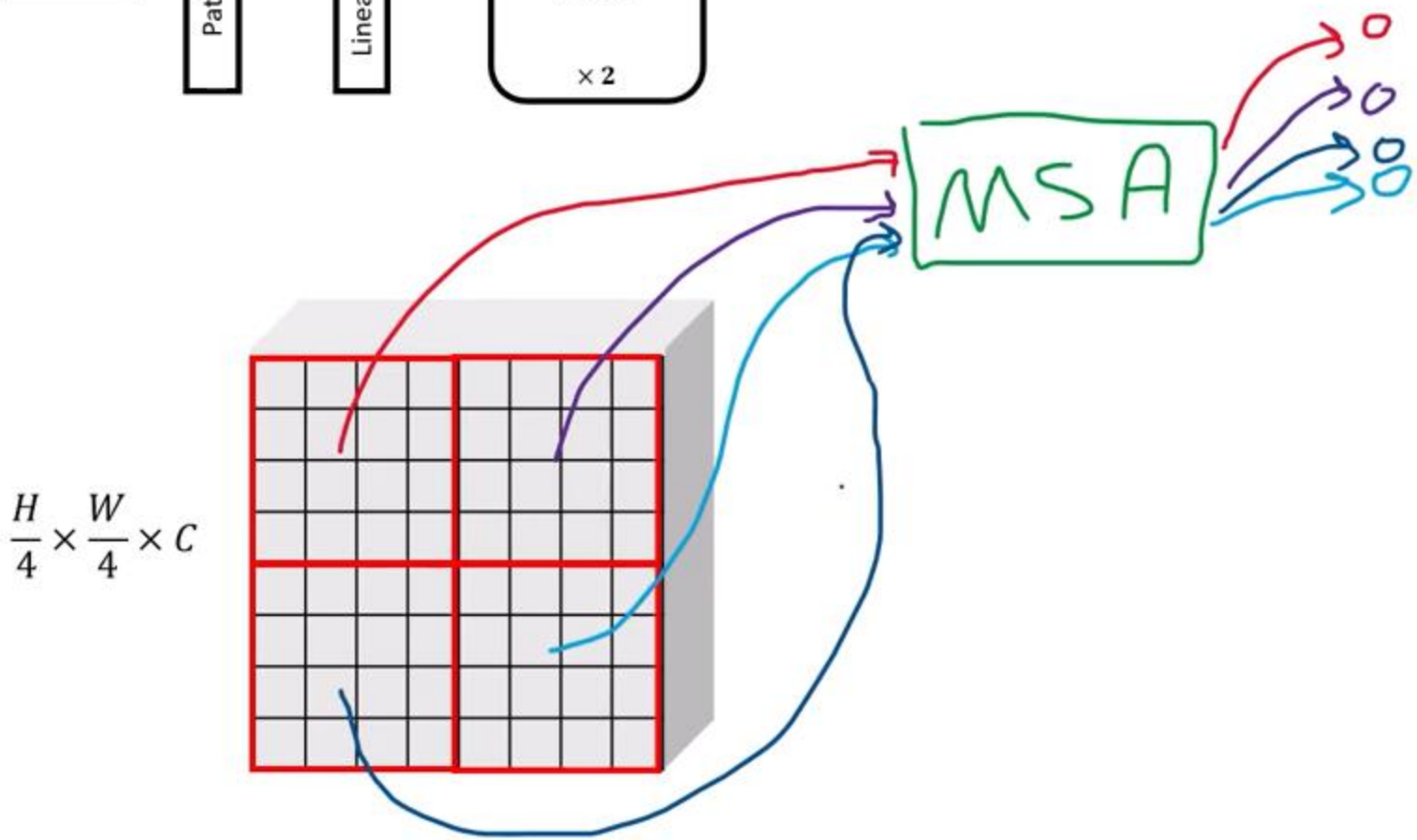
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
Swin Transformer Block
× 2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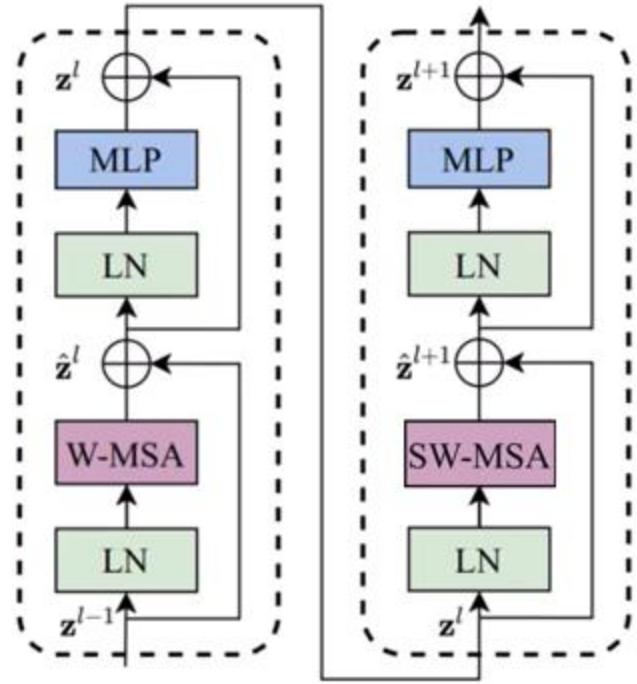
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LN
$\hat{\mathbf{z}}^l$
W-MSA
LN
$\mathbf{z}^{l-1}$
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MLP
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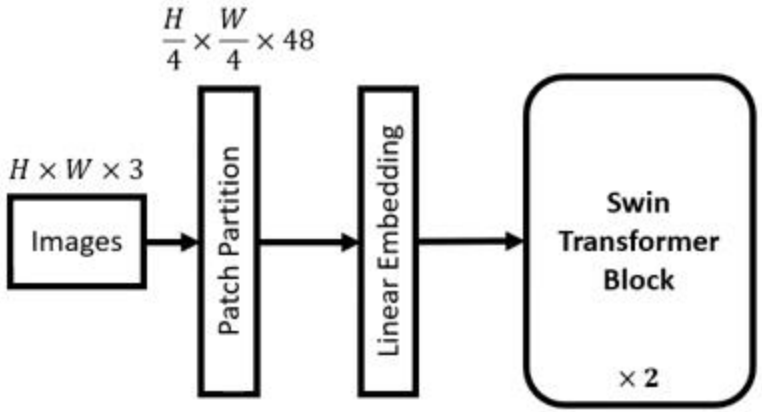
$\hat{\mathbf{z}}^{l+1}$
SW-MSA
LN
$\mathbf{z}^l$

W-MSA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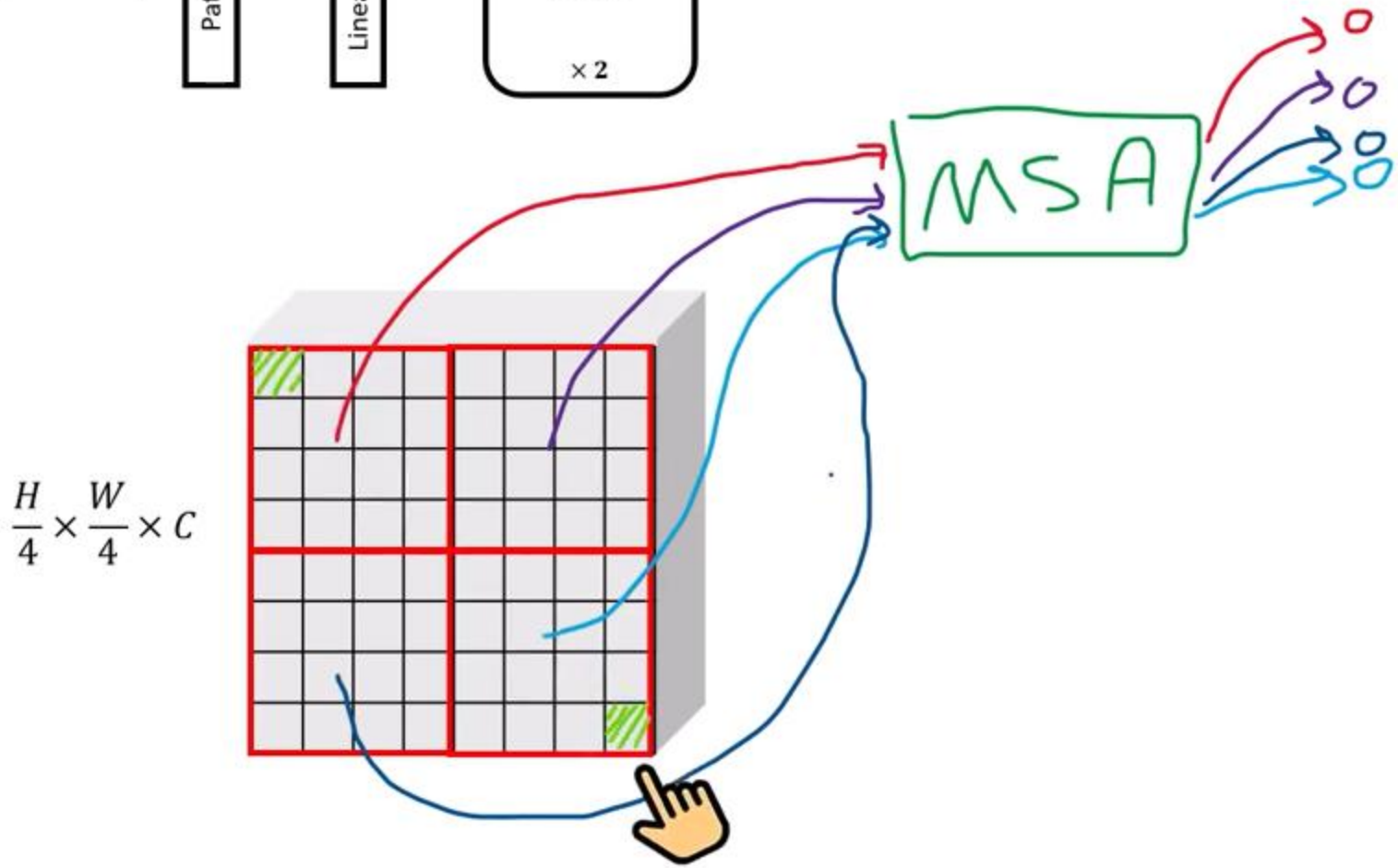
Images
Patch Partition
Linear Embedding
Swin Transformer Block
$\times 2$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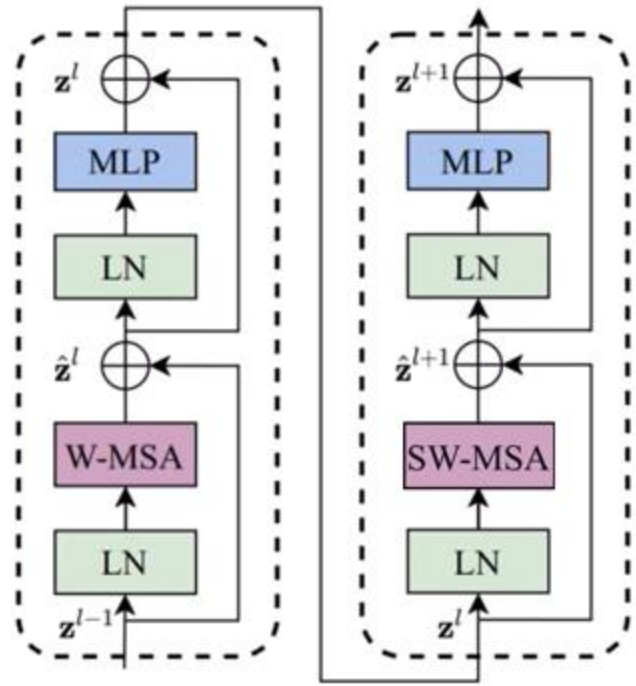
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$\hat{\mathbf{z}}^l$
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$\mathbf{z}^{l-1}$
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MLP
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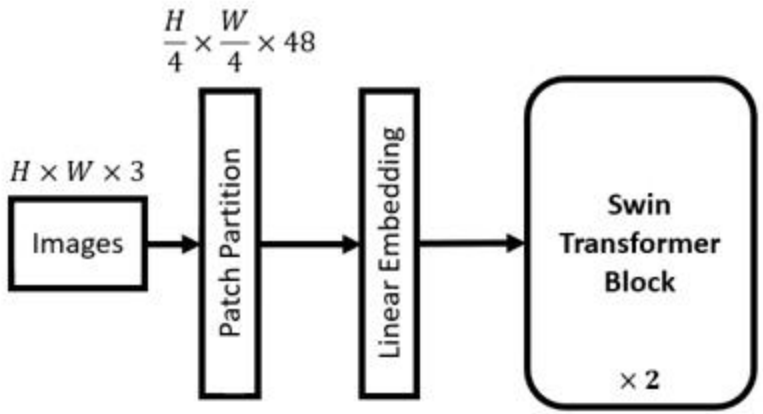
SW-MSA
LN
$\mathbf{z}^l$

W-MSA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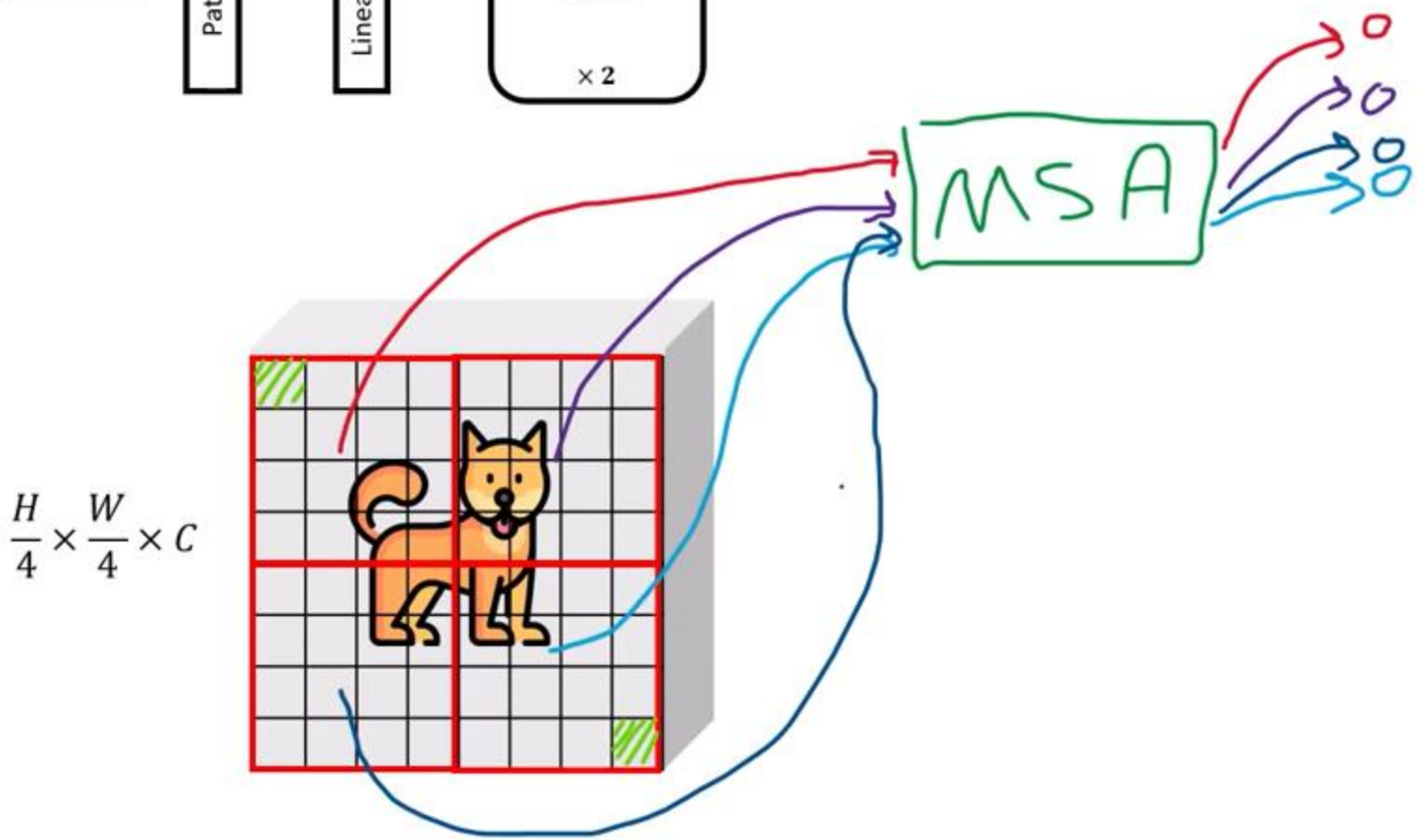
Images
Patch Partition
Linear Embedding
Swin Transformer Block
$\times 2$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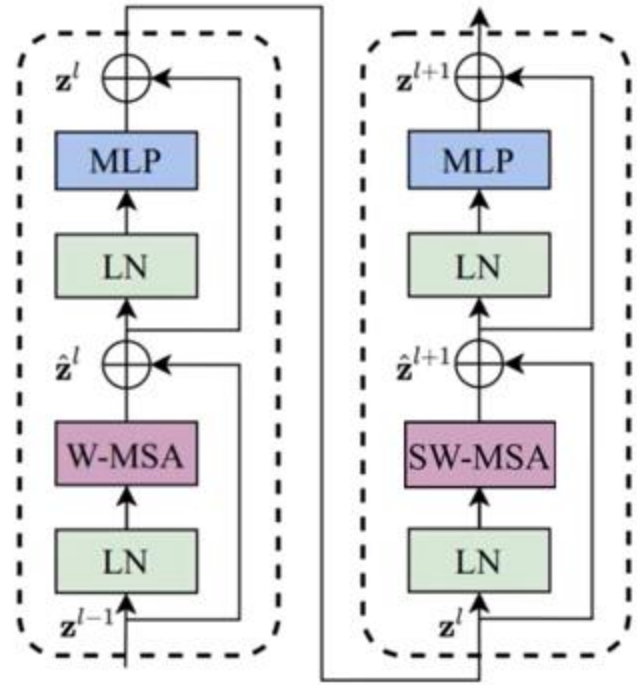
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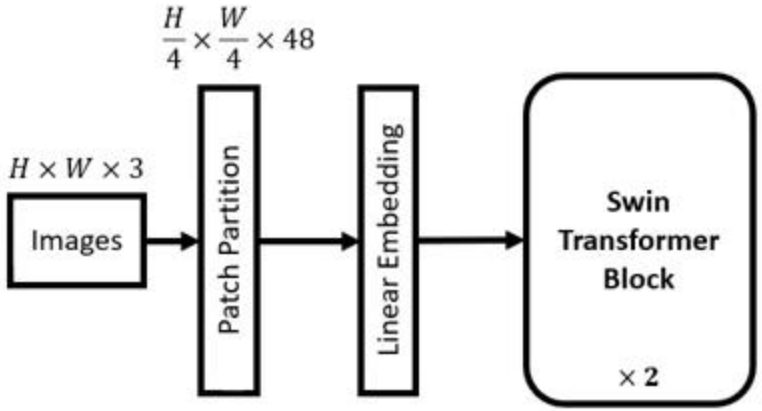
SW-MSA
LN
$\mathbf{z}^l$

W-MSA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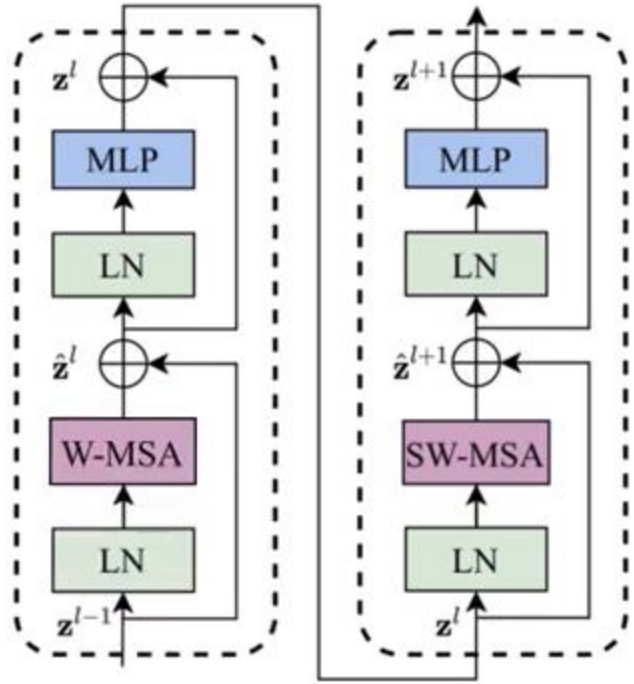
Images
Patch Partition
Linear Embedding
Swin Transformer Block
$\times 2$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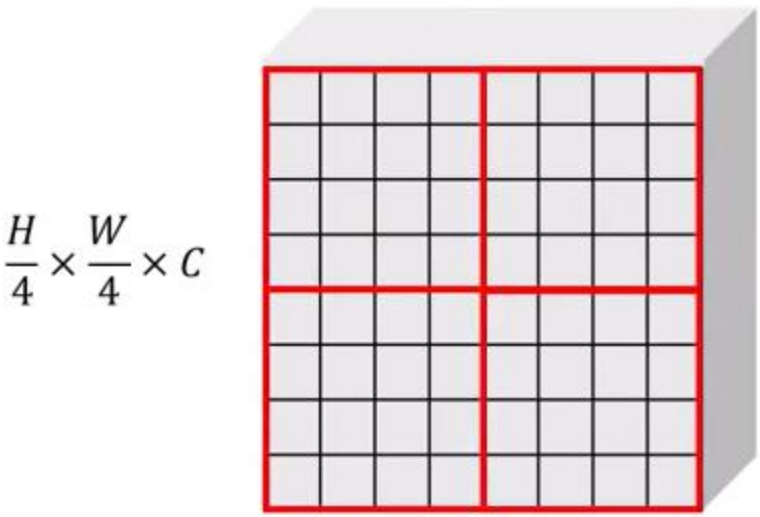
LN
$\mathbf{z}^{l}$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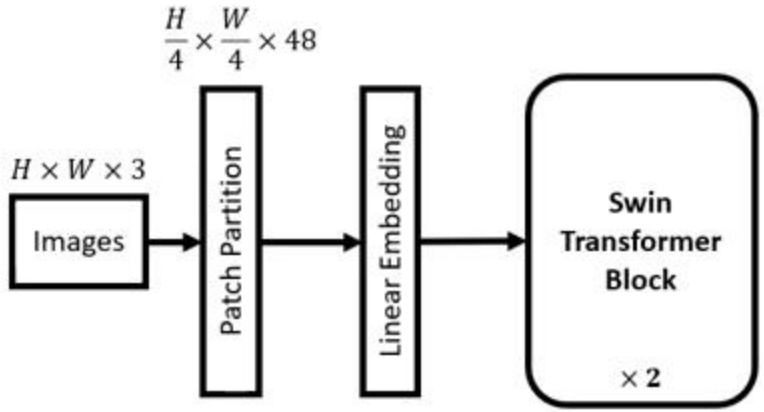
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Patch Partition
Linear Embedding
Swin Transformer Block
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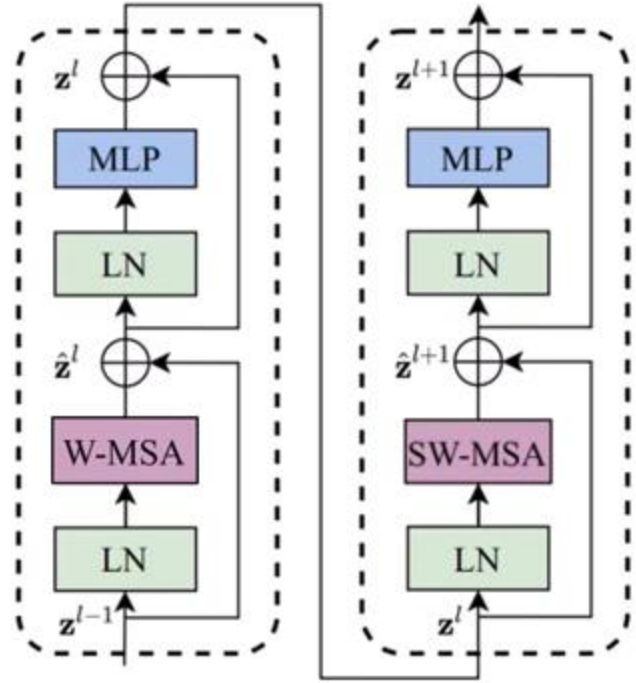
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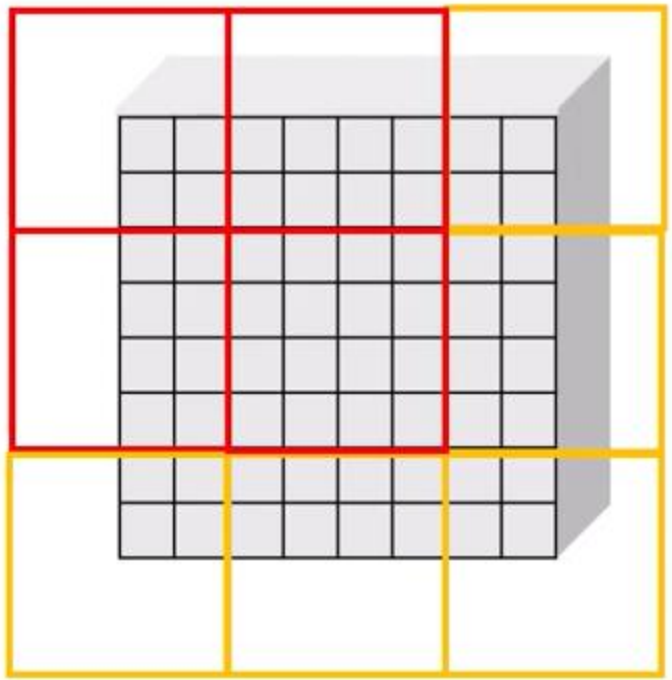
SW-MSA
LN
$\mathbf{z}^l$



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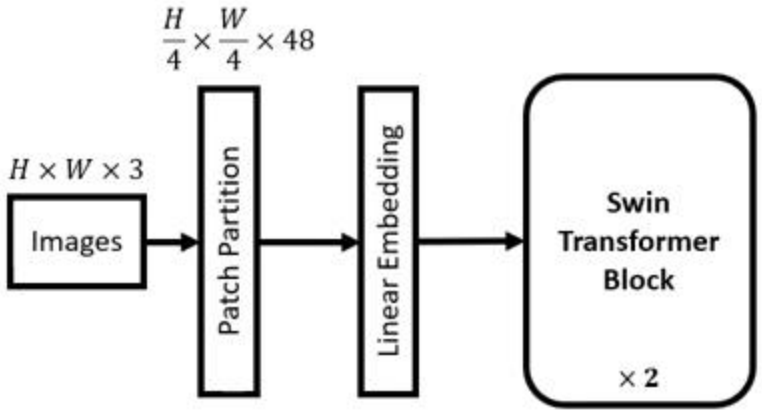
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Linear Embedding
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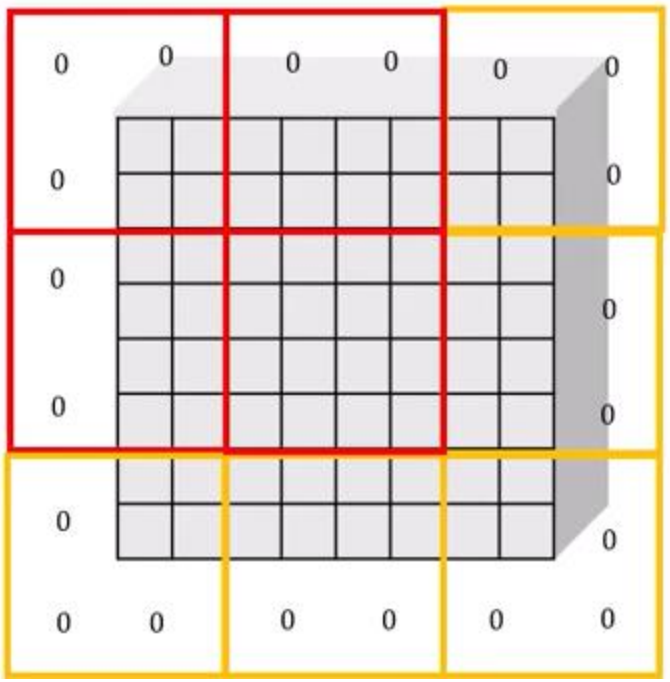
× 2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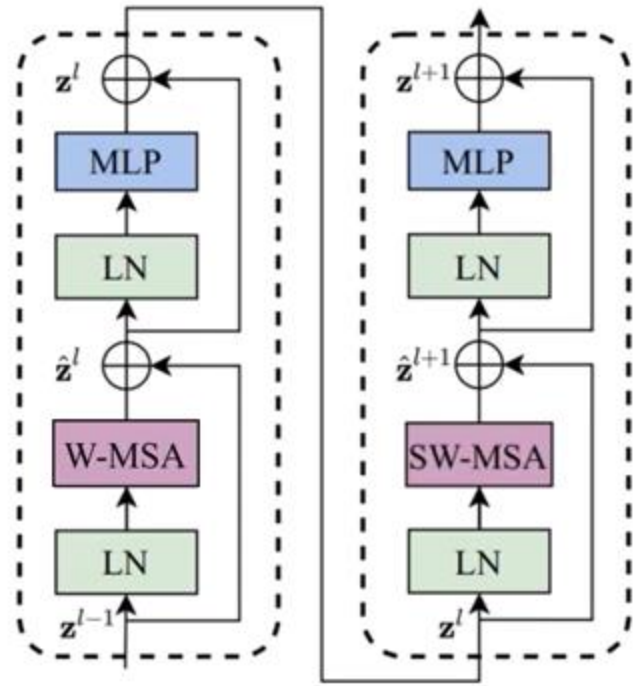
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$\hat{\mathbf{z}}^{l}$
W-MSA
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LN
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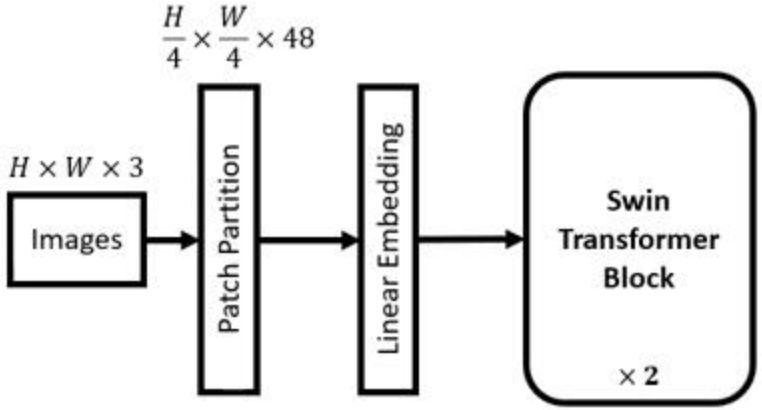
SW-MSA
LN
$\mathbf{z}^{l}$

SW-MSA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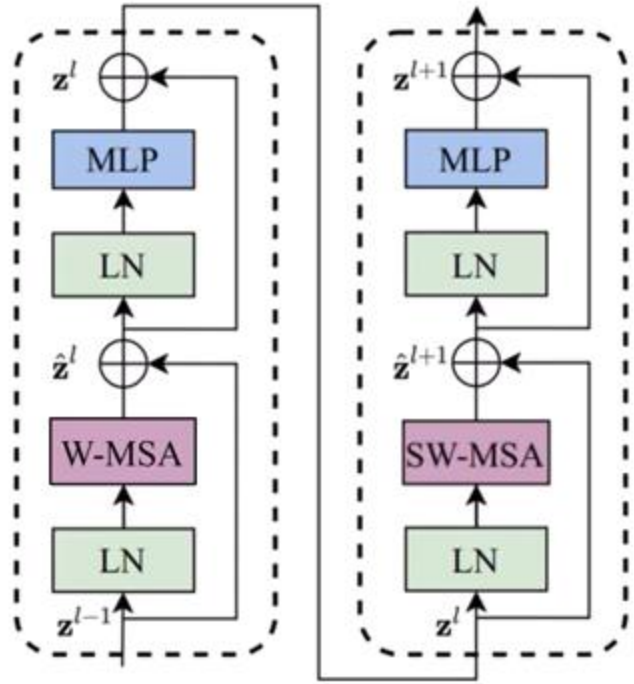
Images
Patch Partition
Linear Embedding
Swin Transformer Block
× 2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W-MSA
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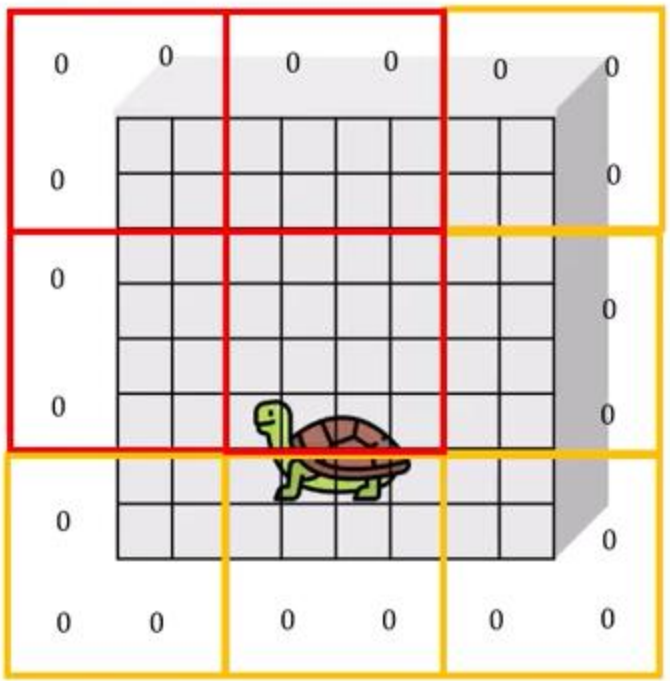
SW-MSA
LN
$\mathbf{z}^l$



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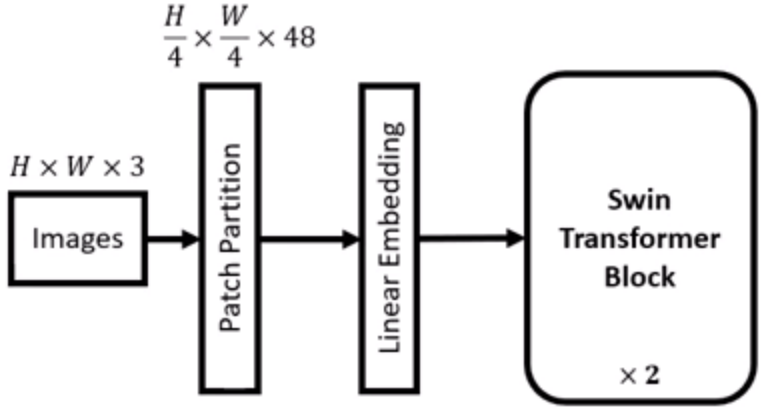
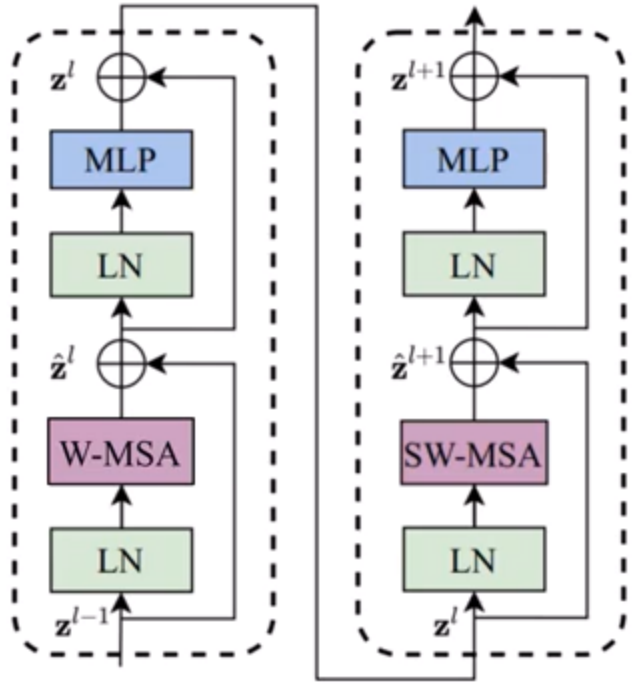
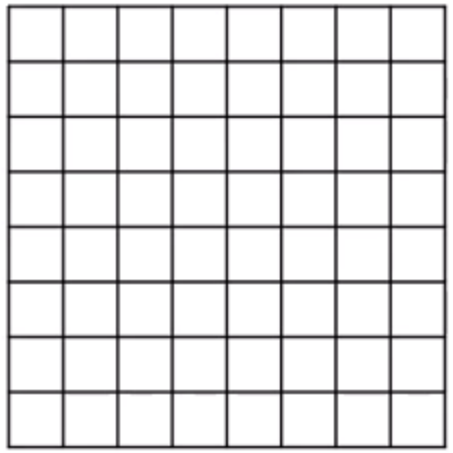
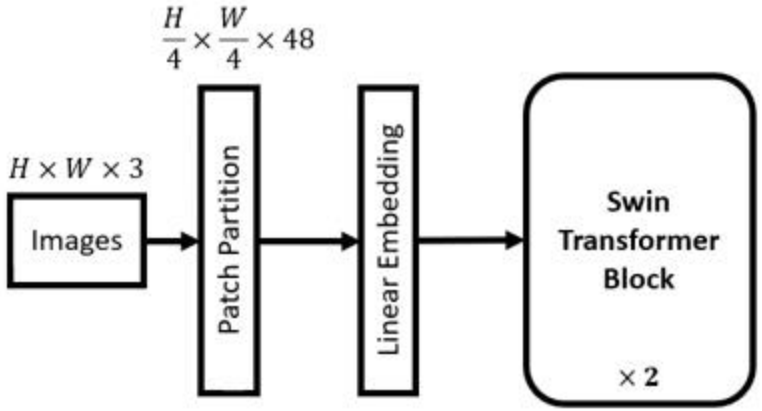


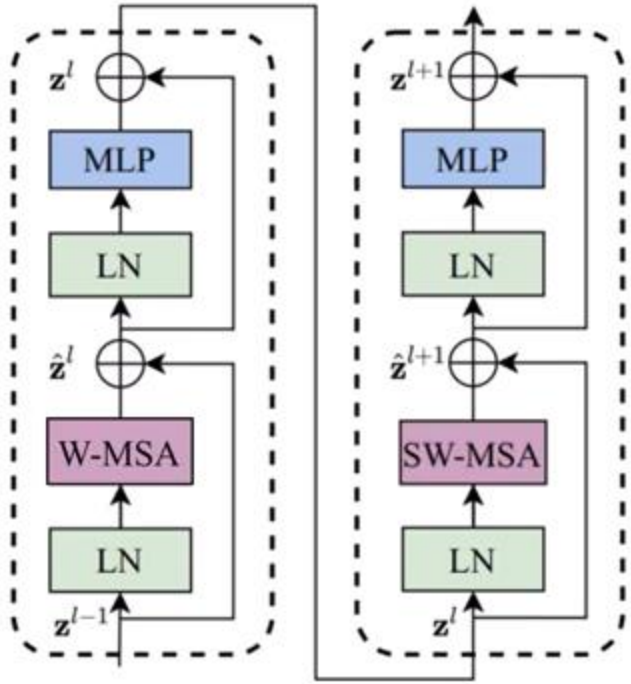




Original Patches

SW-MSA


$\frac{H}{4} \times \frac{W}{4} \times 48$
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
Swin Transformer Block
$\times 2$


$\mathbf{z}^{l}$
MLP
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W-MSA
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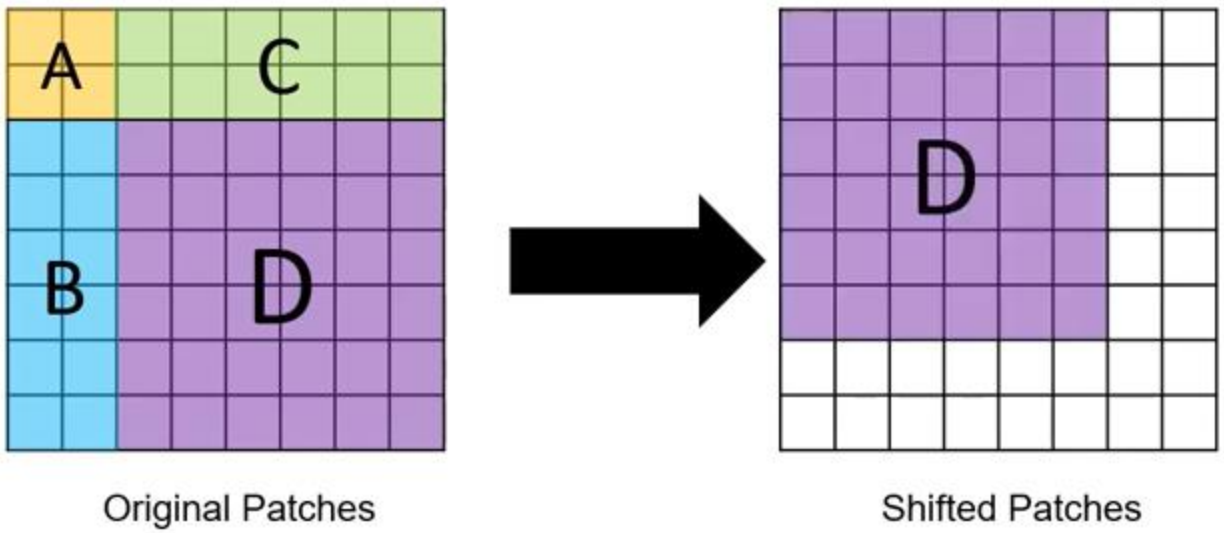
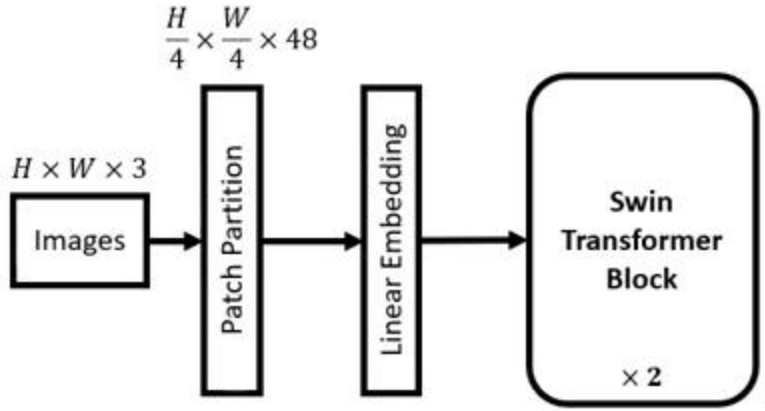
SW-MSA
LN
$\mathbf{z}^{l}$


A
C
B
D
D
Original Patches
Shifted Patches

SW-MSA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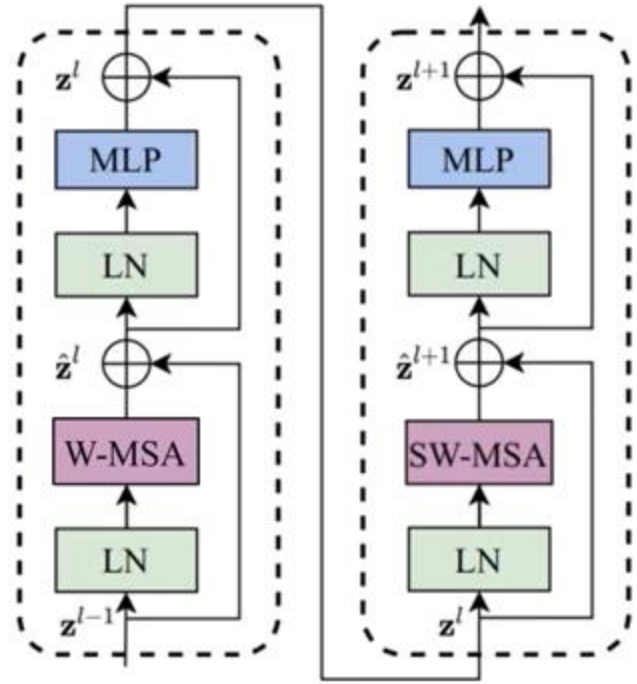
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
Swin Transformer Block
$\times 2$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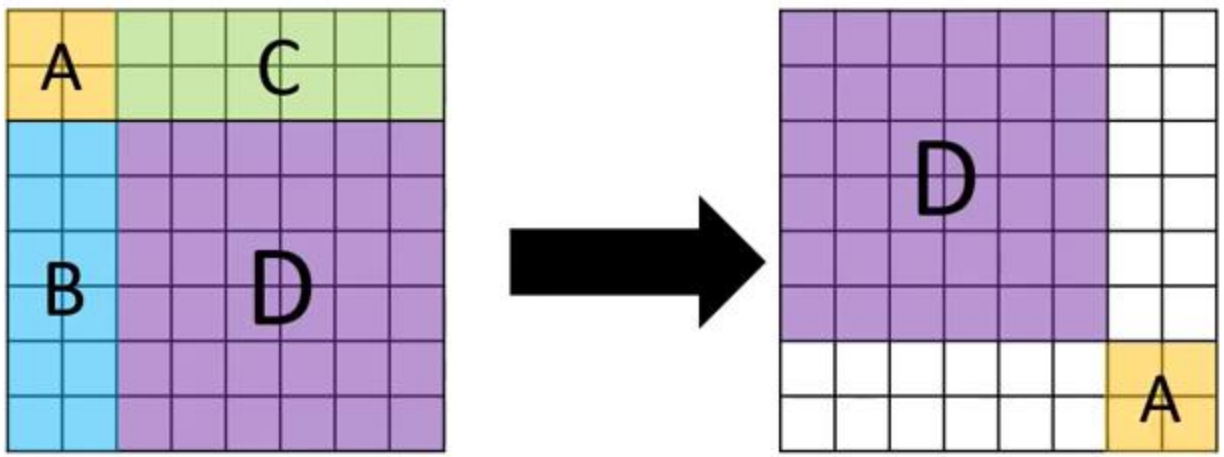
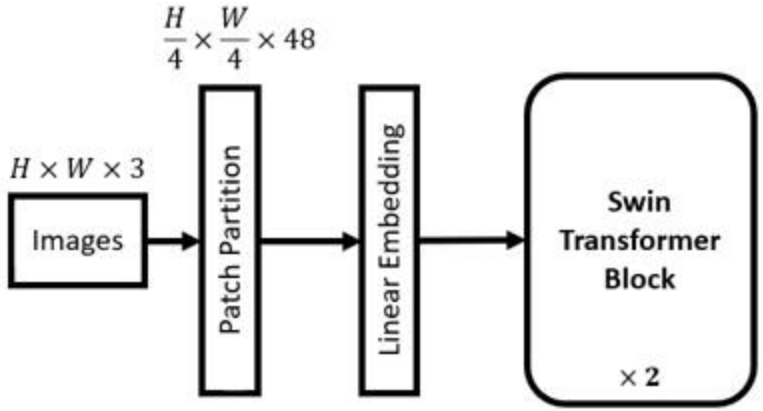
SW-MSA
LN
$\mathbf{z}^{l}$


A
C
B
D
D
A
Original Patches
Shifted Patches

SW-MSA


$\frac{H}{4} \times \frac{W}{4} \times 48$
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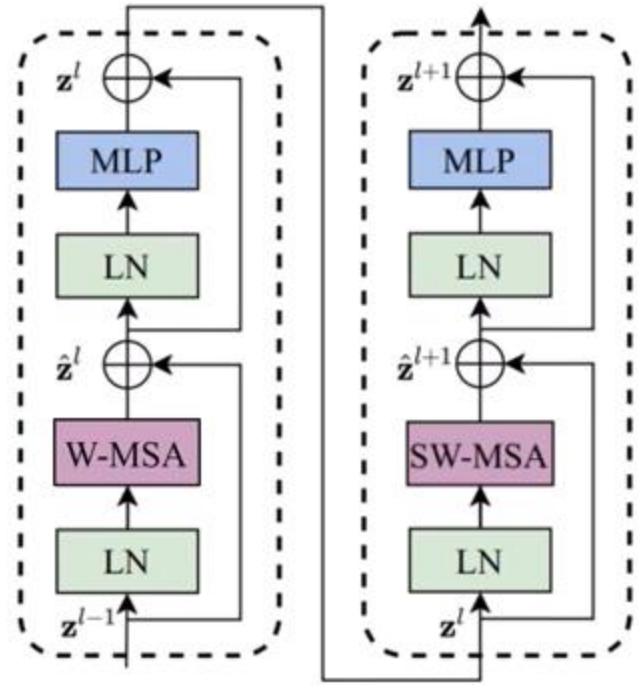
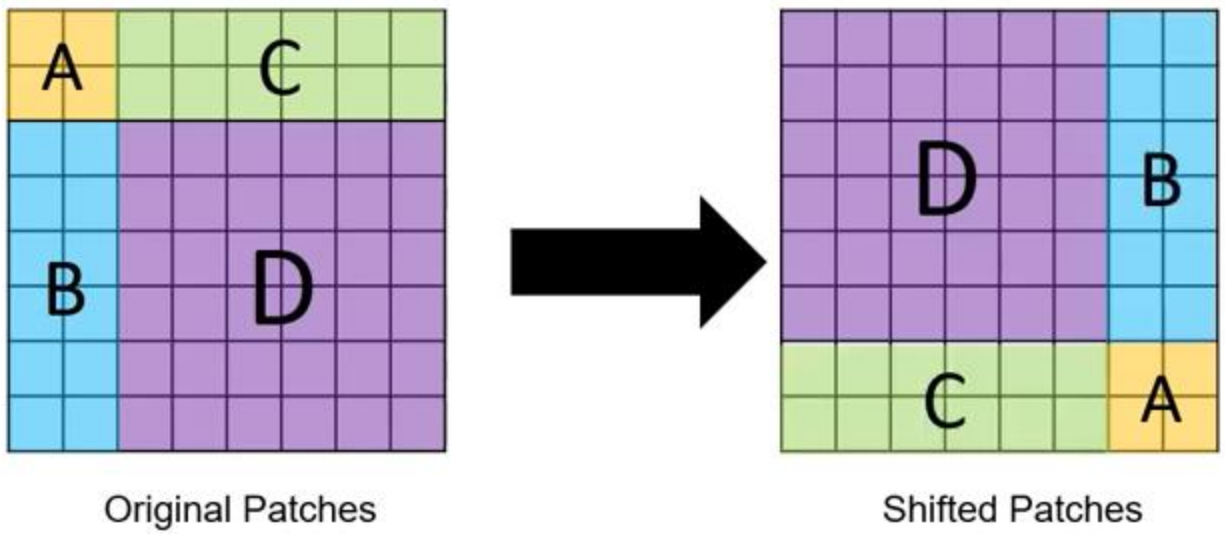
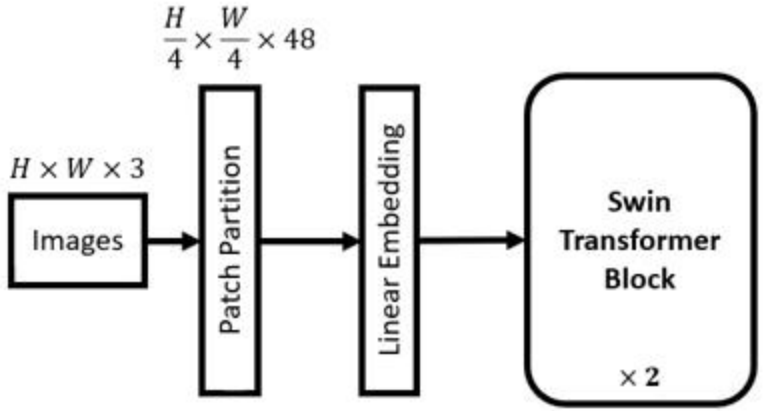
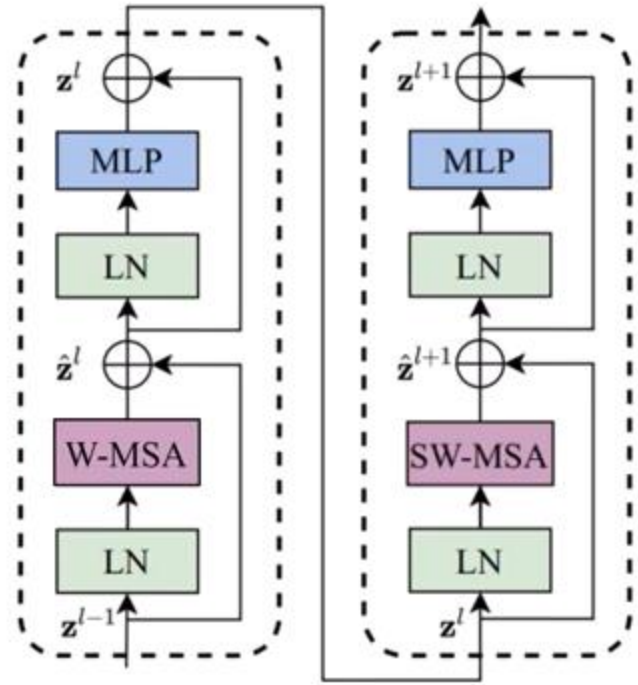
Swin Transformer Block
$\times 2$

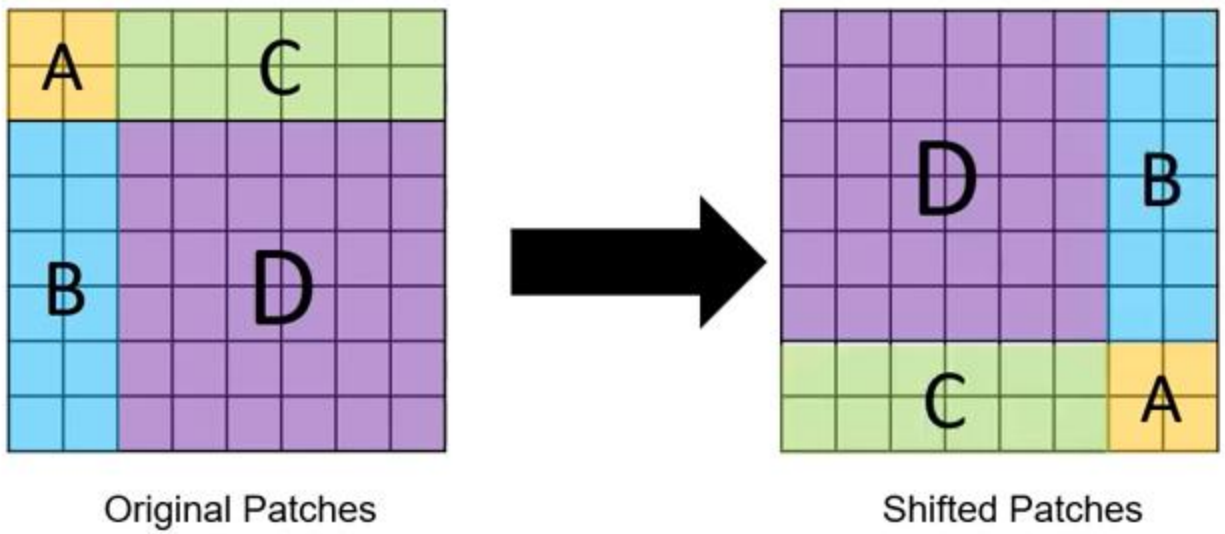

$\mathbf{z}^{l}$
MLP
LN
$\hat{\mathbf{z}}^{l}$
W-MSA
LN
$\mathbf{z}^{l-1}$
$\mathbf{z}^{l+1}$
MLP
LN
$\hat{\mathbf{z}}^{l+1}$
SW-MSA
LN
$\mathbf{z}^{l}$


A
C
B
D
D
B
C
A
Original Patches
Shifted Patches

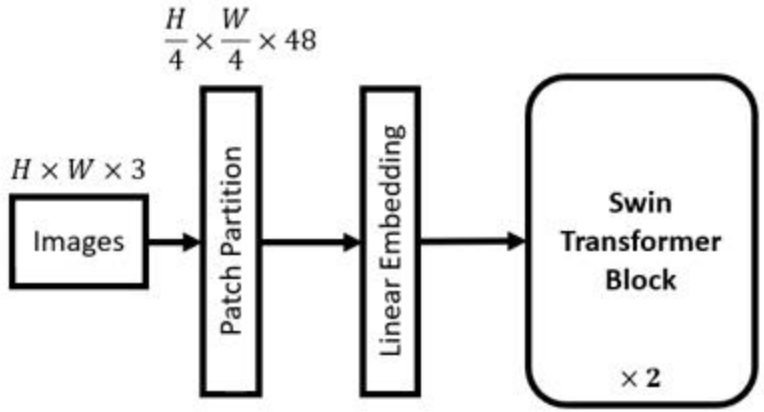
SW-MSA


$\frac{H}{4} \times \frac{W}{4} \times 48$
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
Swin Transformer Block
$\times 2$

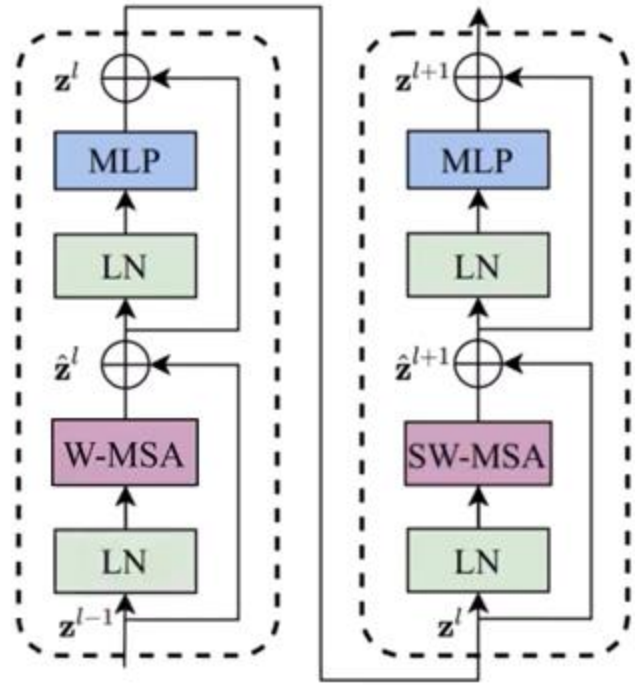

$\mathbf{z}^{l}$
MLP
LN
$\hat{\mathbf{z}}^{l}$
W-MSA
LN
$\mathbf{z}^{l-1}$
$\mathbf{z}^{l+1}$
MLP
LN
$\hat{\mathbf{z}}^{l+1}$
SW-MSA
LN
$\mathbf{z}^{l}$

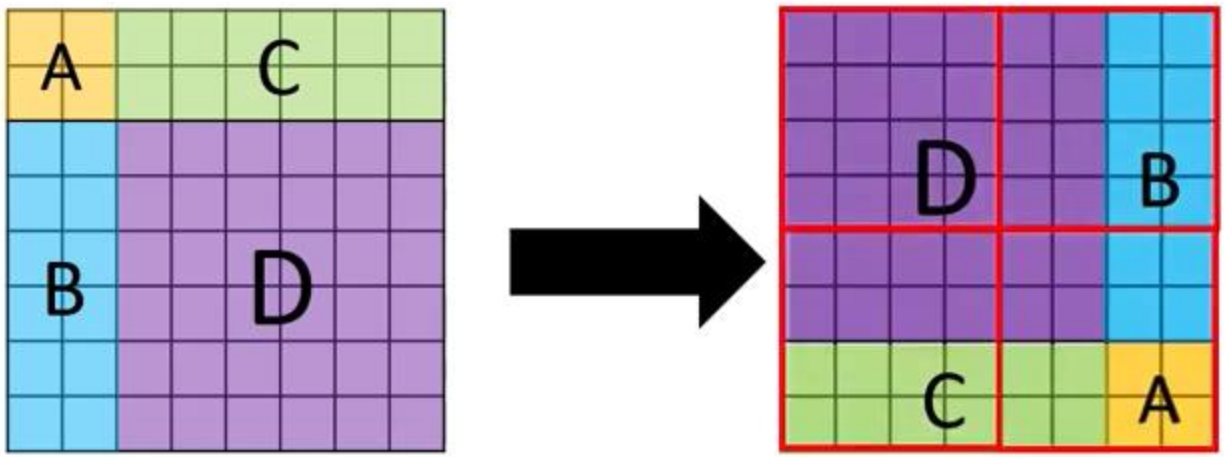

A
C
B
D
D
B
C
A
Original Patches
Shifted Patches

SW-MSA



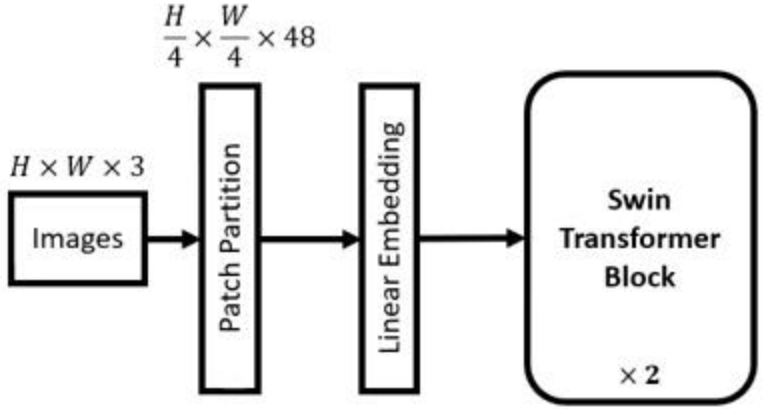
SW-MSA



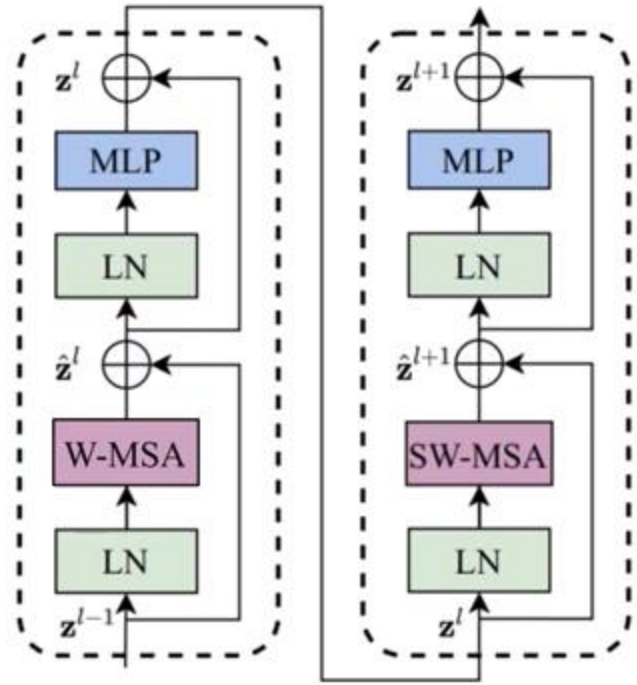


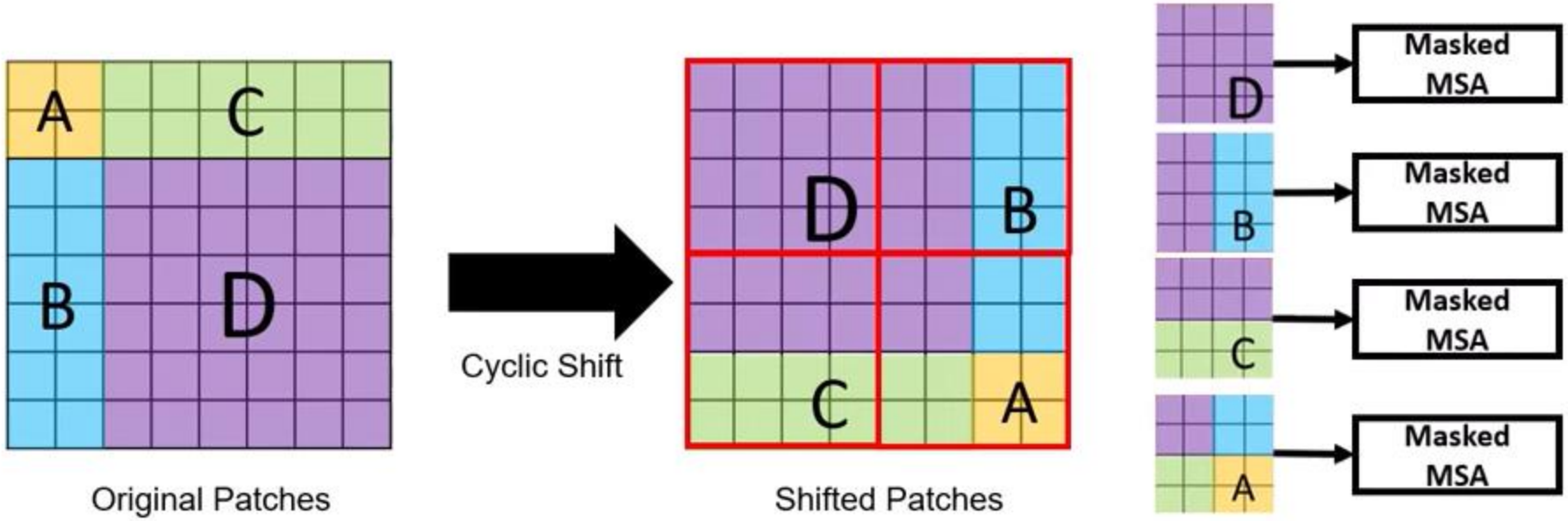
Original Patches

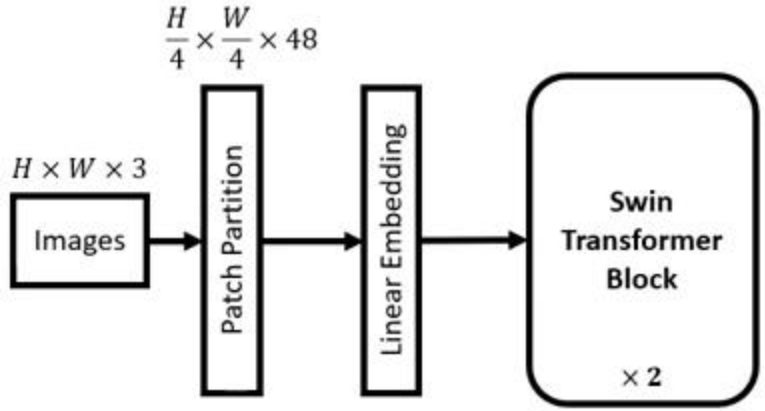
Shifted Patches


$\frac{H}{4} \times \frac{W}{4} \times 48$
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
Swin Transformer Block
× 2

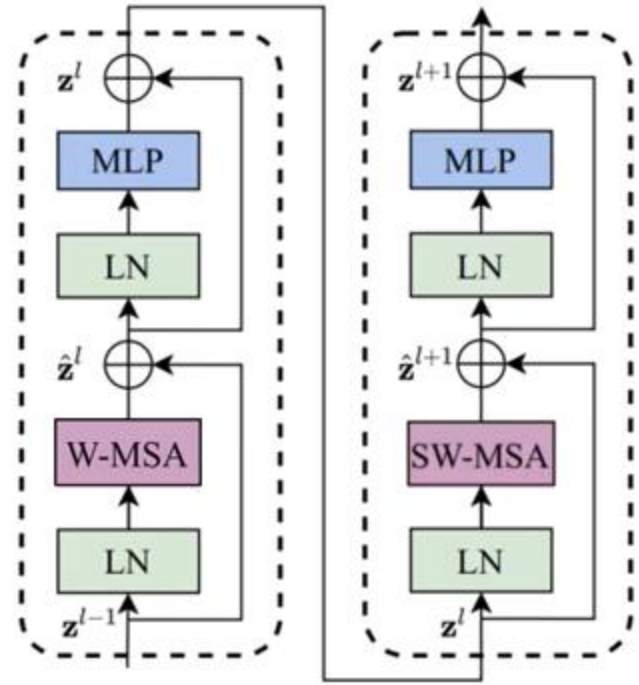
SW-MSA

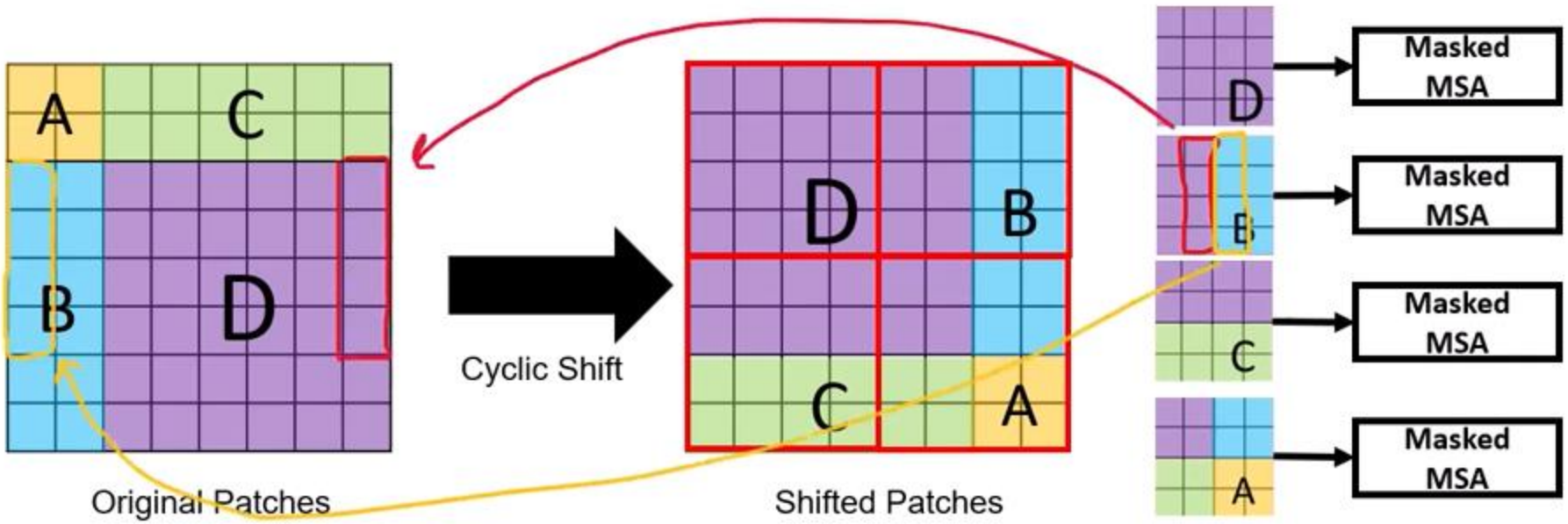

$\mathbf{z}^l$
MLP
LN
$\hat{\mathbf{z}}^l$
W-MSA
LN
$\mathbf{z}^{l-1}$
$\mathbf{z}^{l+1}$
MLP
LN
$\hat{\mathbf{z}}^{l+1}$
SW-MSA
LN
$\mathbf{z}^l$

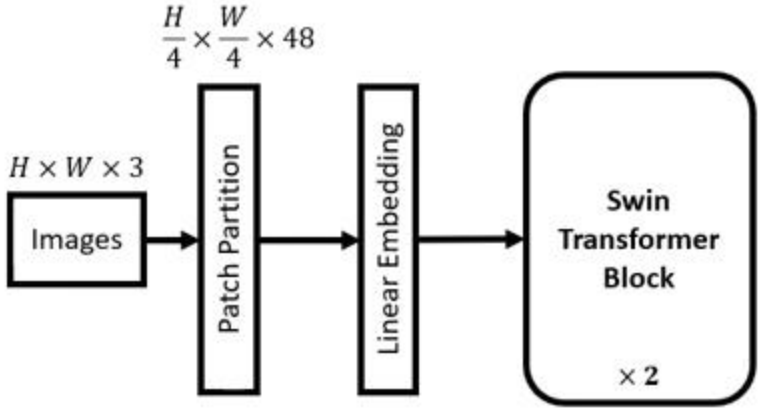

A
C
B
D
Original Patches
Cyclic Shift
D
B
C
A
Shifted Patches
D
B
C
A
Masked MSA
Masked MSA
Masked MSA
Masked MSA


$\frac{H}{4} \times \frac{W}{4} \times 48$
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
Swin Transformer Block
× 2

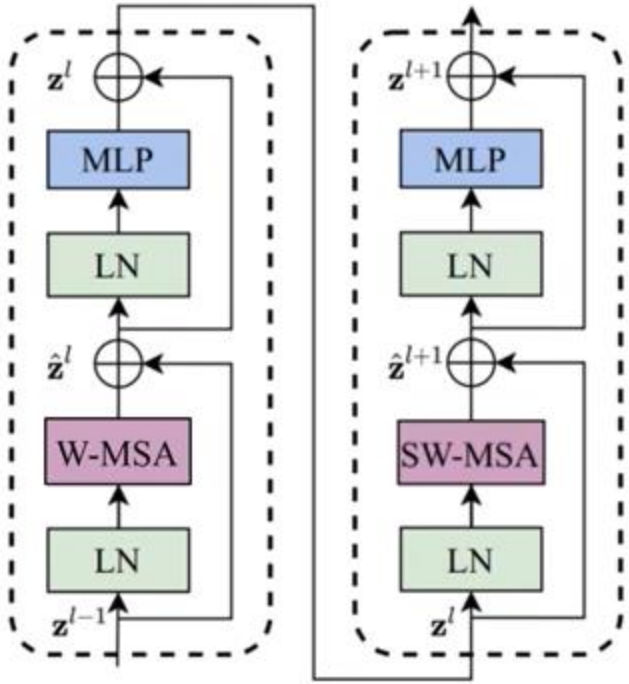
SW-MSA

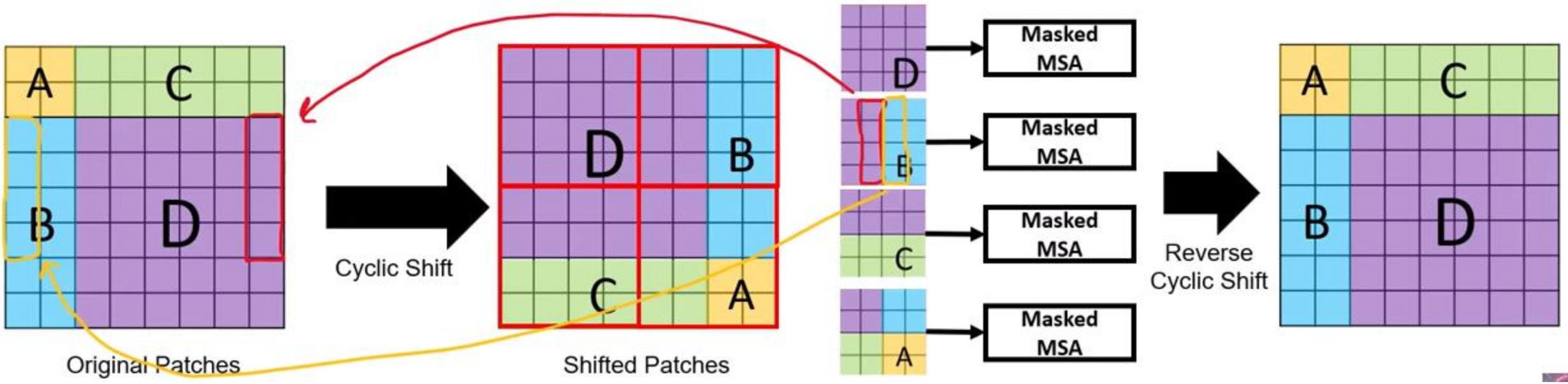

$\mathbf{z}^{l}$
MLP
LN
$\hat{\mathbf{z}}^{l}$
W-MSA
LN
$\mathbf{z}^{l-1}$
$\mathbf{z}^{l+1}$
MLP
LN
$\hat{\mathbf{z}}^{l+1}$
SW-MSA
LN
$\mathbf{z}^{l}$


A
C
B
D
Original Patches
Cyclic Shift
D
B
C
A
Shifted Patches
D
B
C
A
Masked MSA
Masked MSA
Masked MSA
Masked MSA


$\frac{H}{4} \times \frac{W}{4} \times 48$
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
Swin Transformer Block
× 2

SW-MSA


z^l
MLP
LN
$\hat{z}^l$
W-MSA
LN
z^{l-1}
z^{l+1}
MLP
LN
$\hat{z}^{l+1}$
SW-MSA
LN
z^l


A
C
B
D
Original Patches
Cyclic Shift
D
B
C
A
Shifted Patches
D
B
C
A
Masked MSA
Masked MSA
Masked MSA
Masked MSA
Reverse Cyclic Shift
A
C
B
D

```
222         if self.shift_size > 0:
223             # calculate attention mask for SW-MSA
224             H, W = self.input_resolution
225             img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
226             h_slices = (slice(0, -self.window_size),
227                         slice(-self.window_size, -self.shift_size),
228                         slice(-self.shift_size, None))
229             w_slices = (slice(0, -self.window_size),
230                         slice(-self.window_size, -self.shift_size),
231                         slice(-self.shift_size, None))
232             cnt = 0
233             for h in h_slices:
234                 for w in w_slices:
235                     img_mask[:, h, w, :] = cnt
236                     cnt += 1
237 
238             mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
239             mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
240             attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
241             attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
242         else:
243             attn_mask = None
```

```
222         if self.shift_size > 0:
223             # calculate attention mask for SW-MSA
224             H, W = self.input_resolution
225             img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
226             h_slices = (slice(0, -self.window_size), [0: -4]
227                         slice(-self.window_size, -self.shift_size),[-4: -2]
228                         slice(-self.shift_size, None))[-2: ]
229             w_slices = (slice(0, -self.window_size),[0: -4]
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```

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```
222         if self.shift_size > 0:
223             # calculate attention mask for SW-MSA
224             H, W = self.input_resolution
225             img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
226             h_slices = (slice(0, -self.window_size), [0: -4]
227                         slice(-self.window_size, -self.shift_size),[-4: -2]
228                         slice(-self.shift_size, None))[-2: ]
229             w_slices = (slice(0, -self.window_size),[0: -4]
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241             attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
242         else:
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```

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Assumptions:

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window_size = 4

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```python
        if self.shift_size > 0:
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                        slice(-self.shift_size, None)) [-2: ]
            w_slices = (slice(0, -self.window_size), [0: -4]
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        else:
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```

0	0	0	0	1	1	0	0
0	0	0	0	1	1	0	0
0	0	0	0	1	1	0	0
0	0	0	0	1	1	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Assumptions:

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window_size = 4

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```python
        if self.shift_size > 0:
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                        slice(-self.window_size, -self.shift_size),[-4: -2]
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                    cnt += 1

            mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
            mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
            attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
            attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
        else:
            attn_mask = None
```

0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Assumptions:

H = W = 8

window_size = 4

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```
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```

0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
3	3	3	3	0	0	0	0
3	3	3	3	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Assumptions:

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        if self.shift_size > 0:
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                    cnt += 1

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```

0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
3	3	3	3	4	4	0	0
3	3	3	3	4	4	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```
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228                         slice(-self.shift_size, None))[-2: ]
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```

0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
3	3	3	3	4	4	5	5
3	3	3	3	4	4	5	5
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Assumptions:

H = W = 8

window_size = 4

shift_size = 2

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        if self.shift_size > 0:
            # calculate attention mask for SW-MSA
            H, W = self.input_resolution
            img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
            h_slices = (slice(0, -self.window_size), [0: -4]
                        slice(-self.window_size, -self.shift_size),[-4: -2]
                        slice(-self.shift_size, None))[-2: ]
            w_slices = (slice(0, -self.window_size), [0: -4]
                        slice(-self.window_size, -self.shift_size),[-4: -2]
                        slice(-self.shift_size, None)) [-2: ]
            cnt = 0
            for h in h_slices:
                for w in w_slices:
                    img_mask[:, h, w, :] = cnt
                    cnt += 1

            mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
            mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
            attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
            attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
        else:
            attn_mask = None
```

0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
3	3	3	3	4	4	5	5
3	3	3	3	4	4	5	5
6	6	6	6	0	0	0	0
6	6	6	6	0	0	0	0

Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```
222         if self.shift_size > 0:
223             # calculate attention mask for SW-MSA
224             H, W = self.input_resolution
225             img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
226             h_slices = (slice(0, -self.window_size), [0: -4]
227                         slice(-self.window_size, -self.shift_size),[-4: -2]
228                         slice(-self.shift_size, None))[-2: ]
229             w_slices = (slice(0, -self.window_size), [0: -4]
230                         slice(-self.window_size, -self.shift_size),[-4: -2]
231                         slice(-self.shift_size, None)) [-2: ]
232             cnt = 0
233             for h in h_slices:
234                 for w in w_slices:
235                     img_mask[:, h, w, :] = cnt
236                     cnt += 1
237
238             mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
239             mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
240             attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
241             attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
242         else:
243             attn_mask = None
```

0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
3	3	3	3	4	4	5	5
3	3	3	3	4	4	5	5
6	6	6	6	7	7	0	0
6	6	6	6	7	7	0	0

Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```
222         if self.shift_size > 0:
223             # calculate attention mask for SW-MSA
224             H, W = self.input_resolution
225             img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
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227                         slice(-self.window_size, -self.shift_size), [-4: -2]
228                         slice(-self.shift_size, None))[-2: ]
229             w_slices = (slice(0, -self.window_size), [0: -4]
230                         slice(-self.window_size, -self.shift_size), [-4: -2]
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237
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239             mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
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242         else:
243             attn_mask = None
```

0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
0	0	0	0	1	1	2	2
3	3	3	3	4	4	5	5
3	3	3	3	4	4	5	5
6	6	6	6	7	7	8	8
6	6	6	6	7	7	8	8

Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```python
        if self.shift_size > 0:
            # calculate attention mask for SW-MSA
            H, W = self.input_resolution
            img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
            h_slices = (slice(0, -self.window_size), [0: -4]
                        slice(-self.window_size, -self.shift_size), [-4: -2]
                        slice(-self.shift_size, None))[-2: ]
            w_slices = (slice(0, -self.window_size), [0: -4]
                        slice(-self.window_size, -self.shift_size), [-4: -2]
                        slice(-self.shift_size, None)) [-2: ]
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            for h in h_slices:
                for w in w_slices:
                    img_mask[:, h, w, :] = cnt
                    cnt += 1

            mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
            mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
            attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
            attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
        else:
            attn_mask = None
```

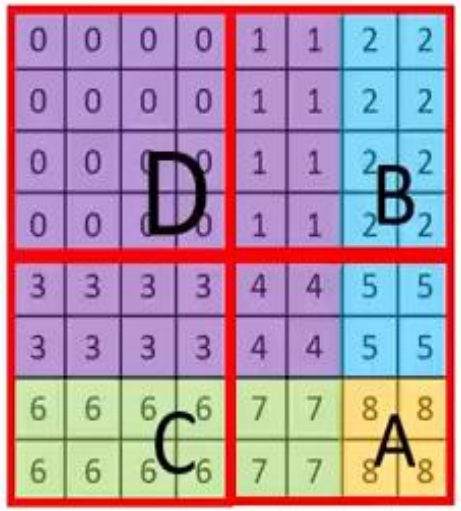

Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```
222         if self.shift_size > 0:
223             # calculate attention mask for SW-MSA
224             H, W = self.input_resolution
225             img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
226             h_slices = (slice(0, -self.window_size), [0: -4]
227                         slice(-self.window_size, -self.shift_size), [-4: -2]
228                         slice(-self.shift_size, None))[-2: ]
229             w_slices = (slice(0, -self.window_size), [0: -4]
230                         slice(-self.window_size, -self.shift_size), [-4: -2]
231                         slice(-self.shift_size, None)) [-2: ]
232             cnt = 0
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235                     img_mask[:, h, w, :] = cnt
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240         attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
241         attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
242     else:
243         attn_mask = None
```
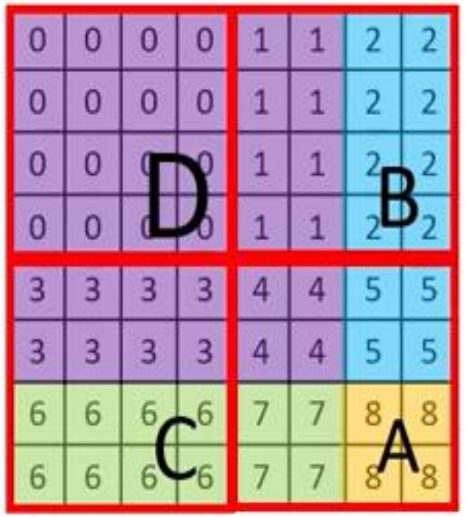

4 4 4



Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```
222         if self.shift_size > 0:
223             # calculate attention mask for SW-MSA
224             H, W = self.input_resolution
225             img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
226             h_slices = (slice(0, -self.window_size), [0: -4]
227                         slice(-self.window_size, -self.shift_size),[-4: -2]
228                         slice(-self.shift_size, None))[-2: ]
229             w_slices = (slice(0, -self.window_size), [0: -4]
230                         slice(-self.window_size, -self.shift_size),[-4: -2]
231                         slice(-self.shift_size, None)) [-2: ]
232             cnt = 0
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234                 for w in w_slices:
235                     img_mask[:, h, w, :] = cnt
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238             mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
239             mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
240             attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
241             attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
242         else:
243             attn_mask = None
```
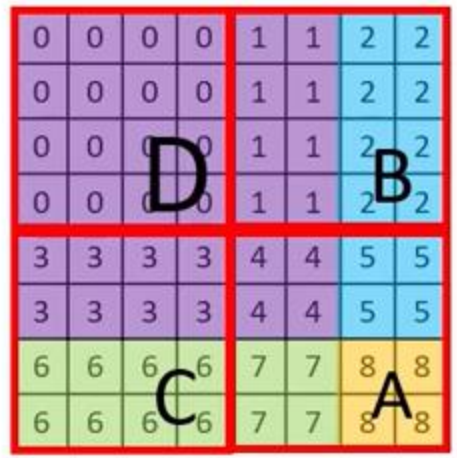

4 4 4

→ [4, 16]



Assumptions:

H = W = 8

window_size = 4

shift_size = 2

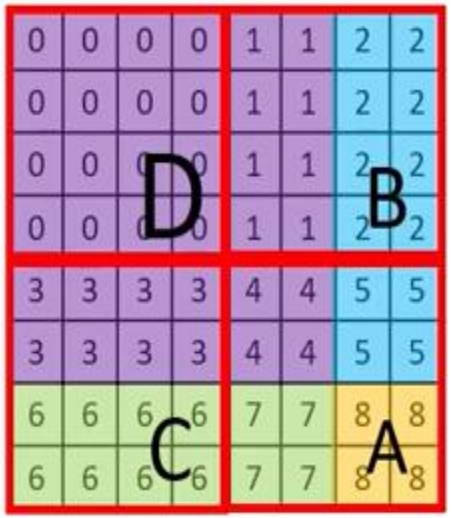
```python
        if self.shift_size > 0:
            # calculate attention mask for SW-MSA
            H, W = self.input_resolution
            img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
            h_slices = (slice(0, -self.window_size), [0: -4]
                        slice(-self.window_size, -self.shift_size), [-4: -2]
                        slice(-self.shift_size, None))[-2: ]
            w_slices = (slice(0, -self.window_size), [0: -4]
                        slice(-self.window_size, -self.shift_size), [-4: -2]
                        slice(-self.shift_size, None)) [-2: ]
            cnt = 0
            for h in h_slices:
                for w in w_slices:
                    img_mask[:, h, w, :] = cnt
                    cnt += 1

            mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
            mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
            attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
            attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
        else:
            attn_mask = None
```

[4,16,1]

[4,1,16]

4 4 4

[4,16]



Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```python
        if self.shift_size > 0:
            # calculate attention mask for SW-MSA
            H, W = self.input_resolution
            img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
            h_slices = (slice(0, -self.window_size), [0: -4]
                        slice(-self.window_size, -self.shift_size), [-4: -2]
                        slice(-self.shift_size, None)) [-2: ]
            w_slices = (slice(0, -self.window_size), [0: -4]
                        slice(-self.window_size, -self.shift_size), [-4: -2]
                        slice(-self.shift_size, None)) [-2: ]
            cnt = 0
            for h in h_slices:
                for w in w_slices:
                    img_mask[:, h, w, :] = cnt
                    cnt += 1

            mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
            mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
            attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
            attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
        else:
            attn_mask = None
```

[4,1,16]

[4,16,1]

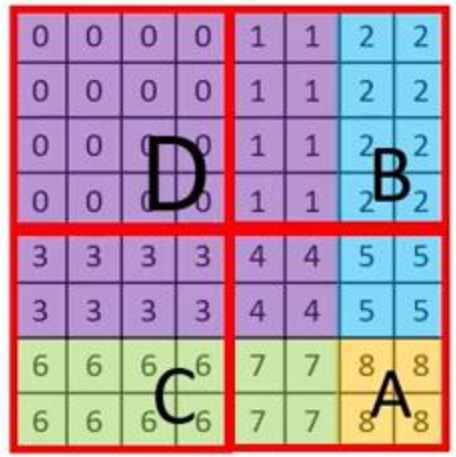
4 4 4

[4,16]

Different

Same

why?



Assumptions:

H = W = 8

window_size = 4

shift_size = 2

```python
if self.shift_size > 0:
    # calculate attention mask for SW-MSA
    H, W = self.input_resolution
    img_mask = torch.zeros((1, H, W, 1))  # 1 H W 1
    h_slices = (slice(0, -self.window_size), [0: -4]
                slice(-self.window_size, -self.shift_size), [-4: -2]
                slice(-self.shift_size, None)) [-2: ]
    w_slices = (slice(0, -self.window_size), [0: -4]
                slice(-self.window_size, -self.shift_size), [-4: -2]
                slice(-self.shift_size, None)) [-2: ]
    cnt = 0
    for h in h_slices:
        for w in w_slices:
            img_mask[:, h, w, :] = cnt
            cnt += 1

    mask_windows = window_partition(img_mask, self.window_size)  # nW, window_size, window_size, 1
    mask_windows = mask_windows.view(-1, self.window_size * self.window_size)
    attn_mask = mask_windows.unsqueeze(1) - mask_windows.unsqueeze(2)
    attn_mask = attn_mask.masked_fill(attn_mask != 0, float(-100.0)).masked_fill(attn_mask == 0, float(0.0))
else:
    attn_mask = None
```

[4,16,1]

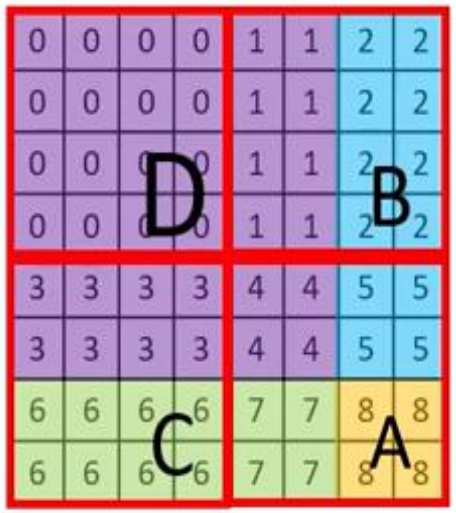
[4,1,16]

4 4 4

[4,16]

Different

Same



why?

Assumptions:

H = W = 8

window_size = 4

shift_size = 2

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

+attn_mask

3. Apply the softmax function to each input:

$$\text{softmax}(-100) = \frac{e^{-100}}{1} \approx 3.72 \times 10^{-44}$$

$$\text{softmax}(0) = \frac{e^{0}}{1} = 1$$

4. Normalize the outputs so that they sum to 1:

$$\text{softmax}(-100) \approx \frac{3.72 \times 10^{-44}}{1 + 3 \times 3.72 \times 10^{-44}} = \frac{3.72 \times 10^{-44}}{1} \approx 3.72 \times 10^{-44}$$

$$\text{softmax}(0) \approx \frac{1}{1 + 3 \times 3.72 \times 10^{-44}} = \frac{1}{1} = 1$$

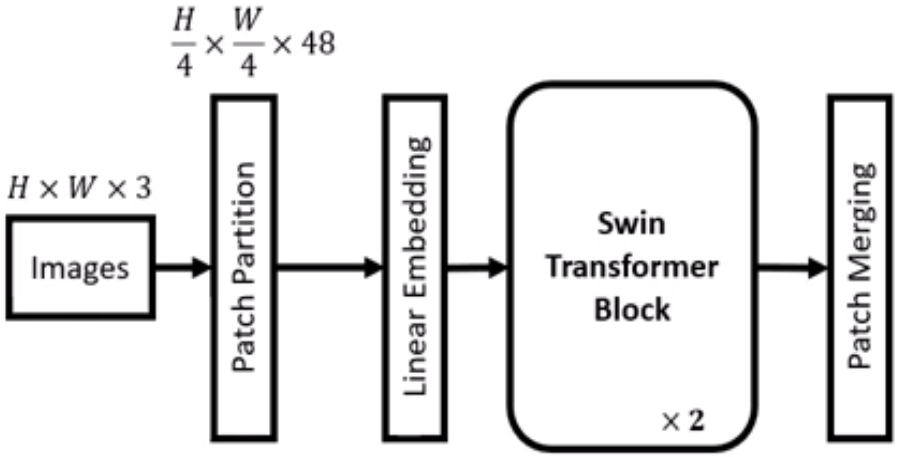
Since the terms 3.72×10^{-44} are exceedingly small compared to 1, the output for the softmax will effectively be:

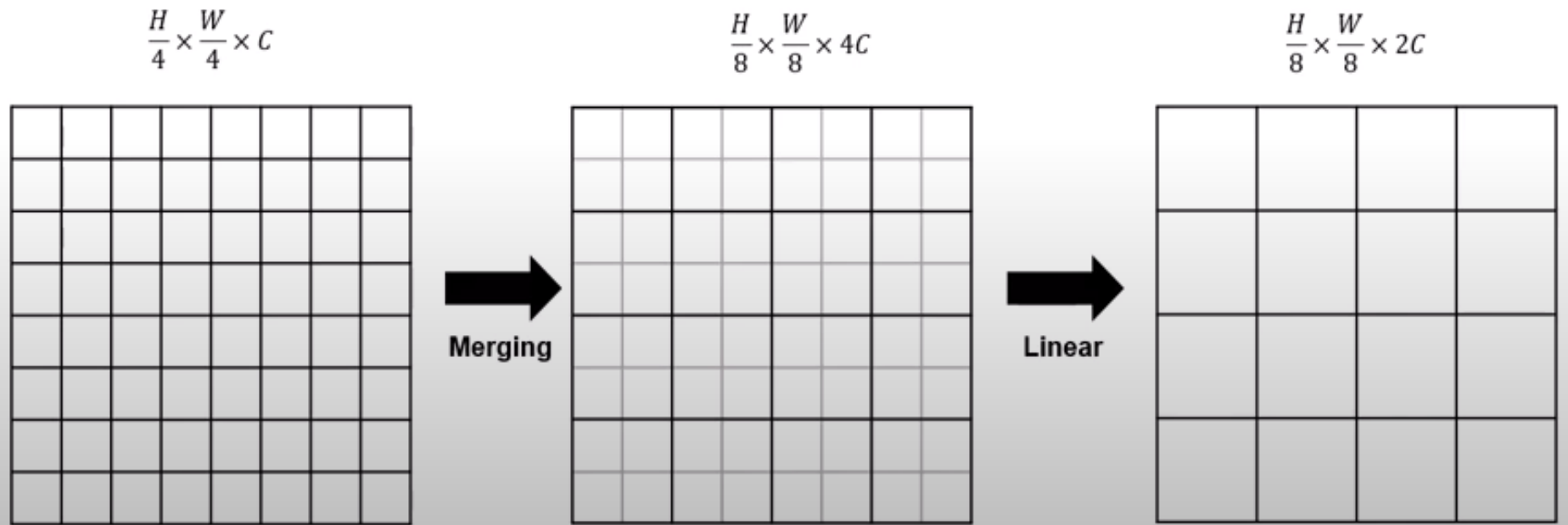
$$\text{softmax}([-100, -100, -100, 0]) = [3.72 \times 10^{-44}, 3.72 \times 10^{-44}, 3.72 \times 10^{-44}, 1]$$

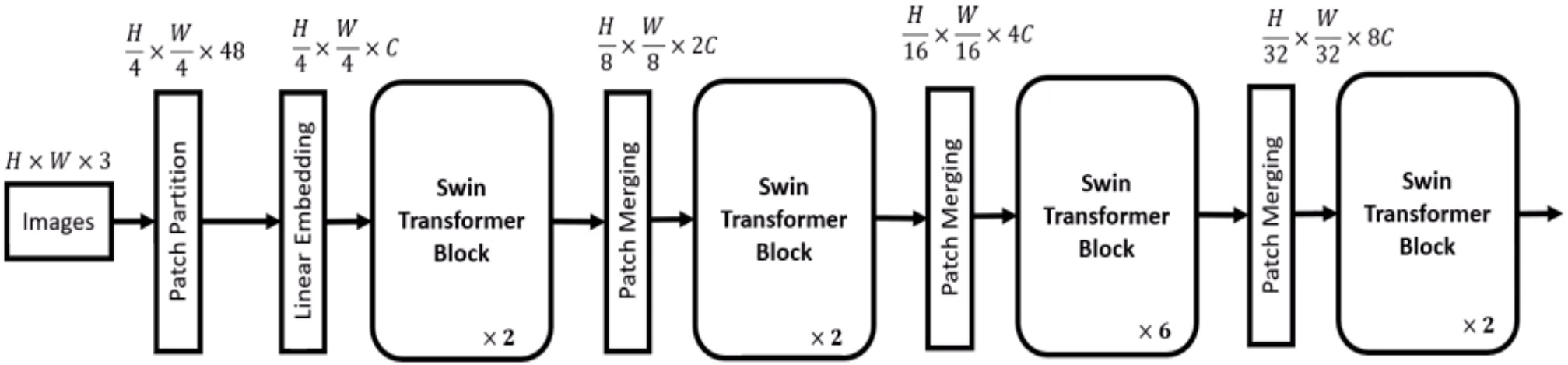
When normalized, the values will sum to 1:

$$\text{softmax}([-100, -100, -100, 0]) \approx [0, 0, 0, 1]$$

This indicates that the probability is almost entirely concentrated on the last input, which is 0, as it is significantly larger than the others.


$\frac{H}{4} \times \frac{W}{4} \times 48$
$H \times W \times 3$
Images
Patch Partition
Linear Embedding
Swin Transformer Block
$\times 2$
Patch Merging


$\frac{H}{4} \times \frac{W}{4} \times C$
Merging
$\frac{H}{8} \times \frac{W}{8} \times 4C$
Linear
$\frac{H}{8} \times \frac{W}{8} \times 2C$


$H \times W \times 3$
Images
Patch Partition
$\frac{H}{4} \times \frac{W}{4} \times 48$
Linear Embedding
$\frac{H}{4} \times \frac{W}{4} \times C$
Swin Transformer Block
$\times 2$
Patch Merging
$\frac{H}{8} \times \frac{W}{8} \times 2C$
Swin Transformer Block
$\times 2$
Patch Merging
$\frac{H}{16} \times \frac{W}{16} \times 4C$
Swin Transformer Block
$\times 6$
Patch Merging
$\frac{H}{32} \times \frac{W}{32} \times 8C$
Swin Transformer Block
$\times 2$

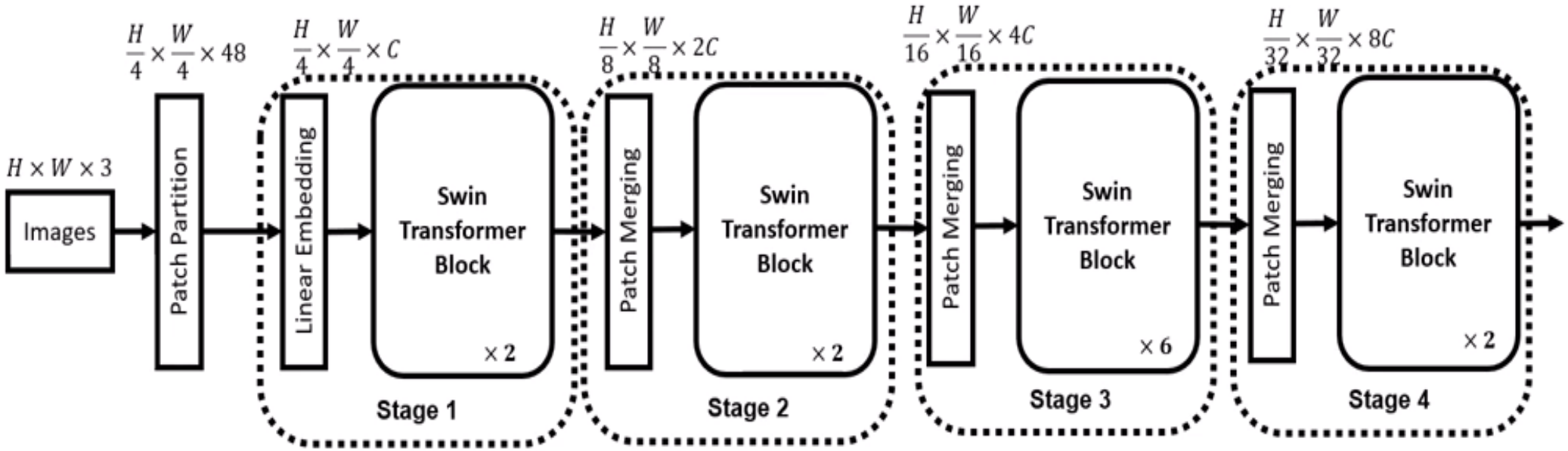


Image classification: Output of the last stage is passed through a linear layer.

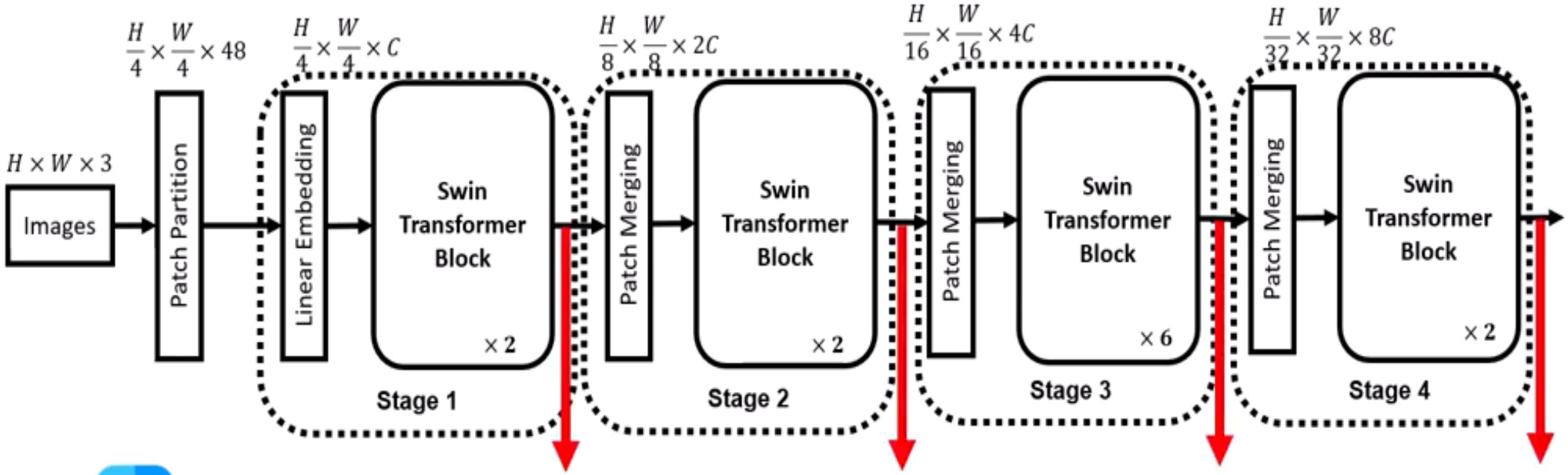


Image classification: Output of the last stage is passed through a linear layer.

Object detection and Image segmentation: Output of all the stages are used as features.

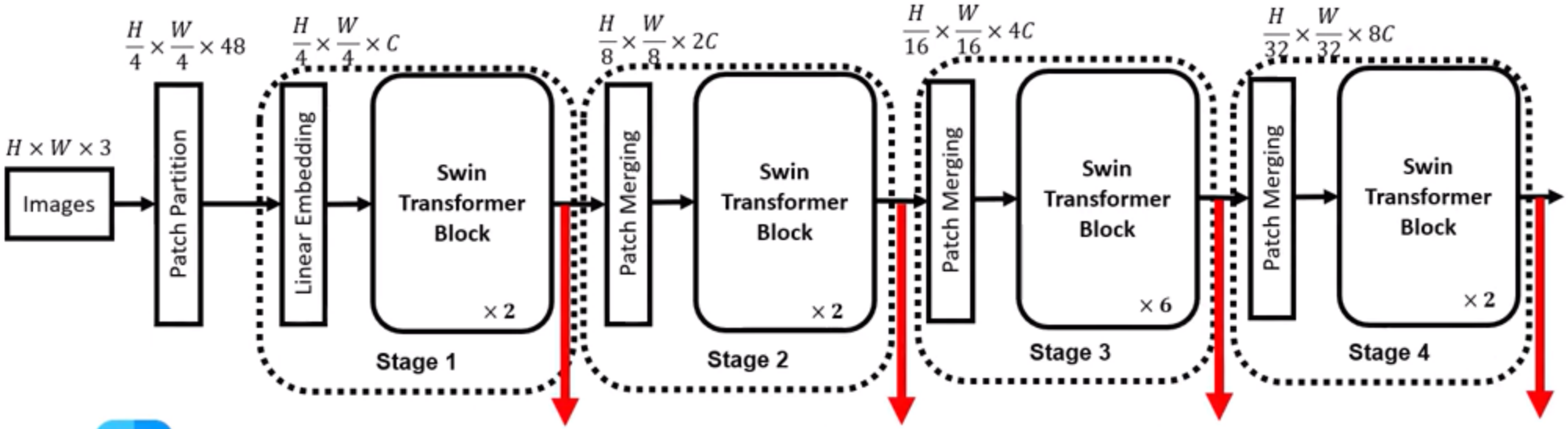


Image classification: Output of the last stage is passed through a linear layer.

Object detection and Image segmentation: Output of all the stages are used as features.

- 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 =$\{2, 2, 18, 2\}$

(a) Regular ImageNet-1K trained models

method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
RegNetY-4G [44]	224^2	21M	4.0G	1156.7	80.0
RegNetY-8G [44]	224^2	39M	8.0G	591.6	81.7
RegNetY-16G [44]	224^2	84M	16.0G	334.7	82.9
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 [57]	224^2	22M	4.6G	940.4	79.8
DeiT-B [57]	224^2	86M	17.5G	292.3	81.8
DeiT-B [57]	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 [34]	384^2	388M	204.6G	-	84.4
R-152x4 [34]	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	86.4
Swin-L	384^2	197M	103.9G	42.1	87.3

	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**

Table 4. Ablation study on the *shifted windows* approach and different position embedding methods on three benchmarks, using the Swin-T architecture. w/o shifting: all self-attention modules adopt regular window partitioning, without *shifting*; abs. pos.: absolute position embedding term of ViT; rel. pos.: the default settings with an additional relative position bias term (see Eq. (4)); app.: the first scaled dot-product term in Eq. (4).

Self-Attention with Relative Position Representations

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Abstract

Relying entirely on an attention mechanism, the Transformer introduced by Vaswani et al. (2017) achieves state-of-the-art results for machine translation. In contrast to recurrent and convolutional neural networks, it does not explicitly model relative or absolute position information in its structure. Instead, it requires adding representations of absolute positions to its inputs. In this work we present an alternative approach, extending the self-attention mechanism to efficiently consider representations of the relative positions, or distances between sequence elements. On the WMT 2014 English-to-German and English-to-French translation tasks, this approach yields improvements of 1.3 BLEU and

time dimension directly through their sequential structure. Non-recurrent models do not necessarily consider input elements sequentially and may hence require explicitly encoding position information to be able to use sequence order.

One common approach is to use position encodings which are combined with input elements to expose position information to the model. These position encodings can be a deterministic function of position (Sukhbaatar et al., 2015; Vaswani et al., 2017) or learned representations. Convolutional neural networks inherently capture relative positions within the kernel size of each convolution. They have been shown to still benefit from position encodings (Gehring et al., 2017), how-

Transformer

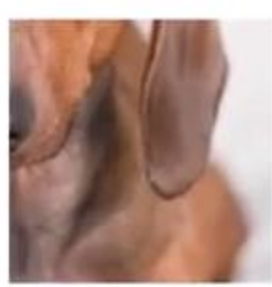
Out1 Out2 Out3 Out4

Transformer




Out4 Out2 Out3 Out1

Transformer




Out1 Out2 Out3 Out4

Transformer

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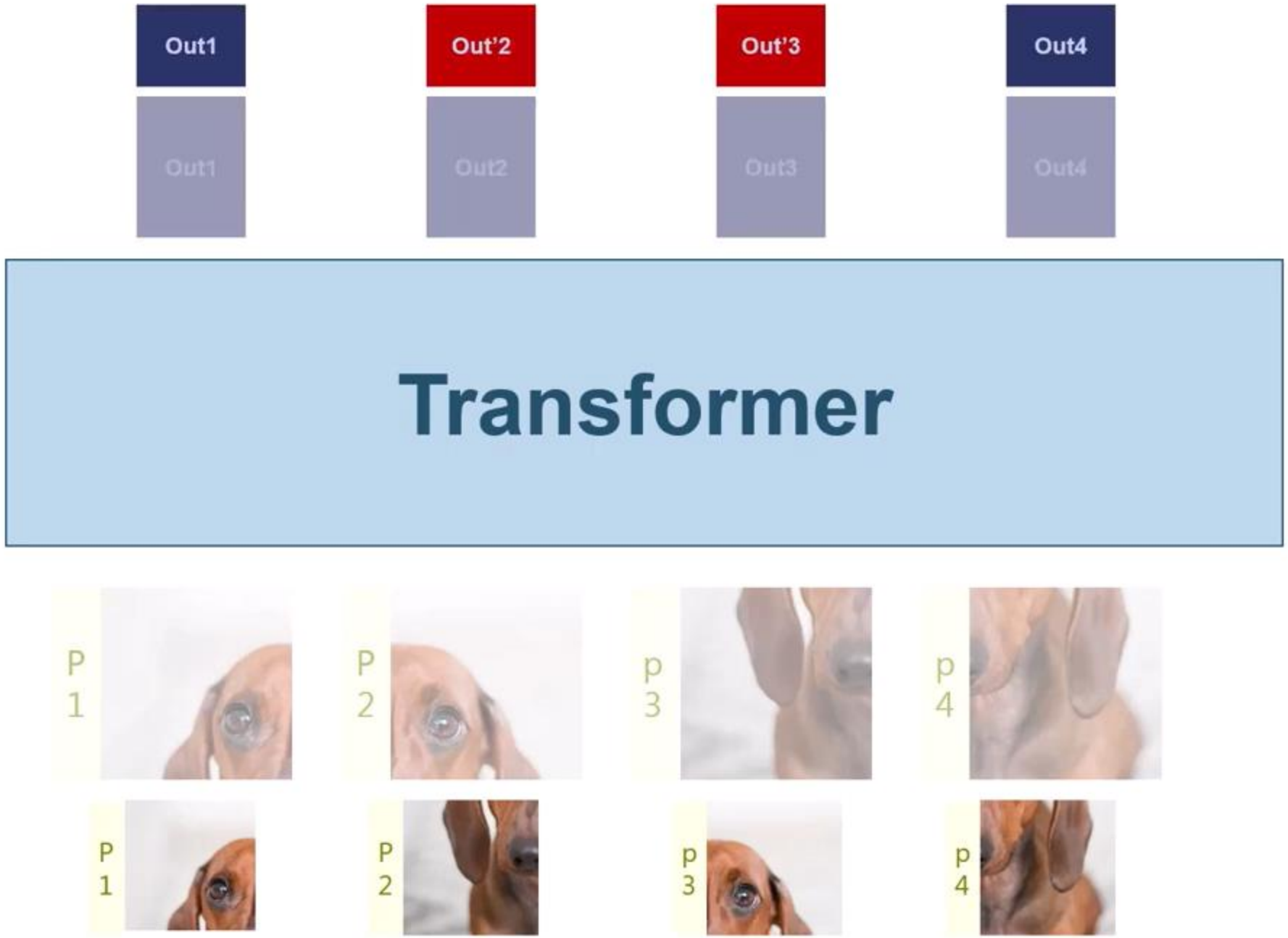
P2 

p3 

p4 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Transformer
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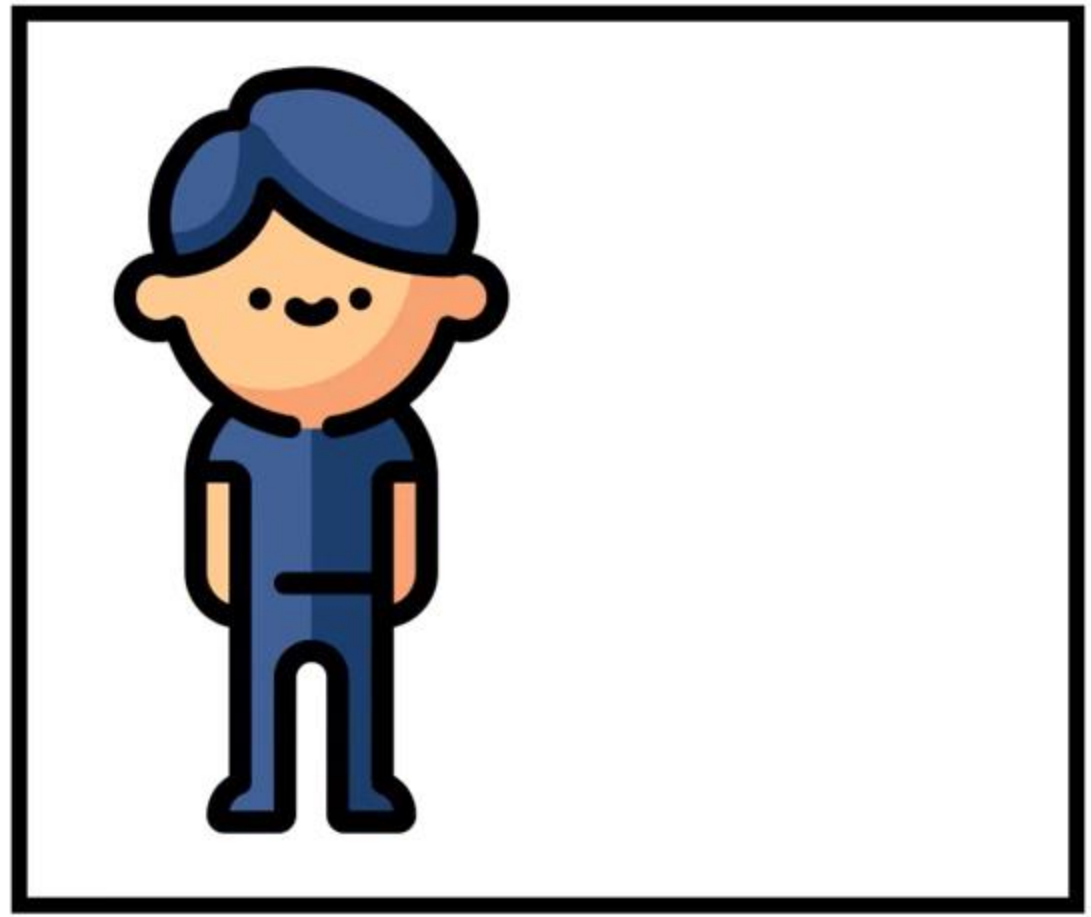

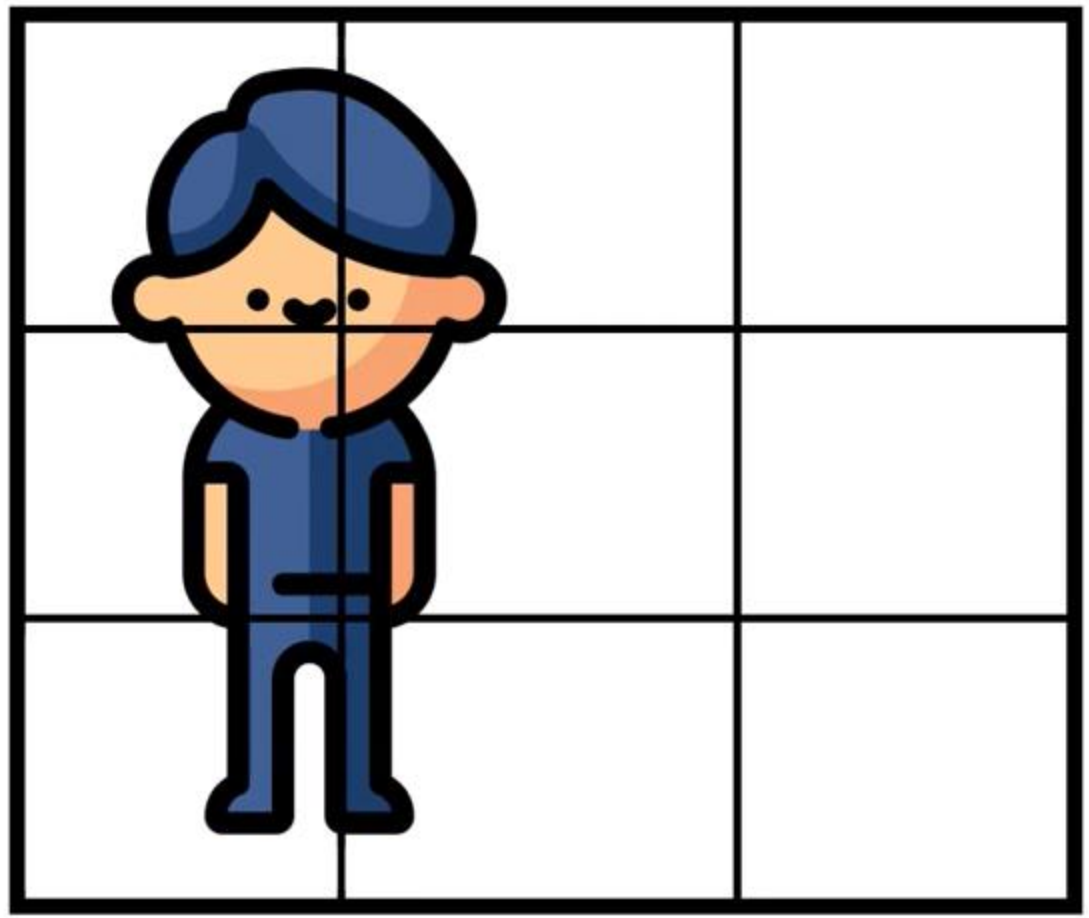

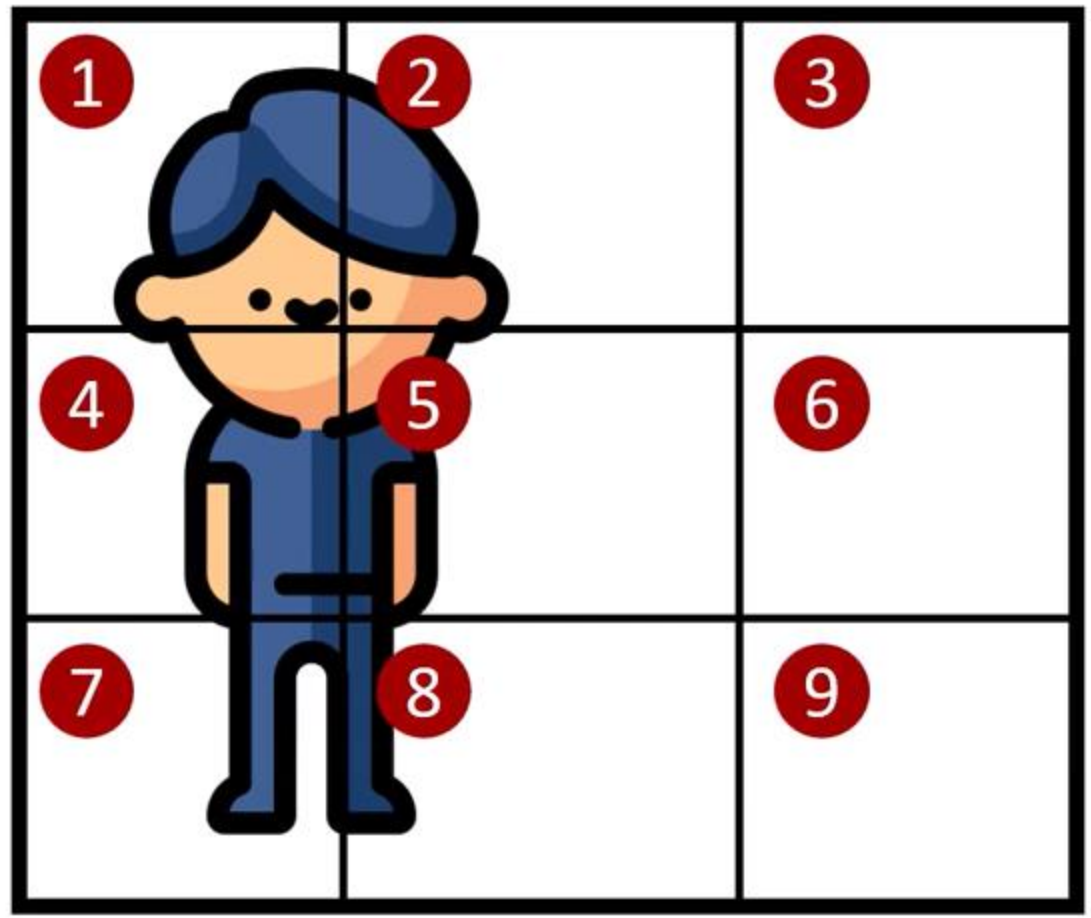
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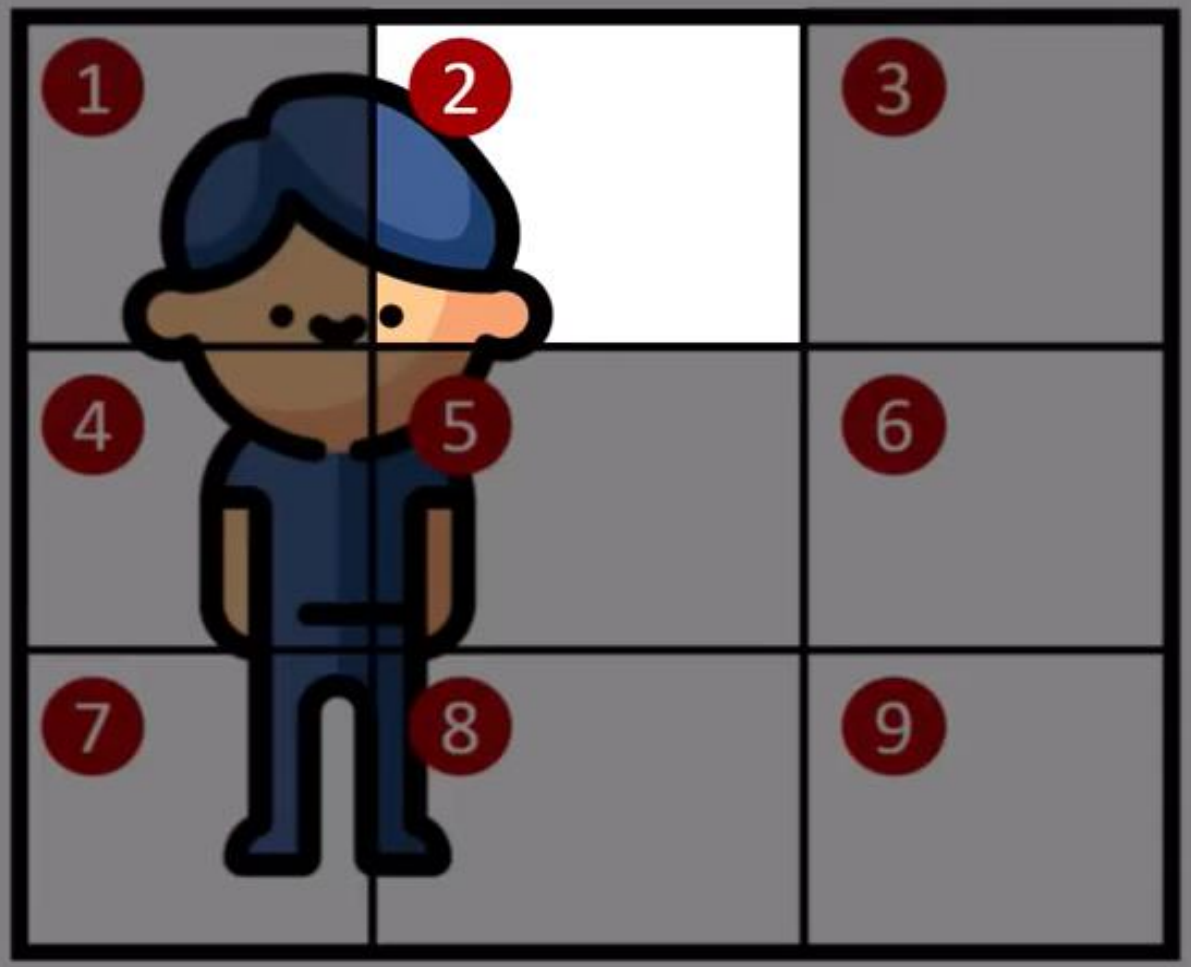
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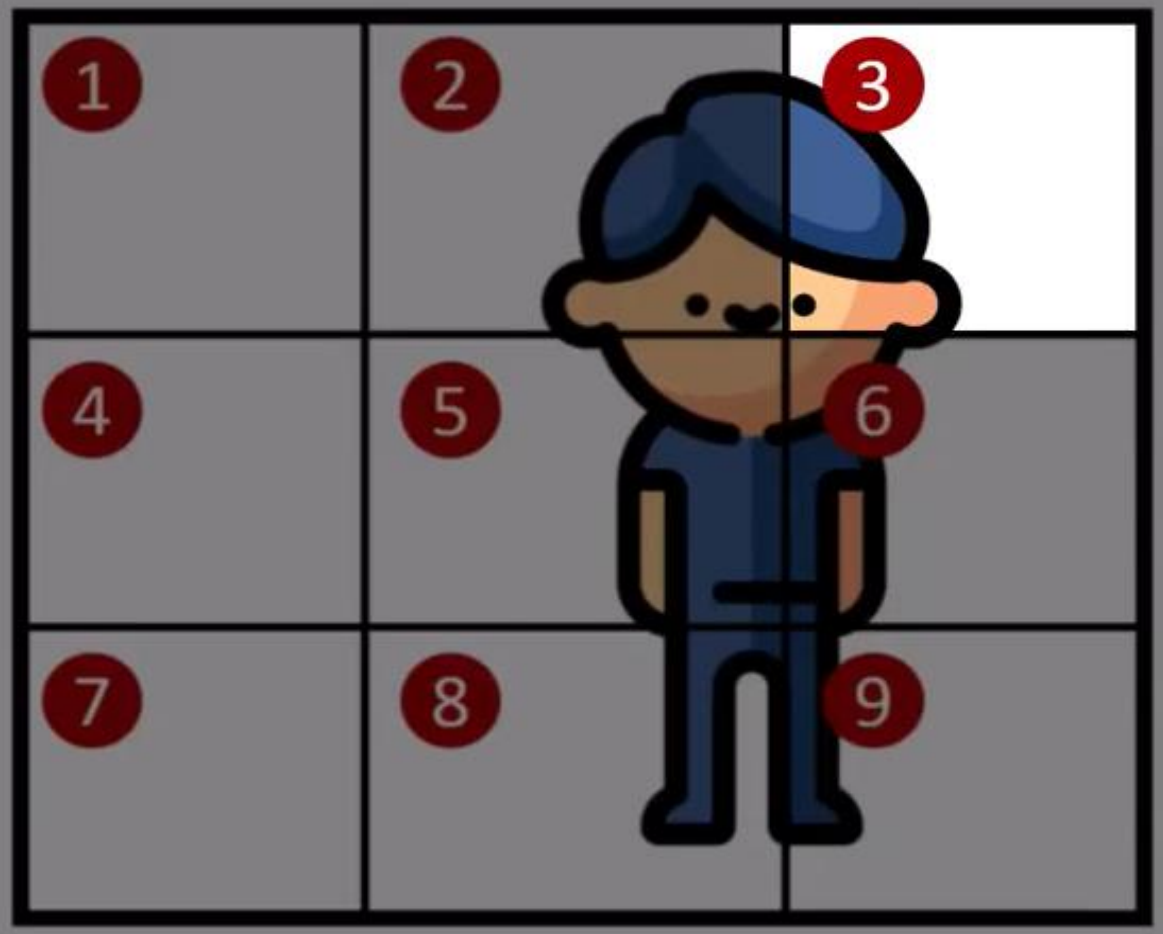
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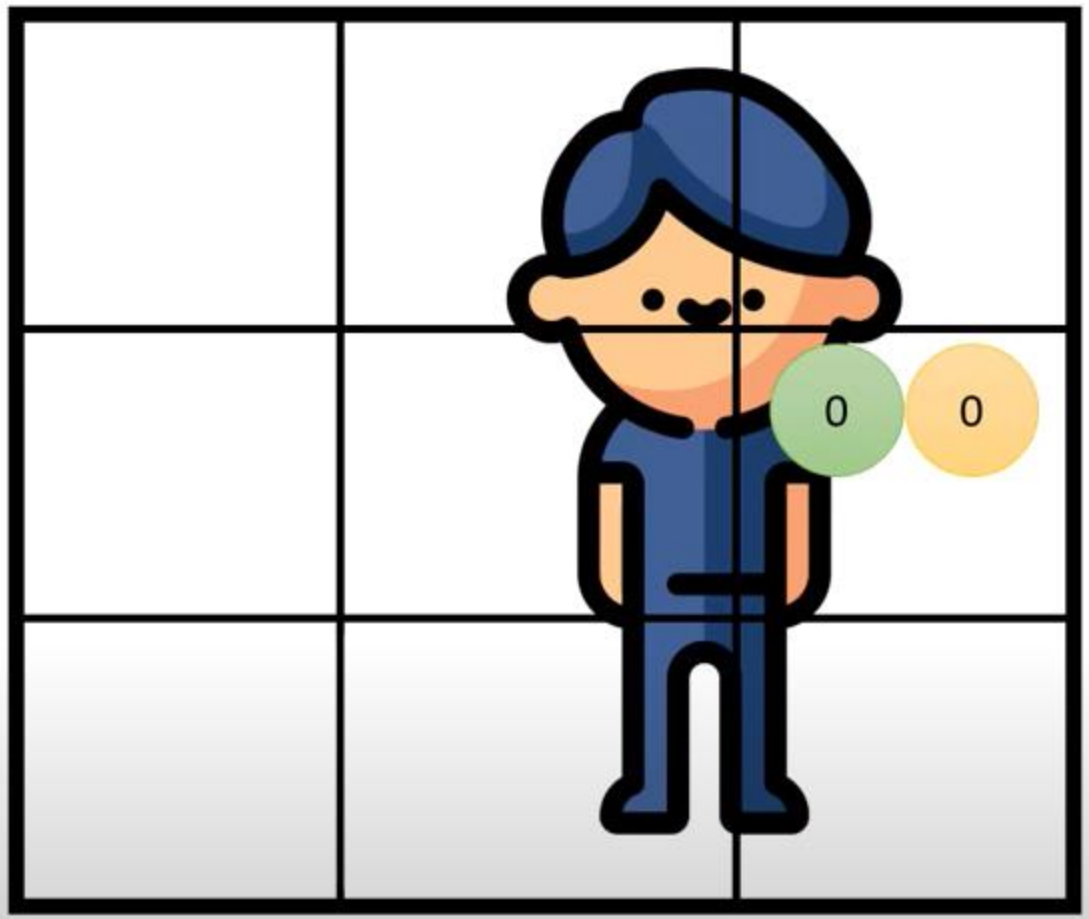
Relative Position Bias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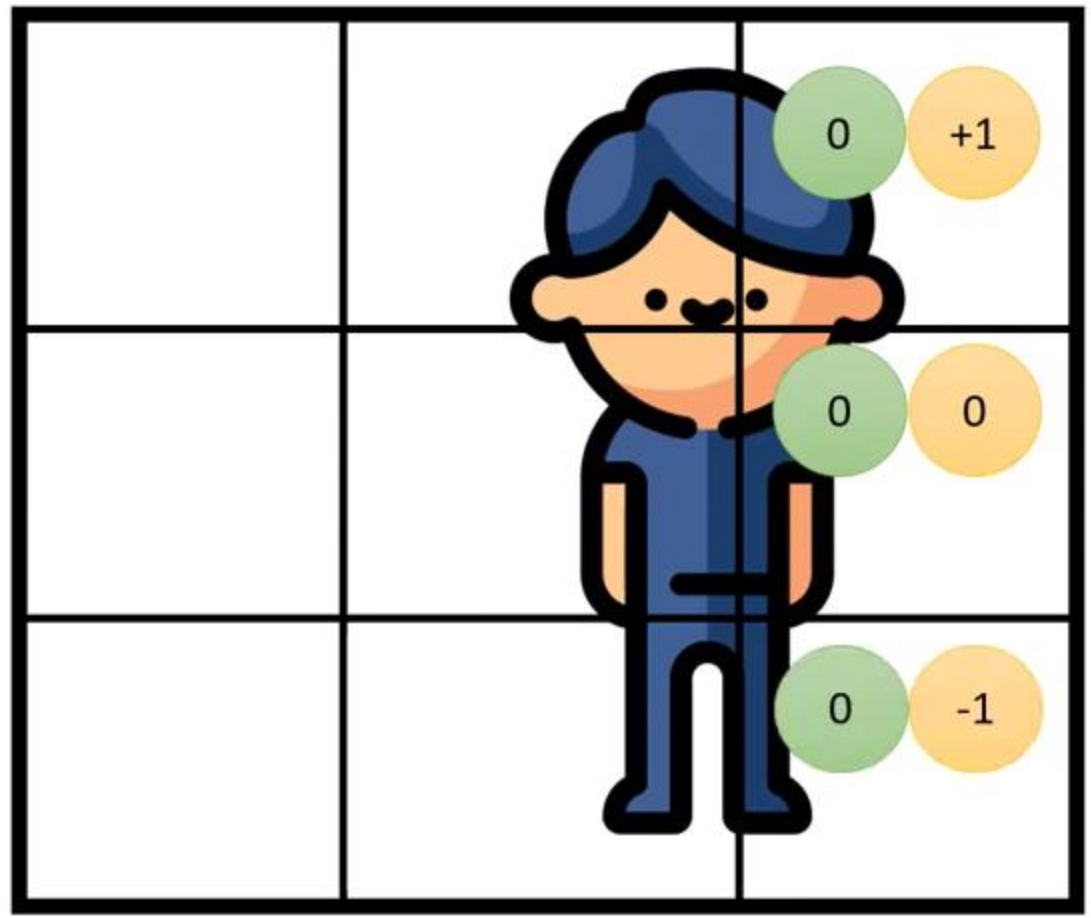
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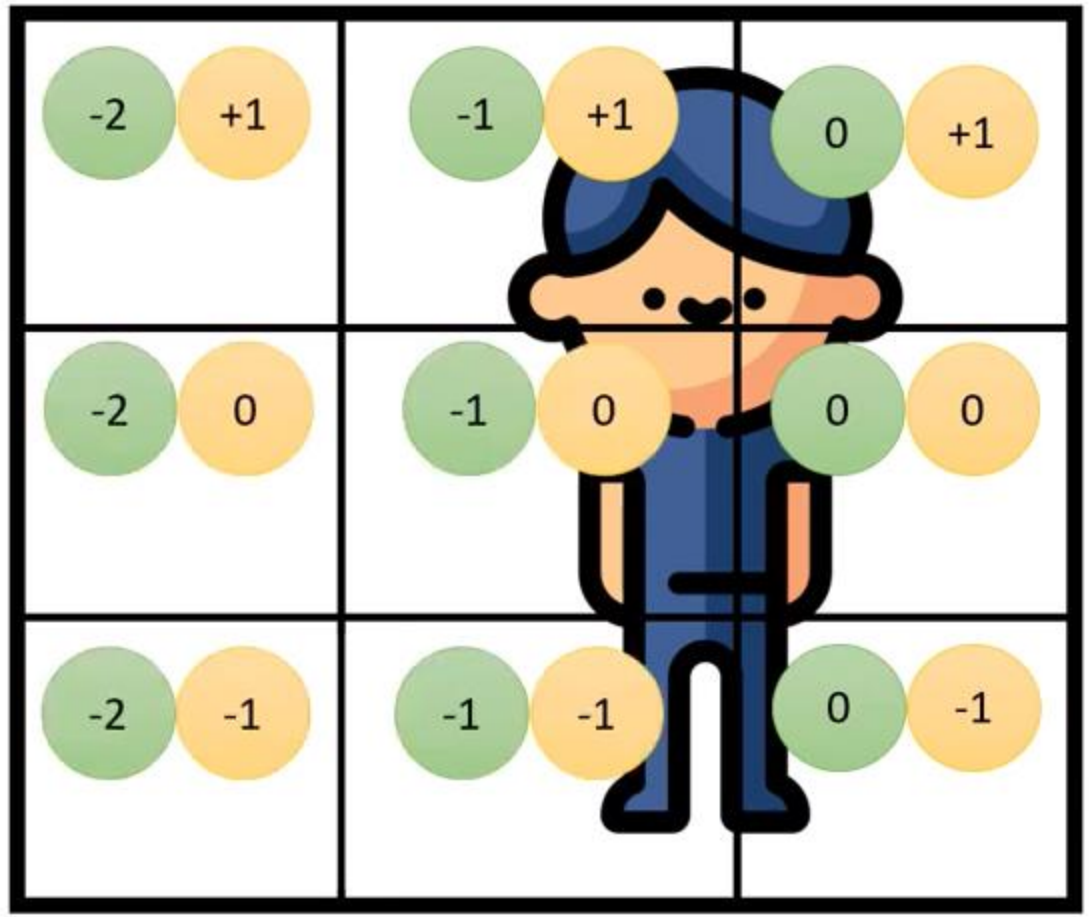
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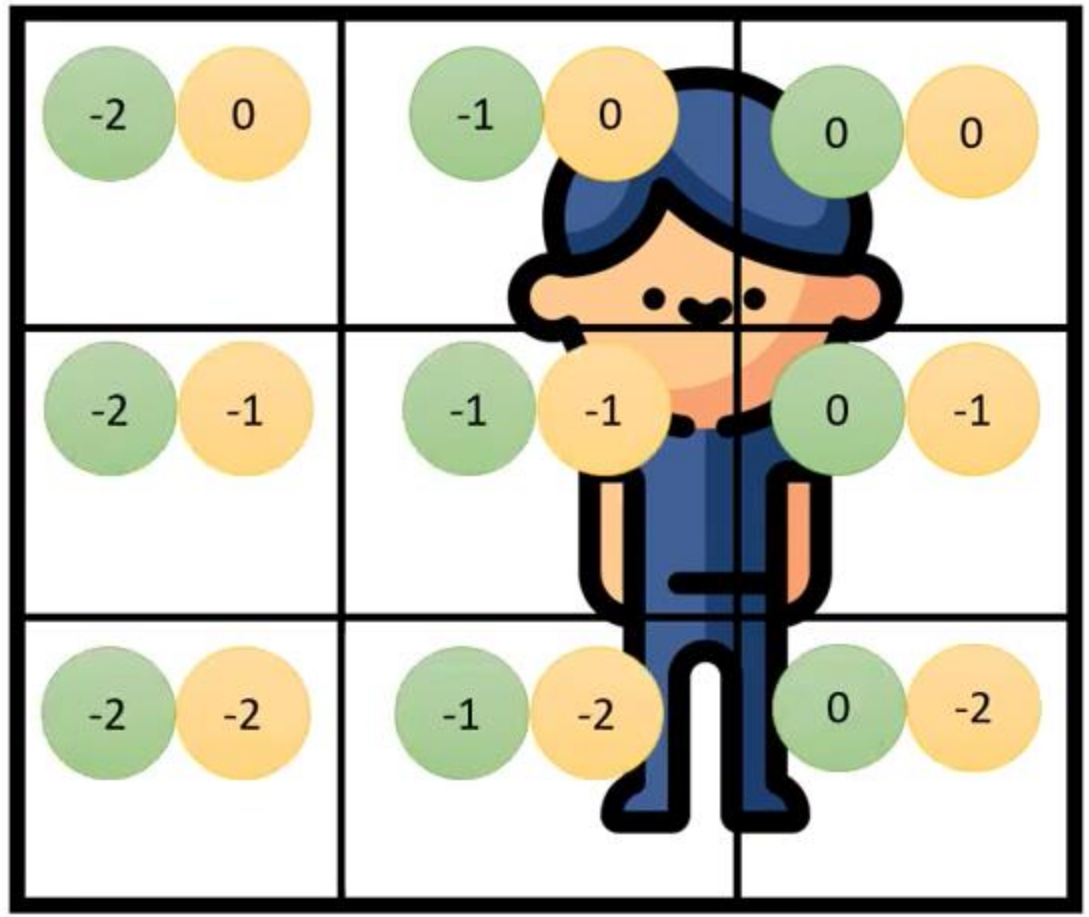
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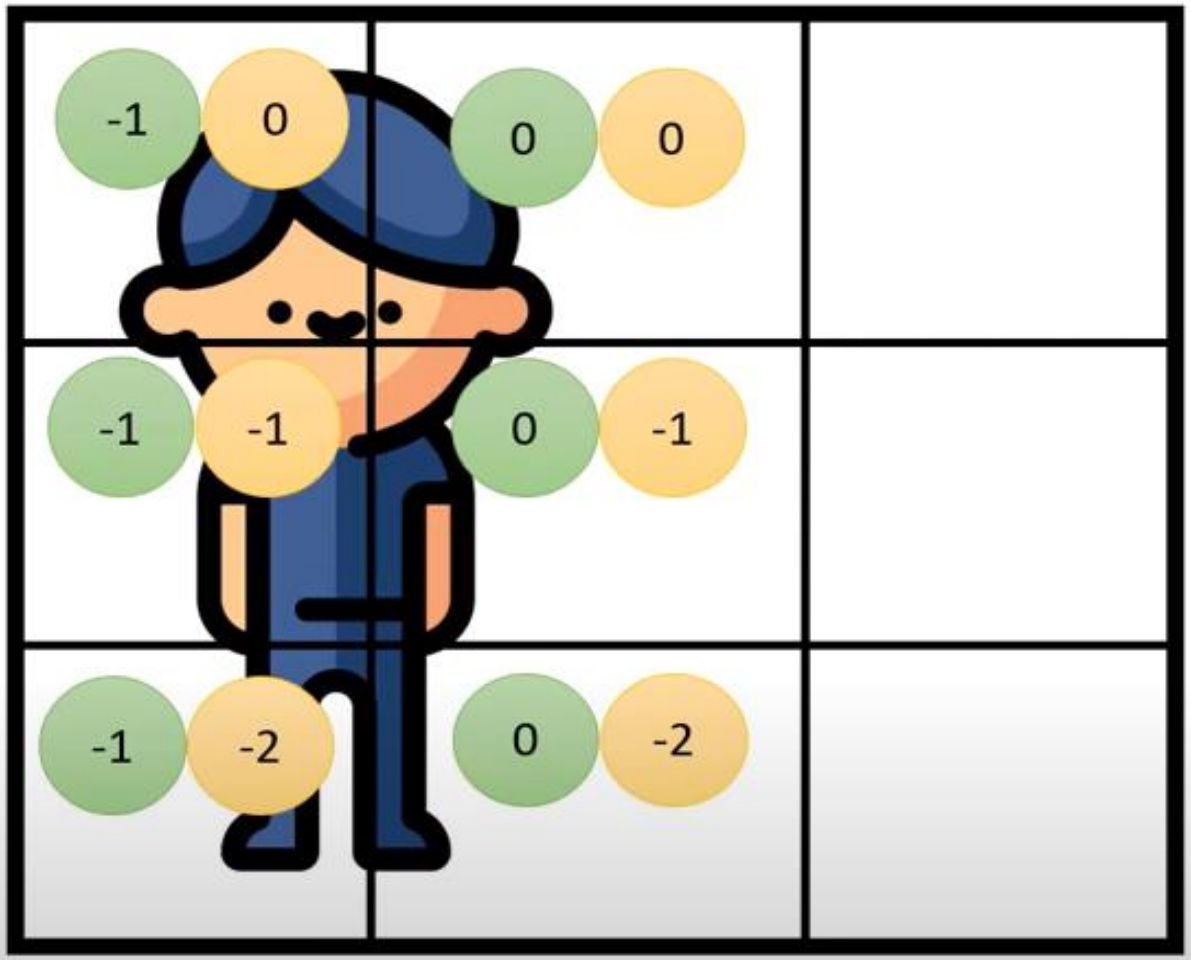
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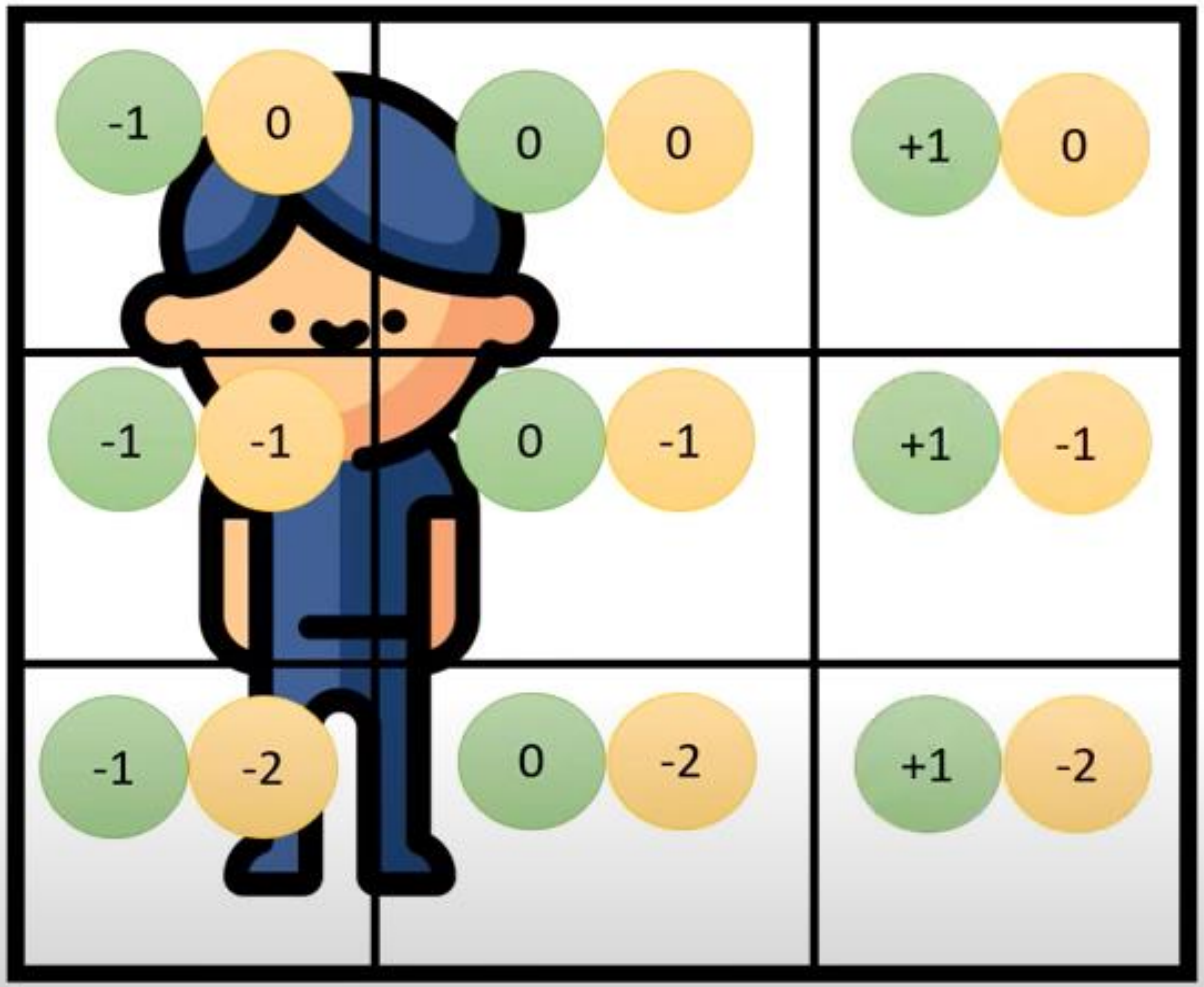
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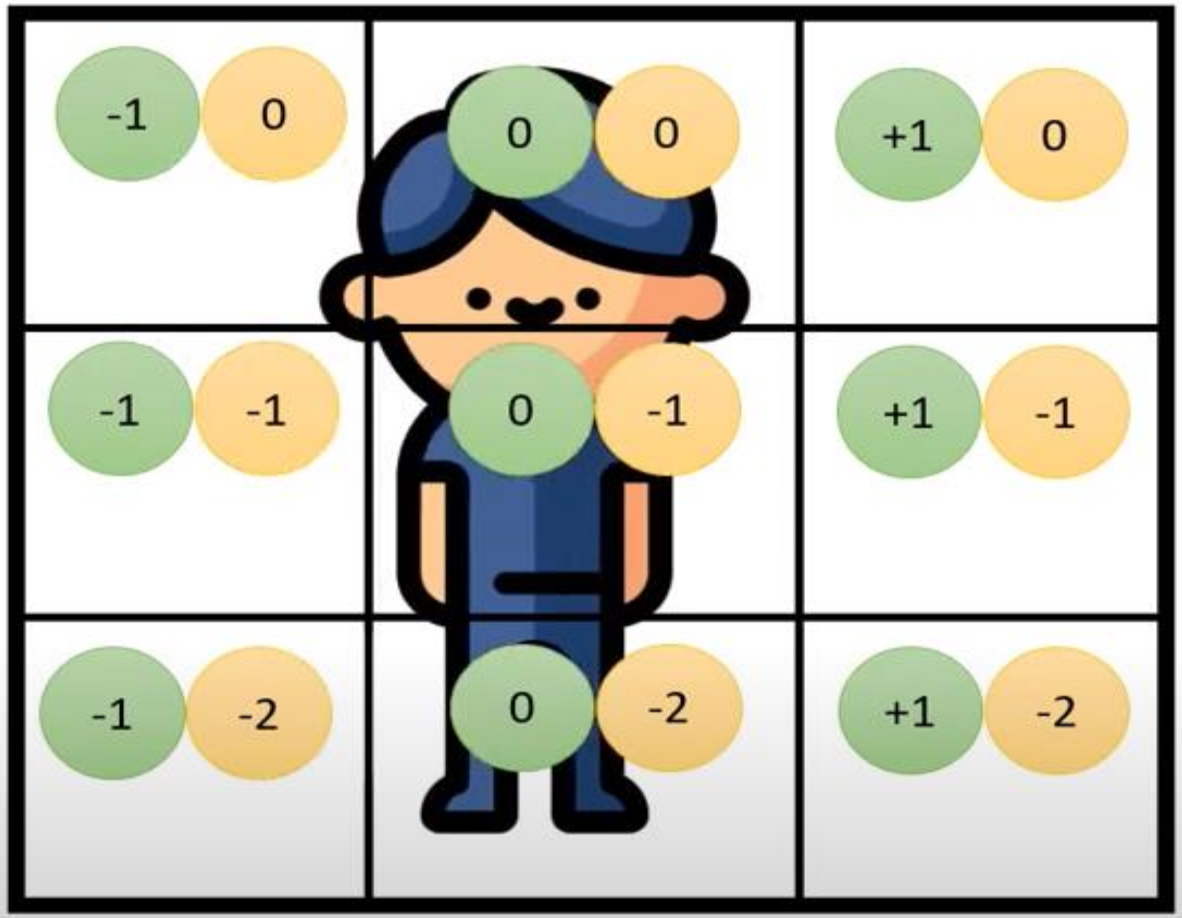
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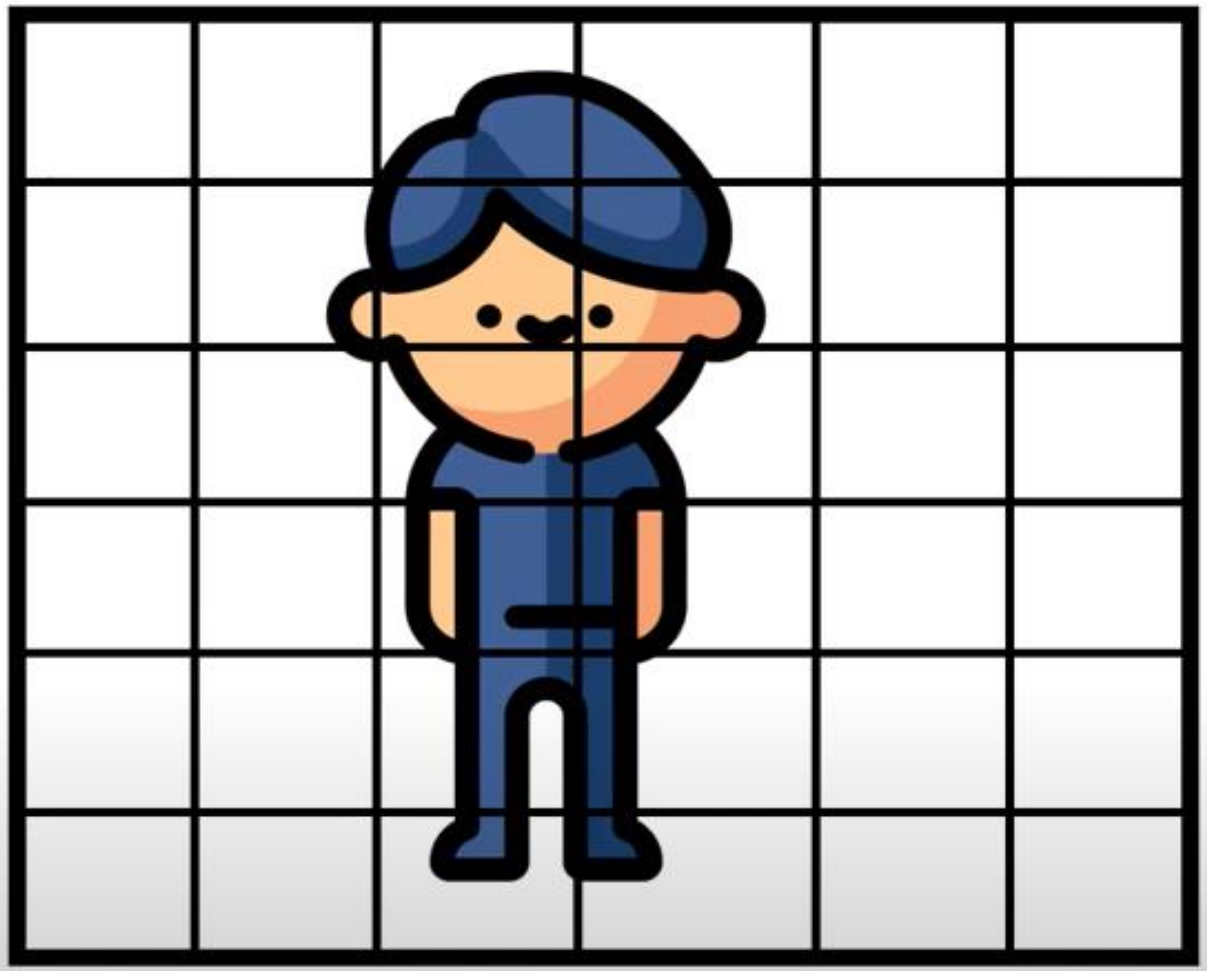

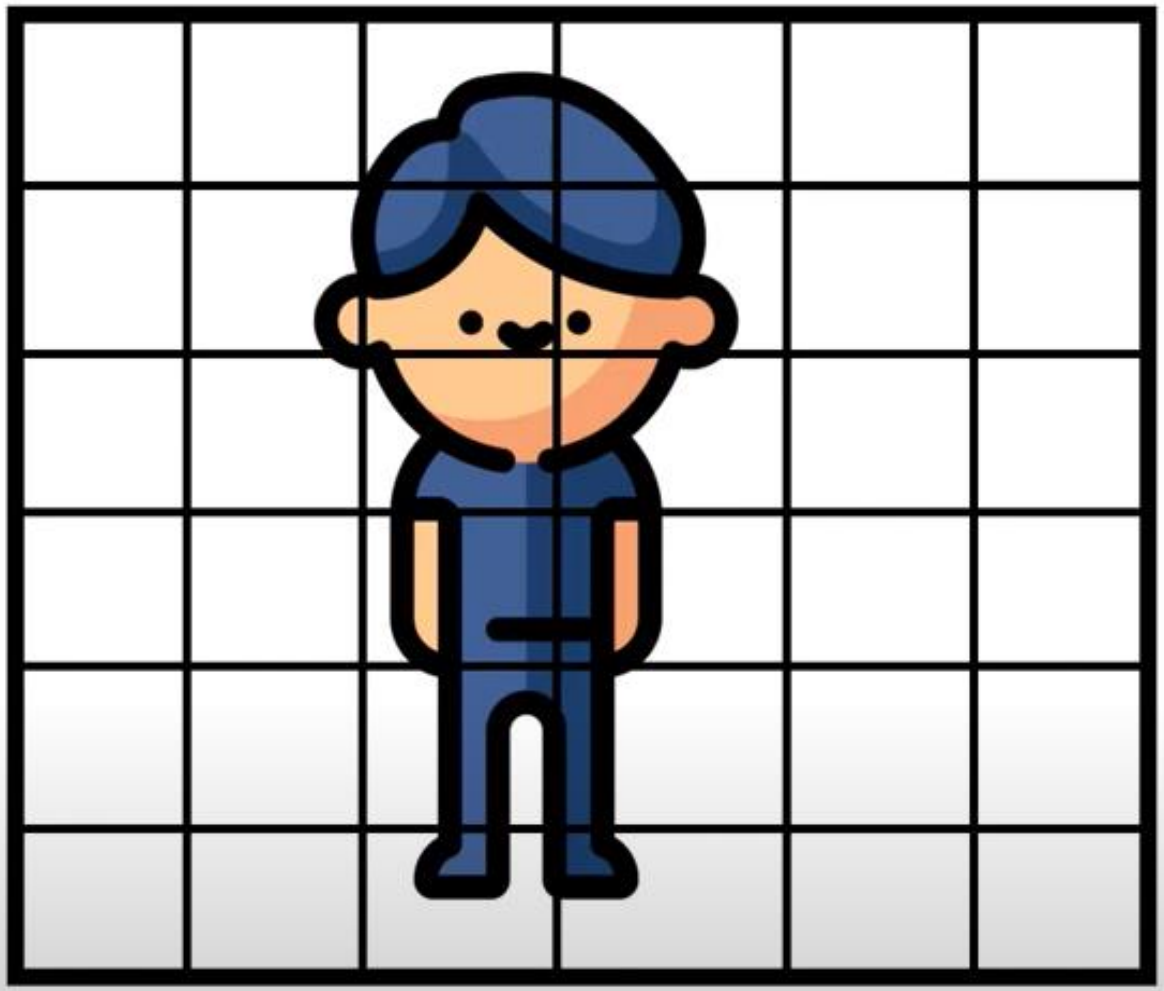

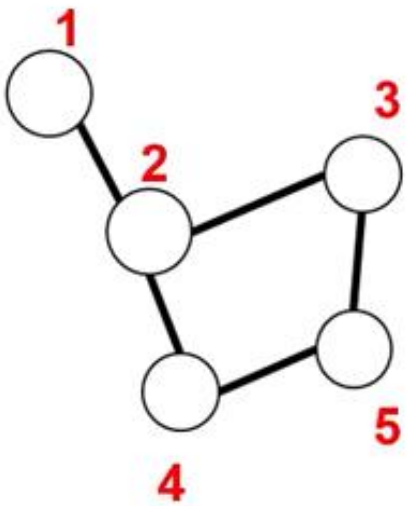
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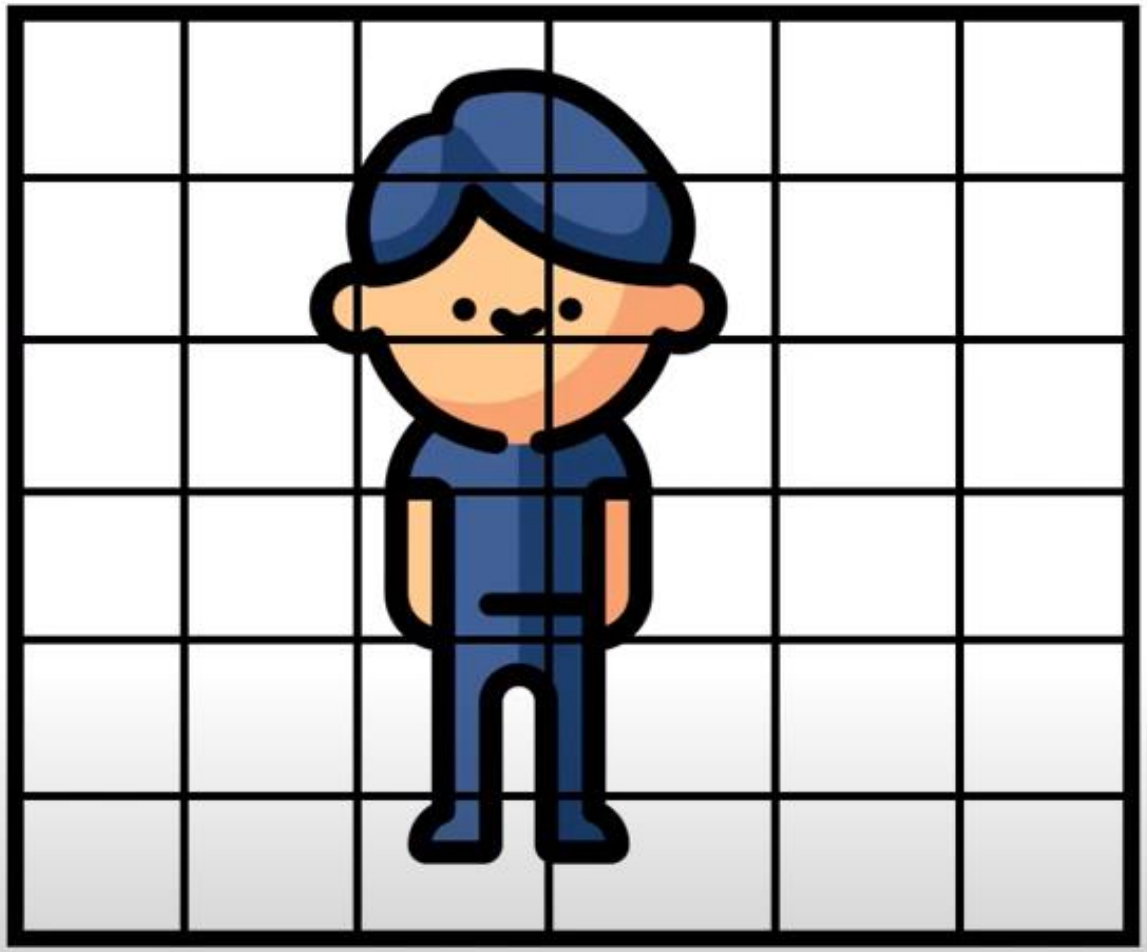

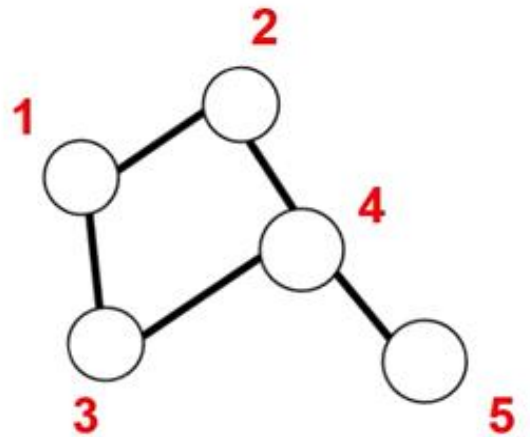
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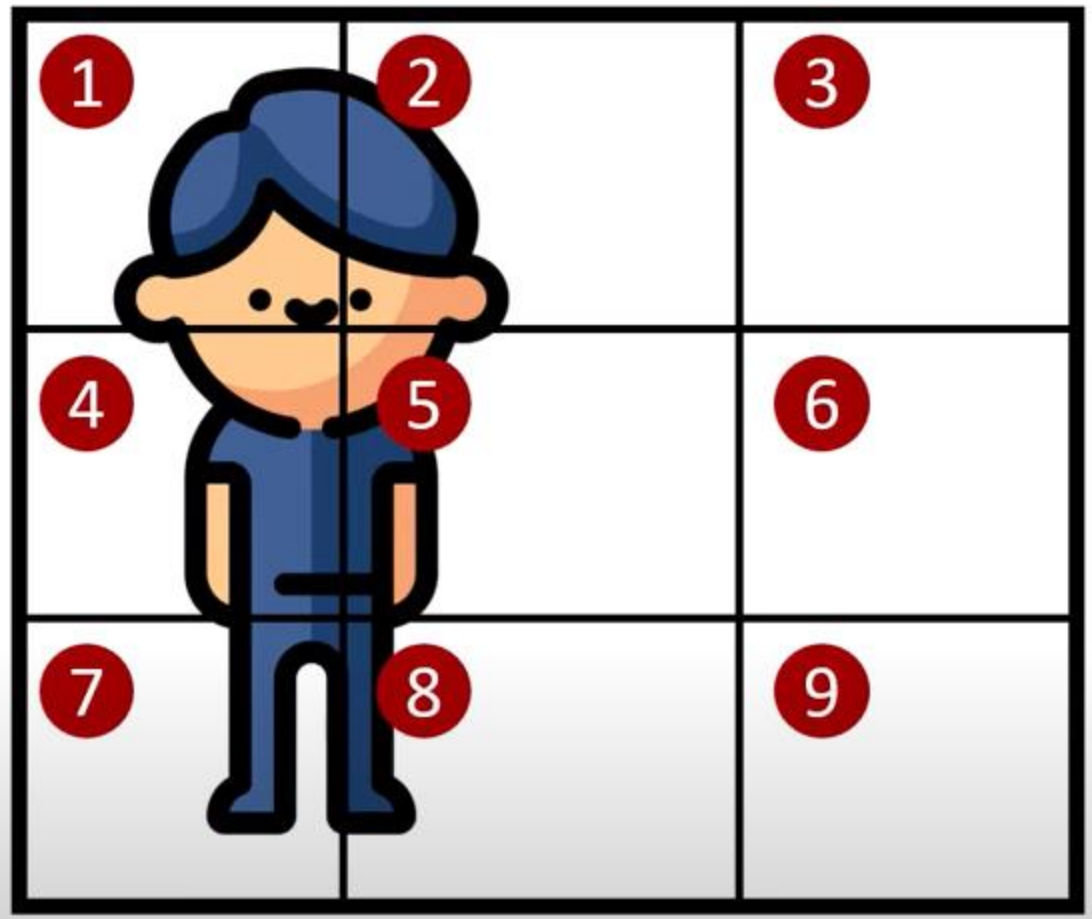
How to apply relative position bias!?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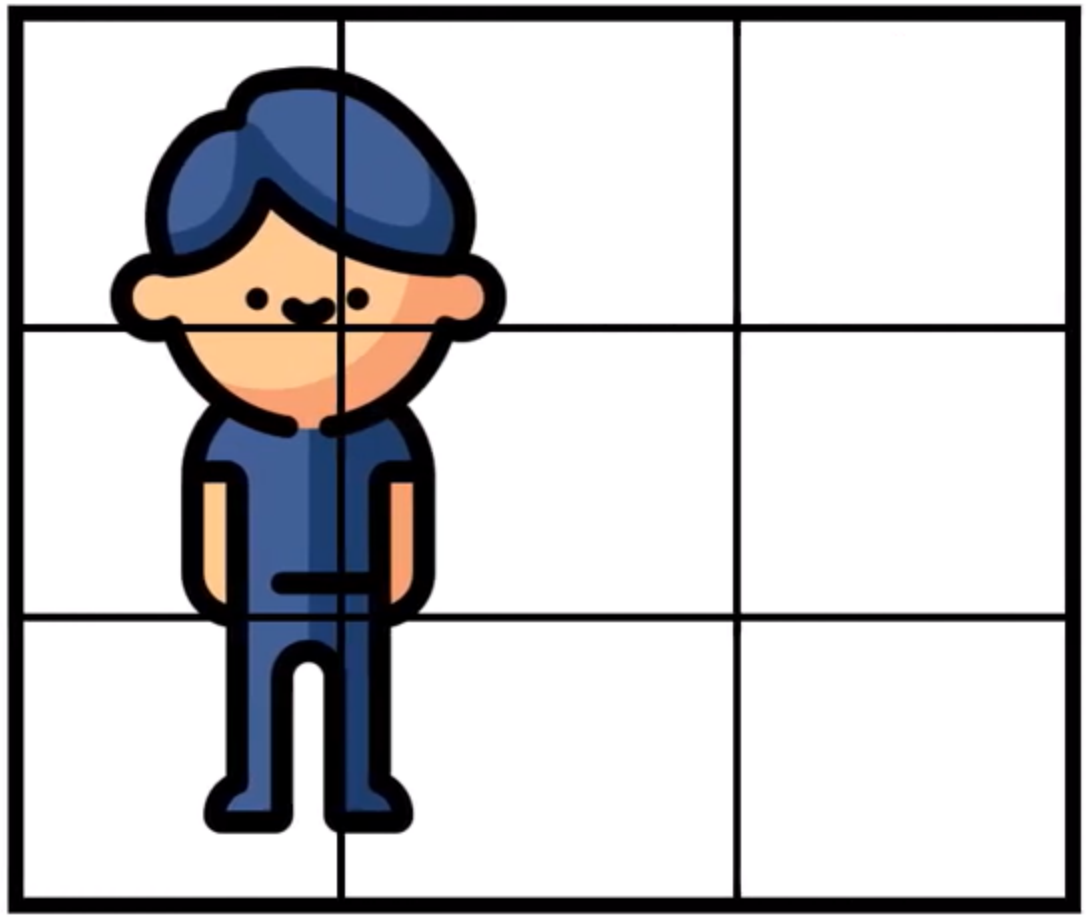

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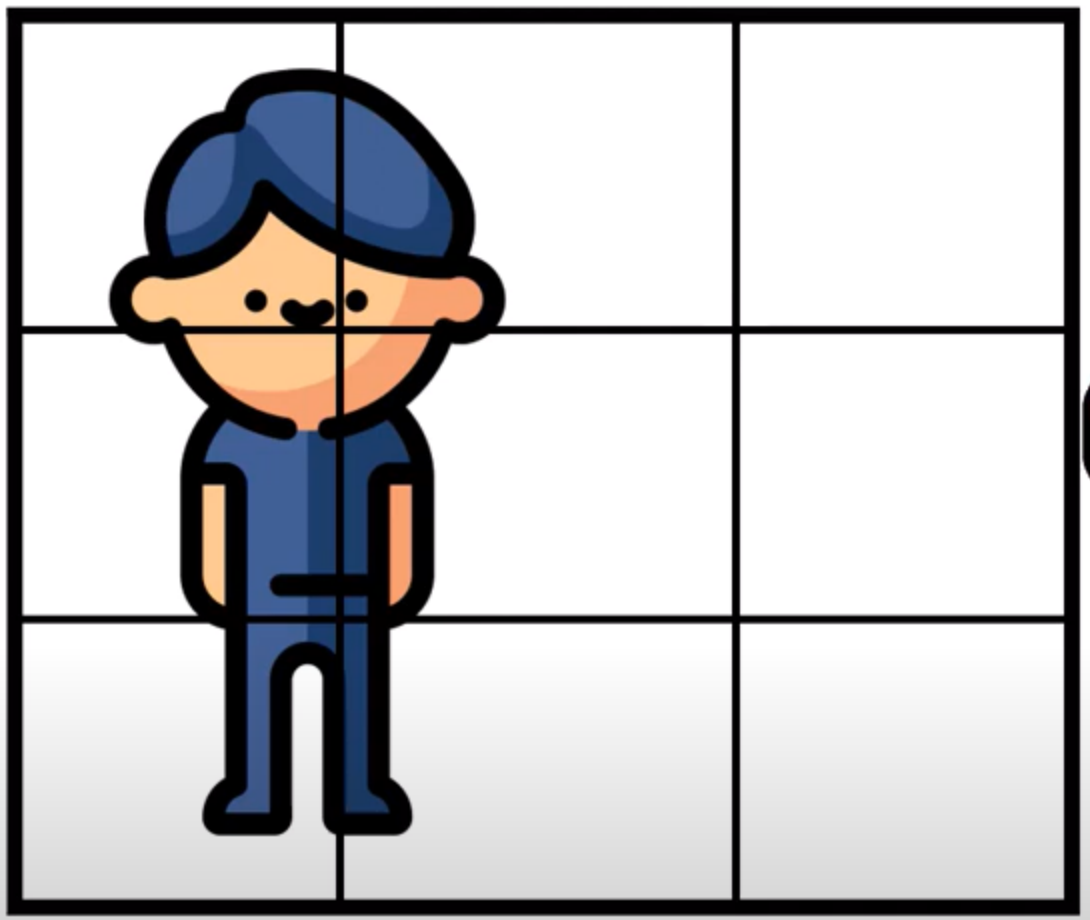

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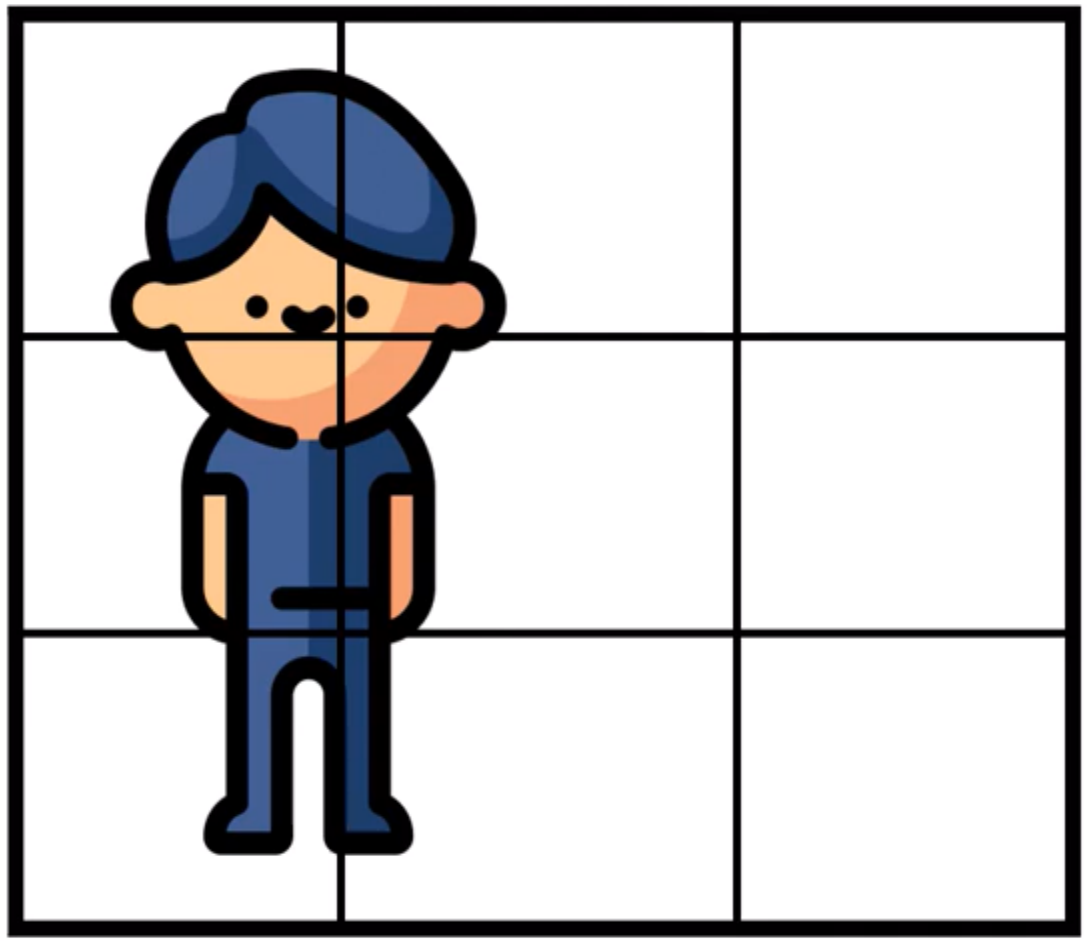

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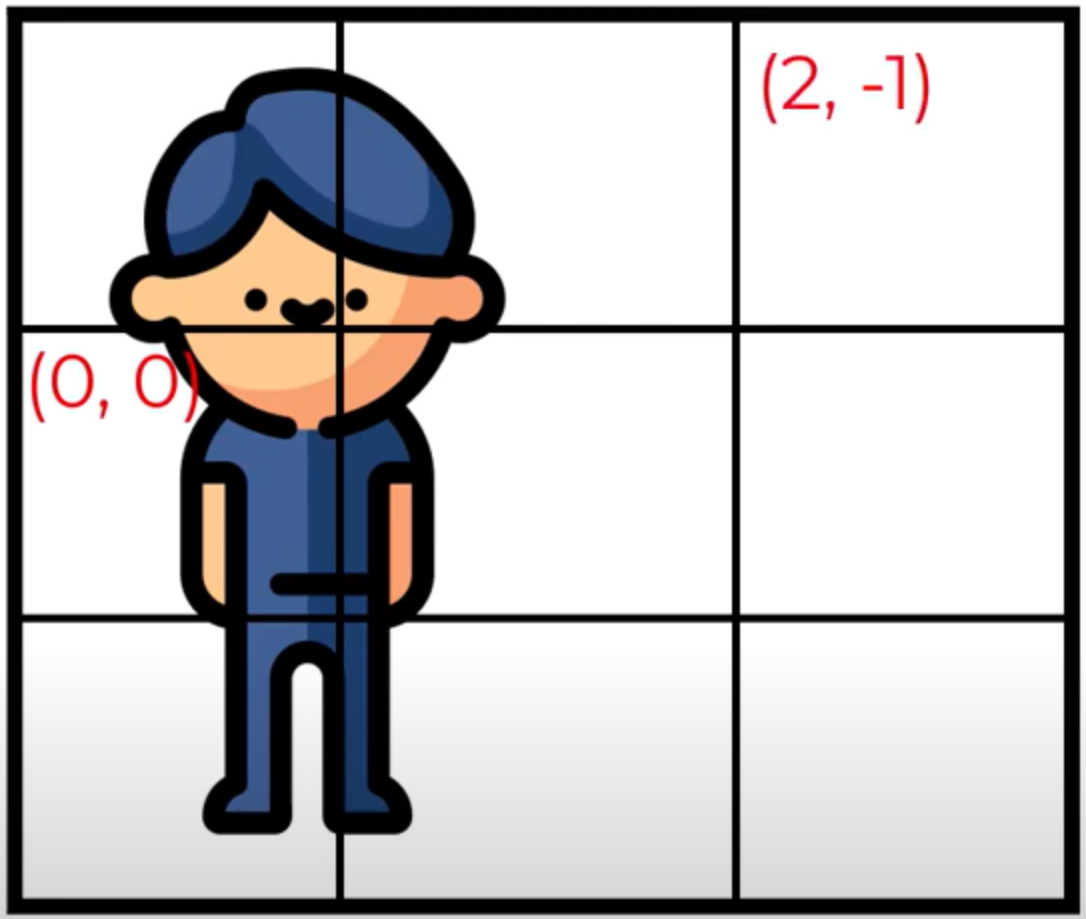

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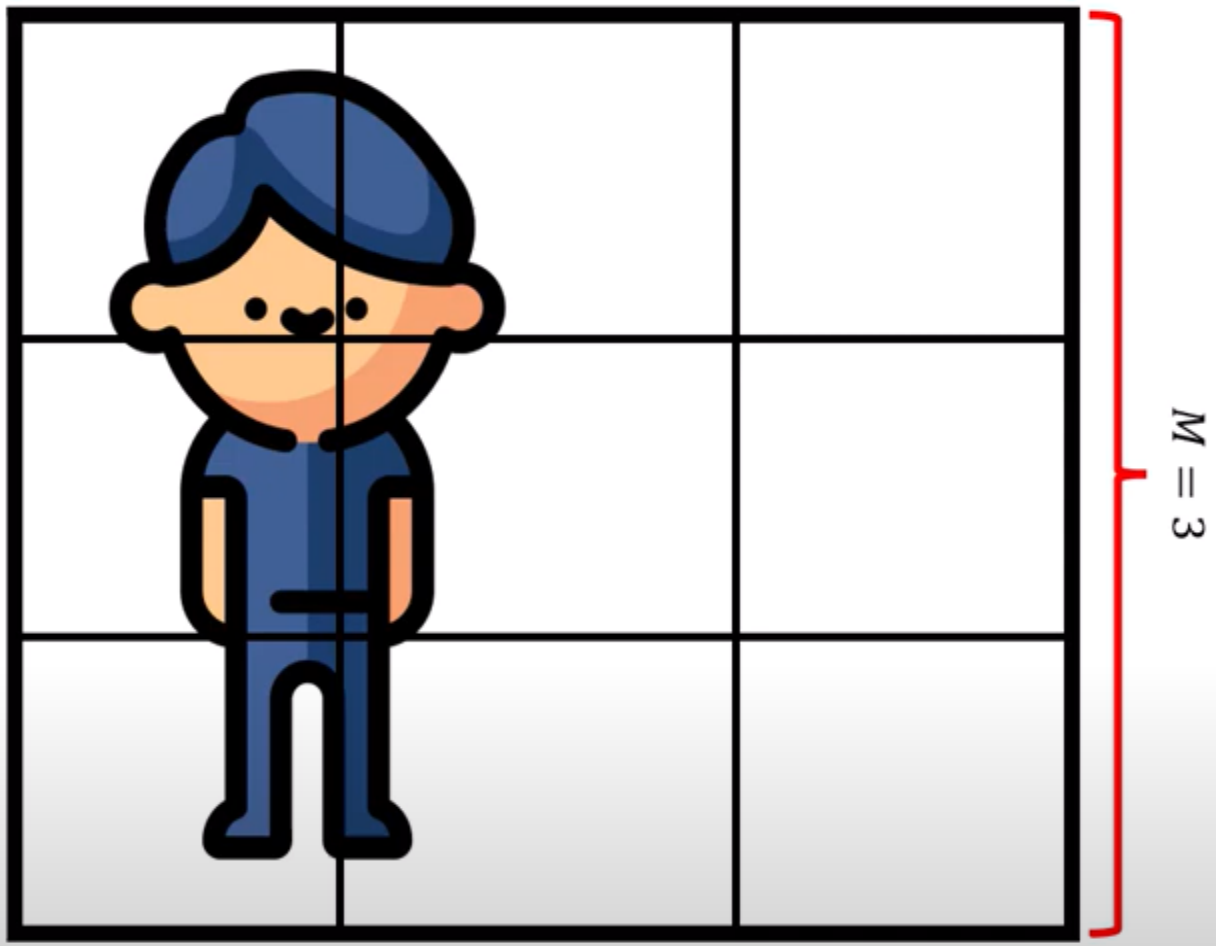

M^2

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M^2

Relative Position Bias

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

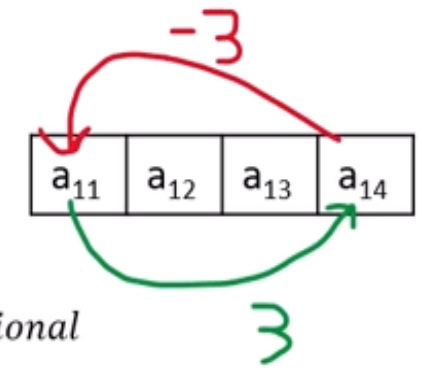
$Q, K, V \in R^{M^2 \times d}$ $B \in R^{M^2 \times M^2}$

Assuming that M is window size, the relative position along each axis lies in the range $[-M+1, M-1]$

$M = 4 \rightarrow range[-3, 3]$

7-dimensional

In General: $(2M-1)$ *dimensional*



Parameterize $\hat{B} \in R^{(2M-1)\times(2M-1)}$ and values in B are taken from $\hat{B}$.