Lecture 3: Convolutional Neural Networks

Today:

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- Expectations of visual recognition systems (10%)

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- A Conv layer, stride, padding etc. (25%)

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- What is encoded in feature maps? (10%)
- Max-pooling, convnet and conv variants (10%)


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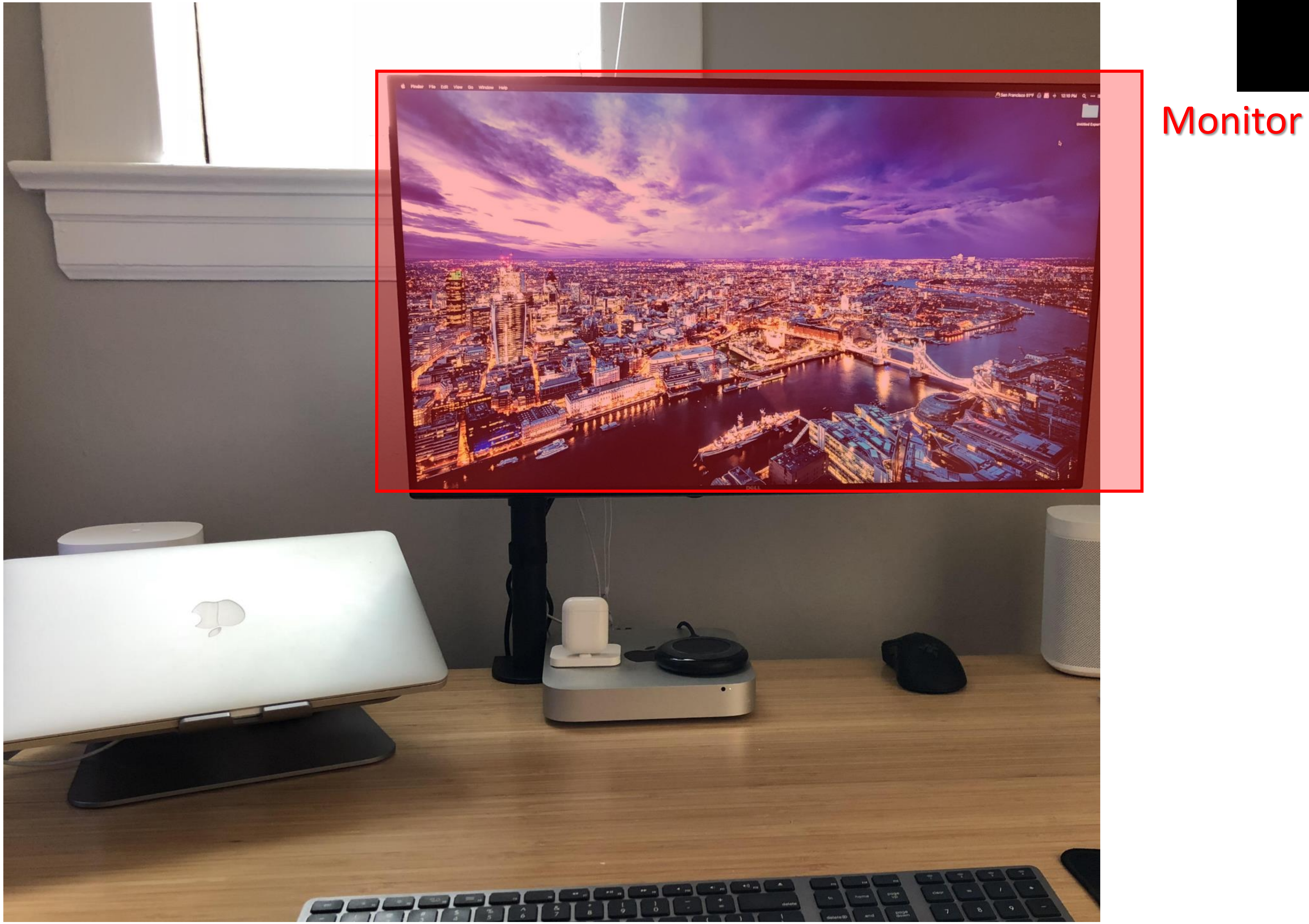
Monitor


Monitor


Monitor

Expectations of visual recognition network

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1. Maintain 2D structure logic

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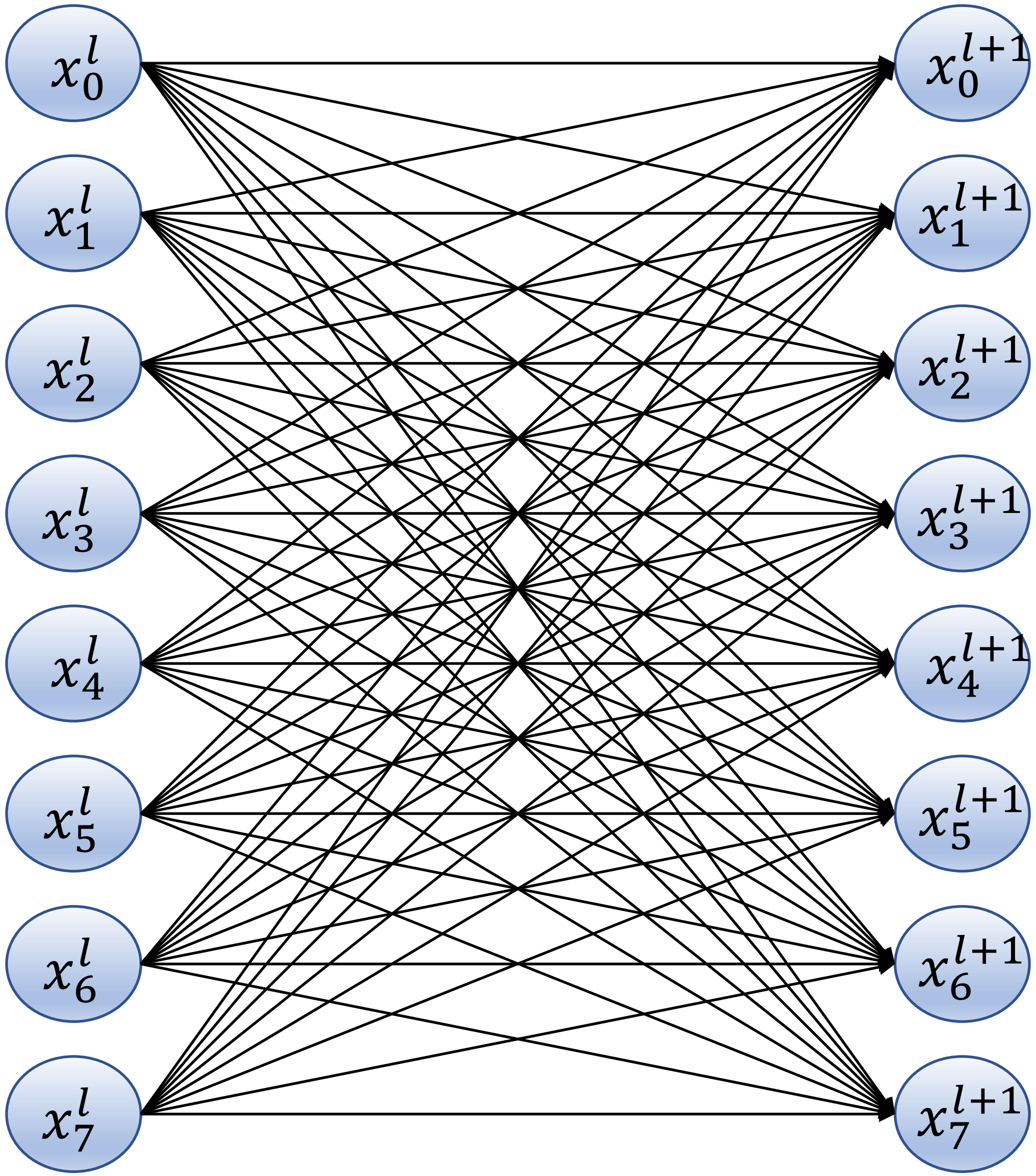
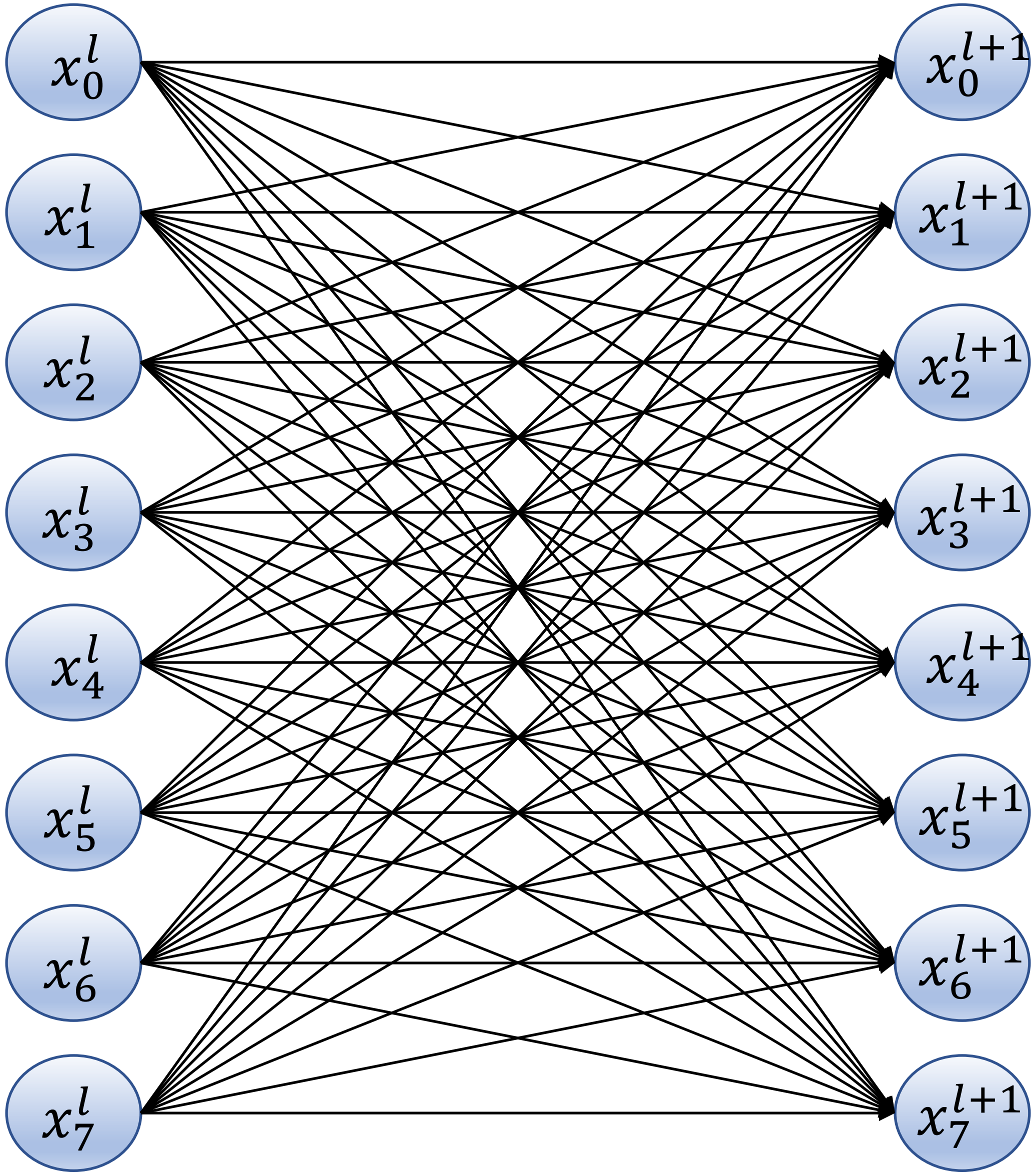
6. Reasonable amount of params

Fully connected layer

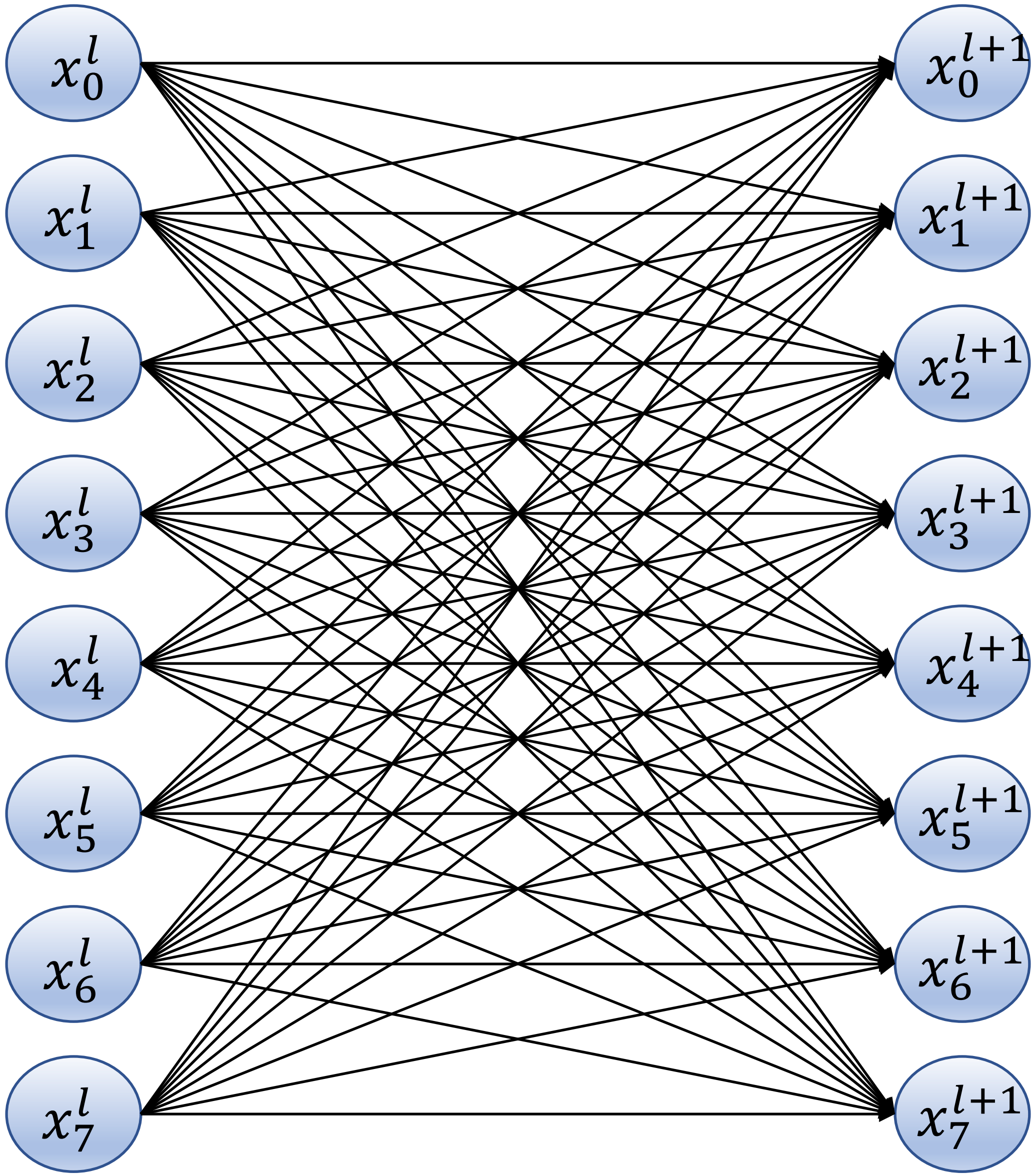


Fully connected layer



$$\begin{bmatrix} w_{00}^l & w_{01}^l & & \\ w_{10}^l & w_{11}^l & & \cdots \\ & & & \\ & \vdots & & \ddots \\ & & & \end{bmatrix}$$

Fully connected layer



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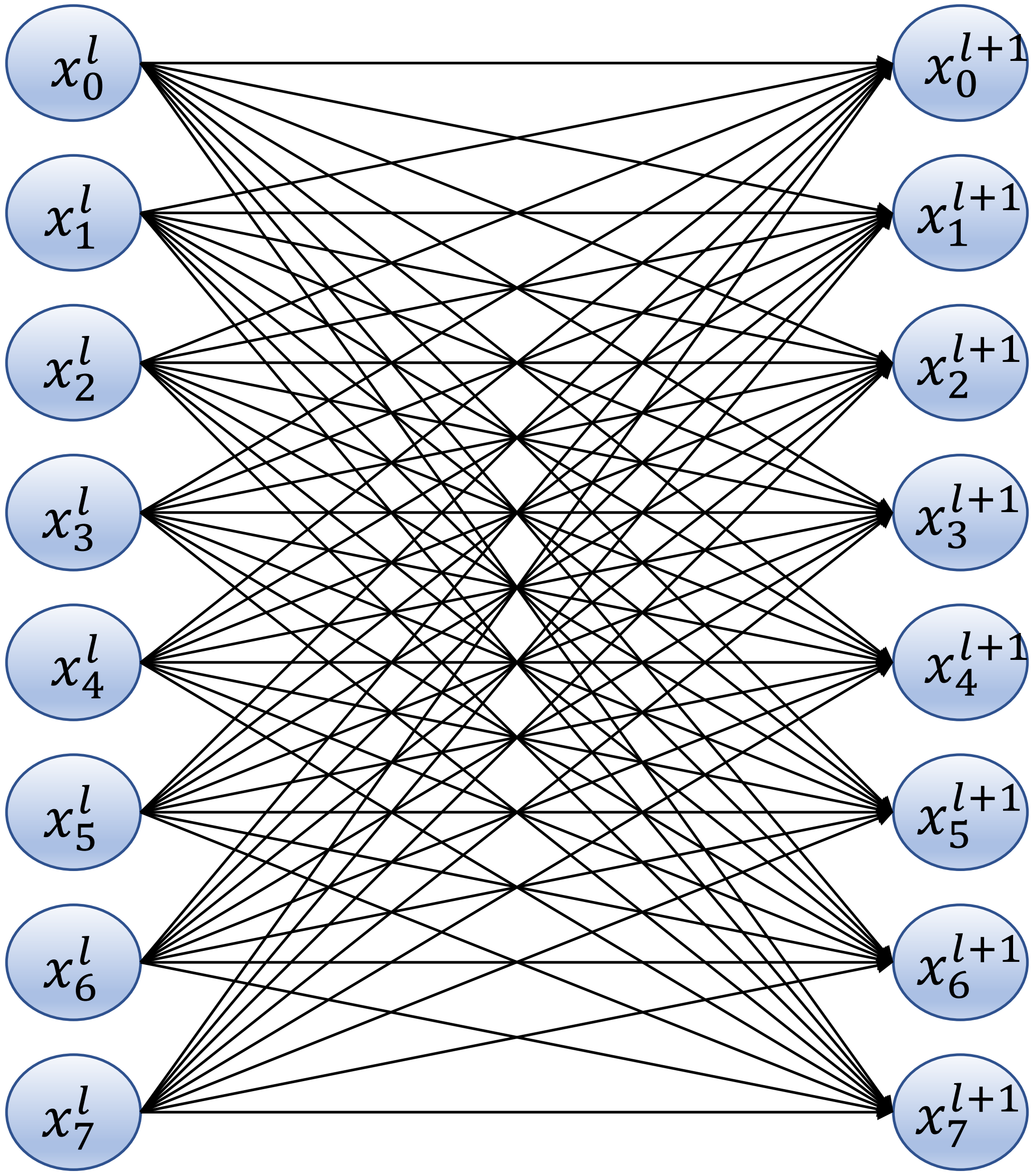

$$\begin{bmatrix} w_{00}^l & w_{01}^l & \\ w_{10}^l & w_{11}^l & \cdots \\ & \vdots & \ddots \end{bmatrix}$$

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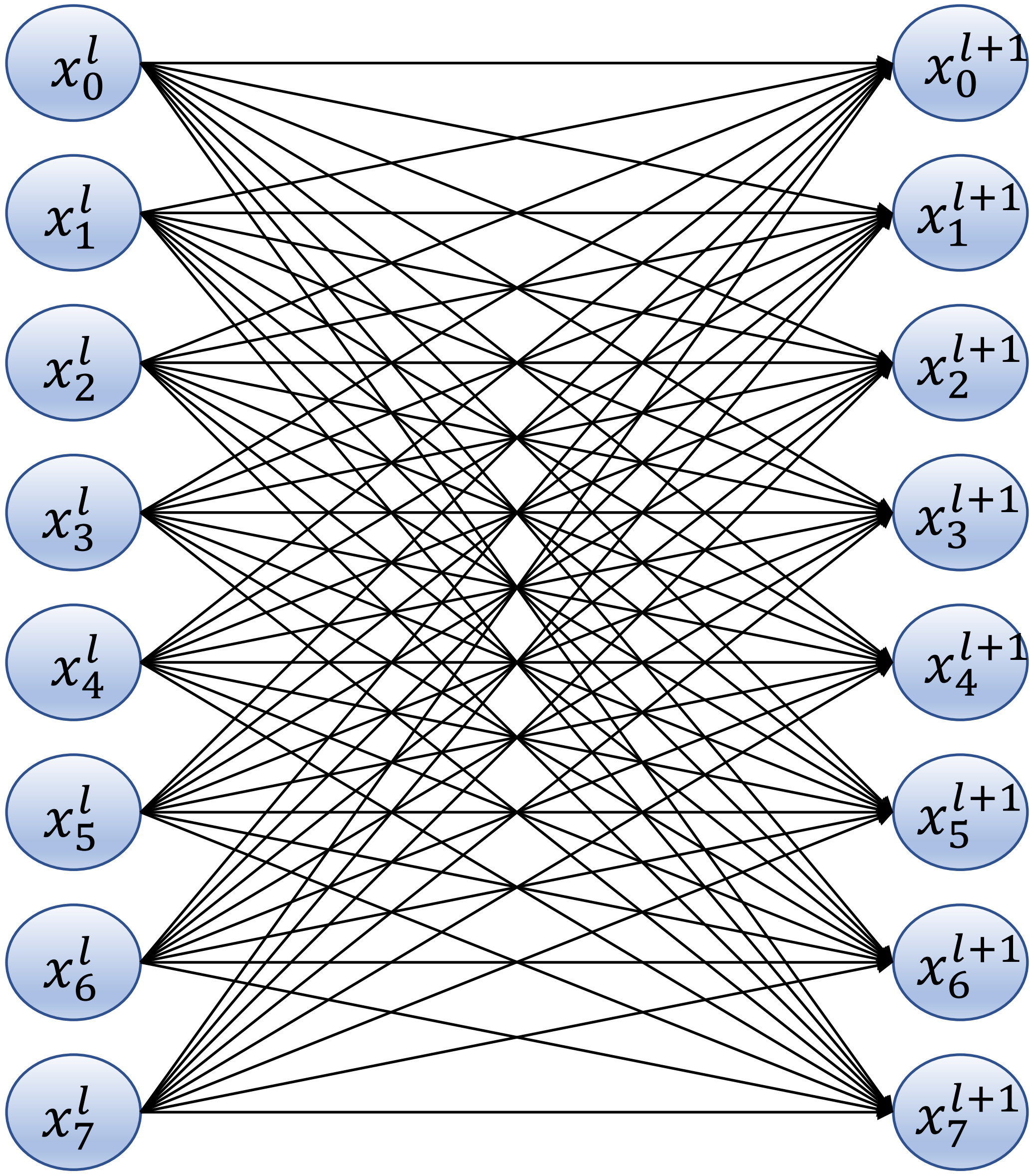

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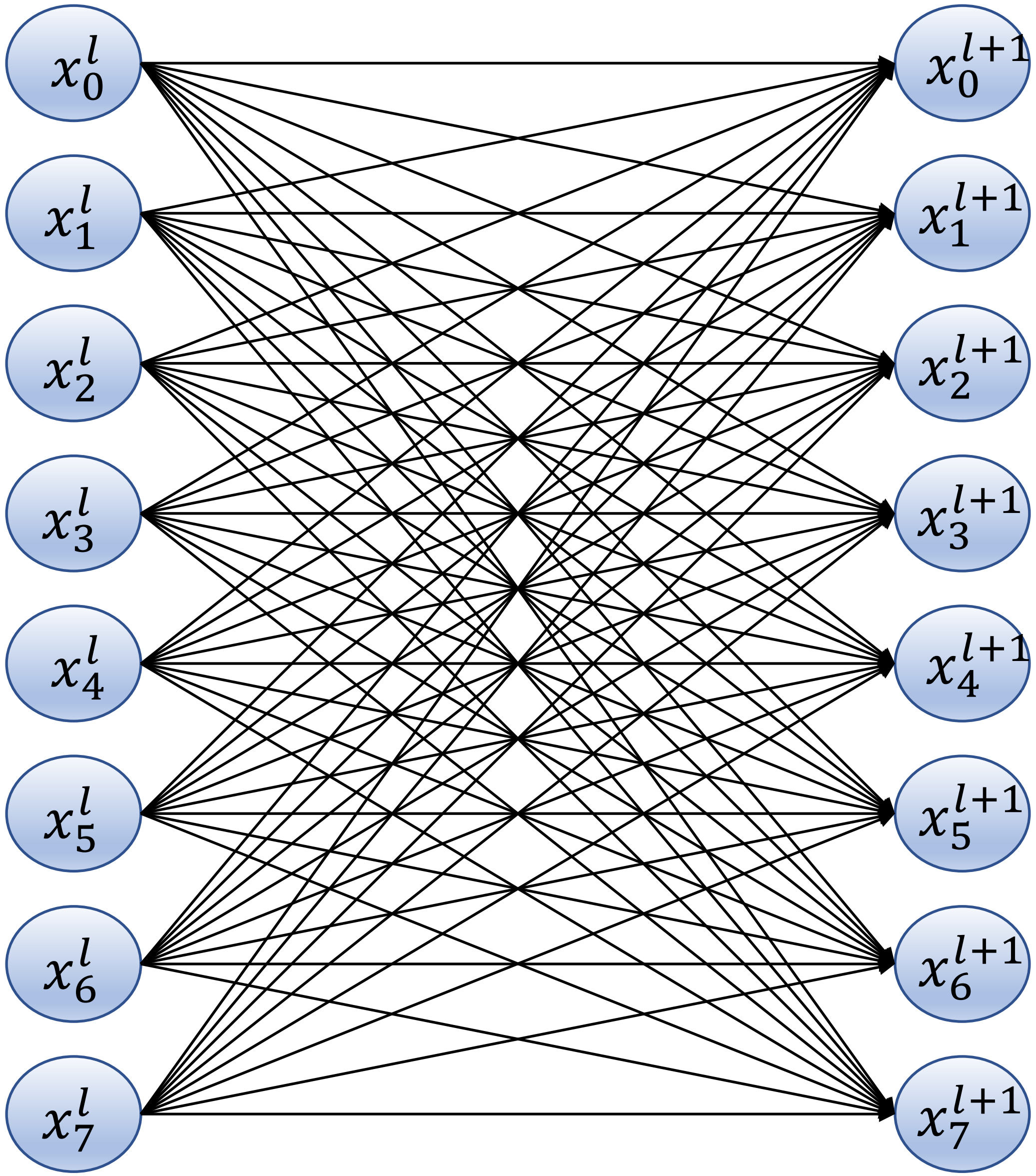

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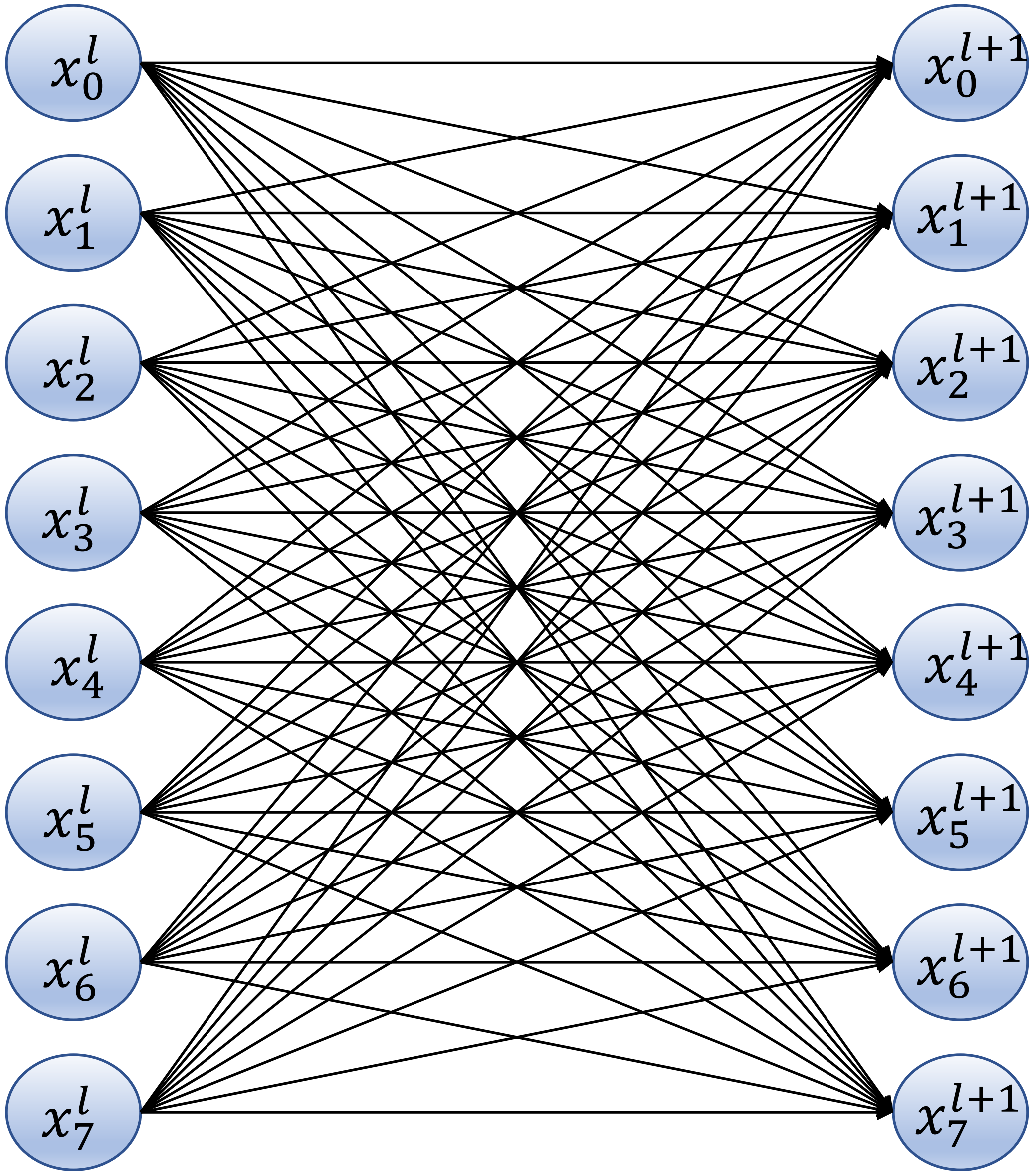

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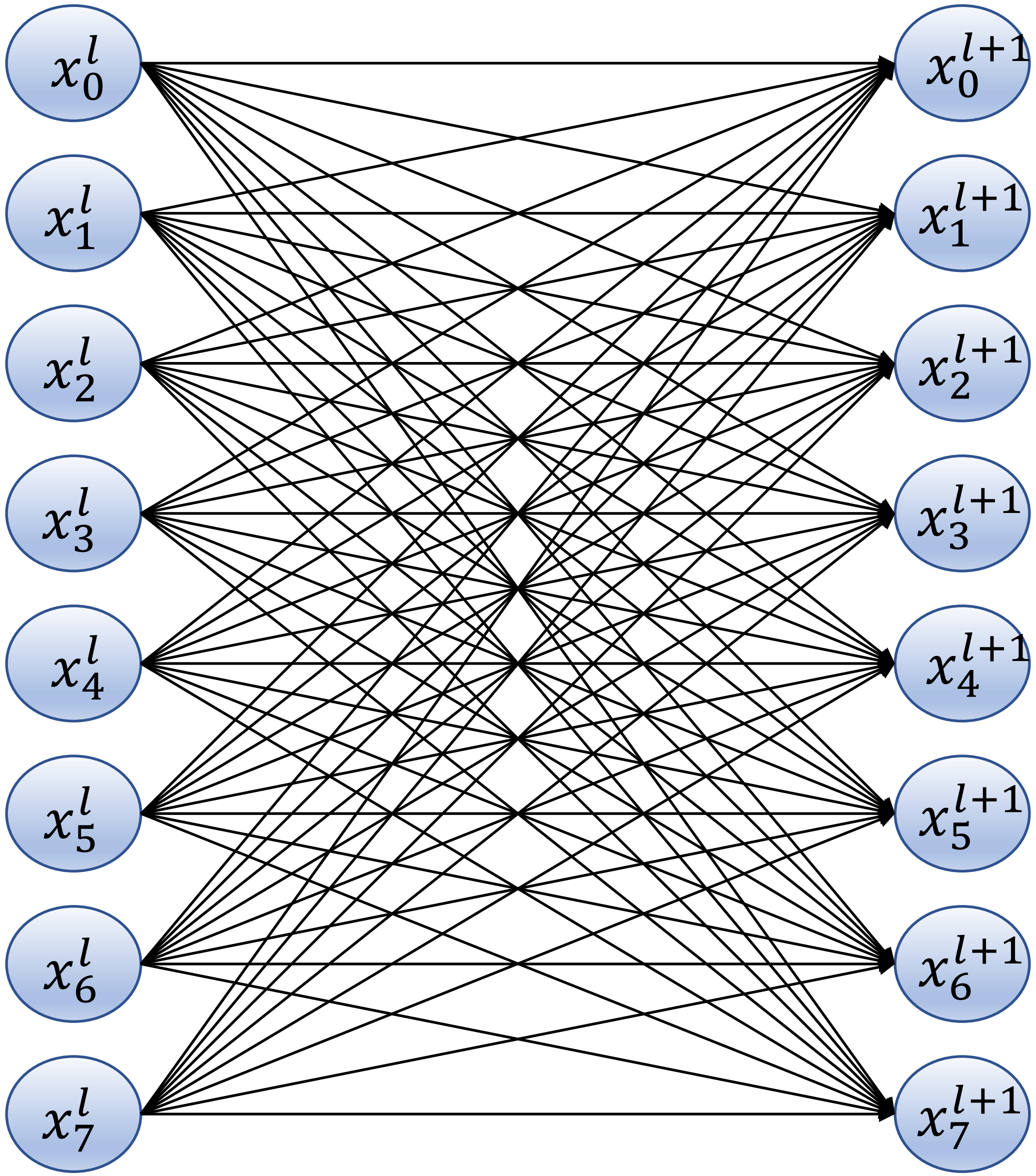

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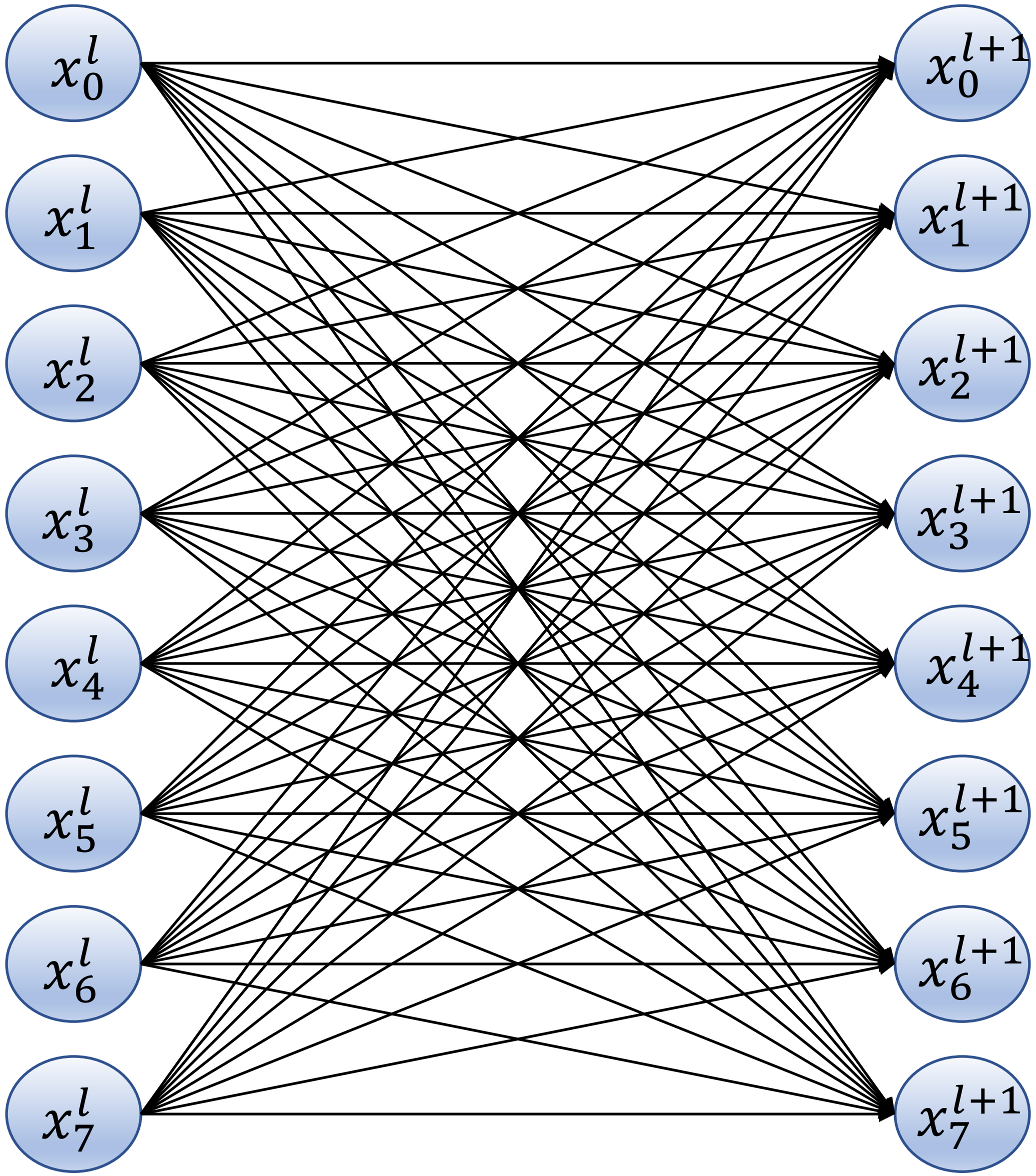

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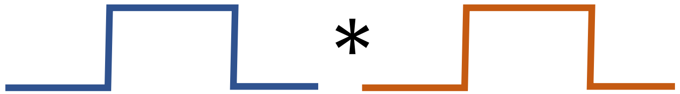
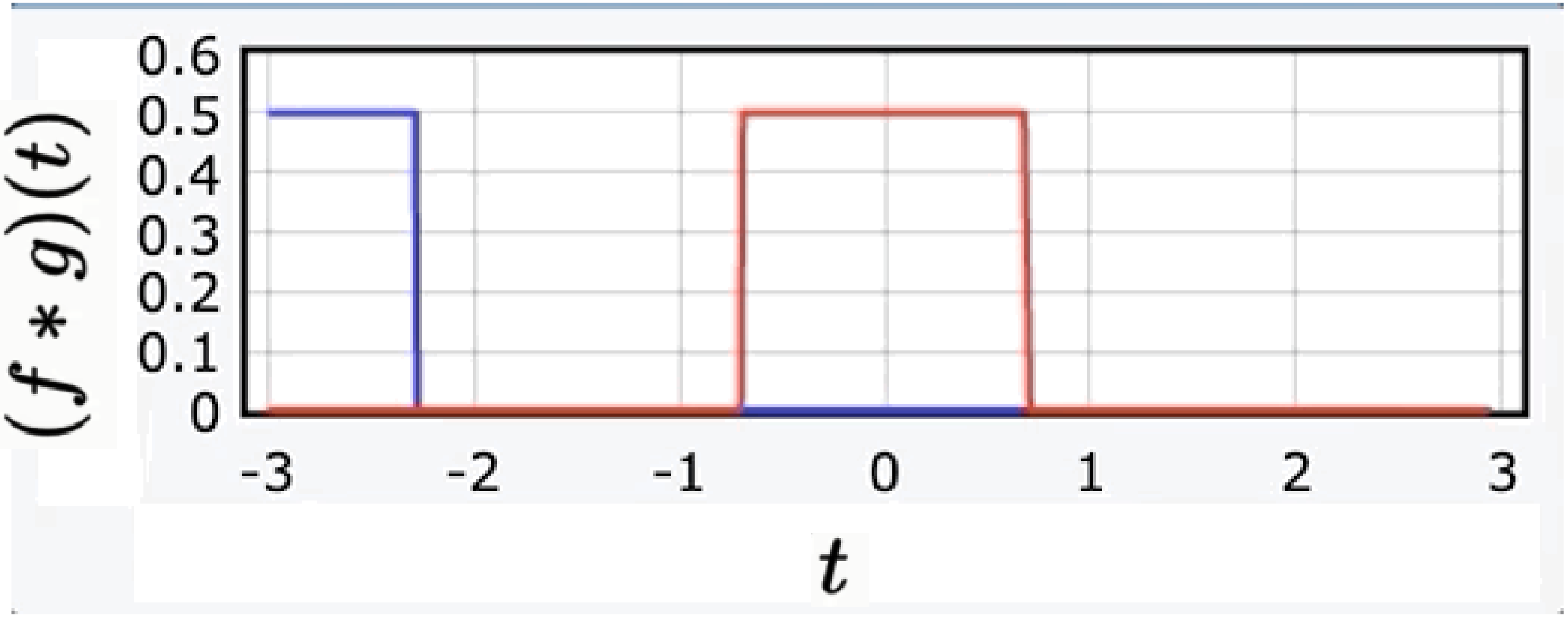
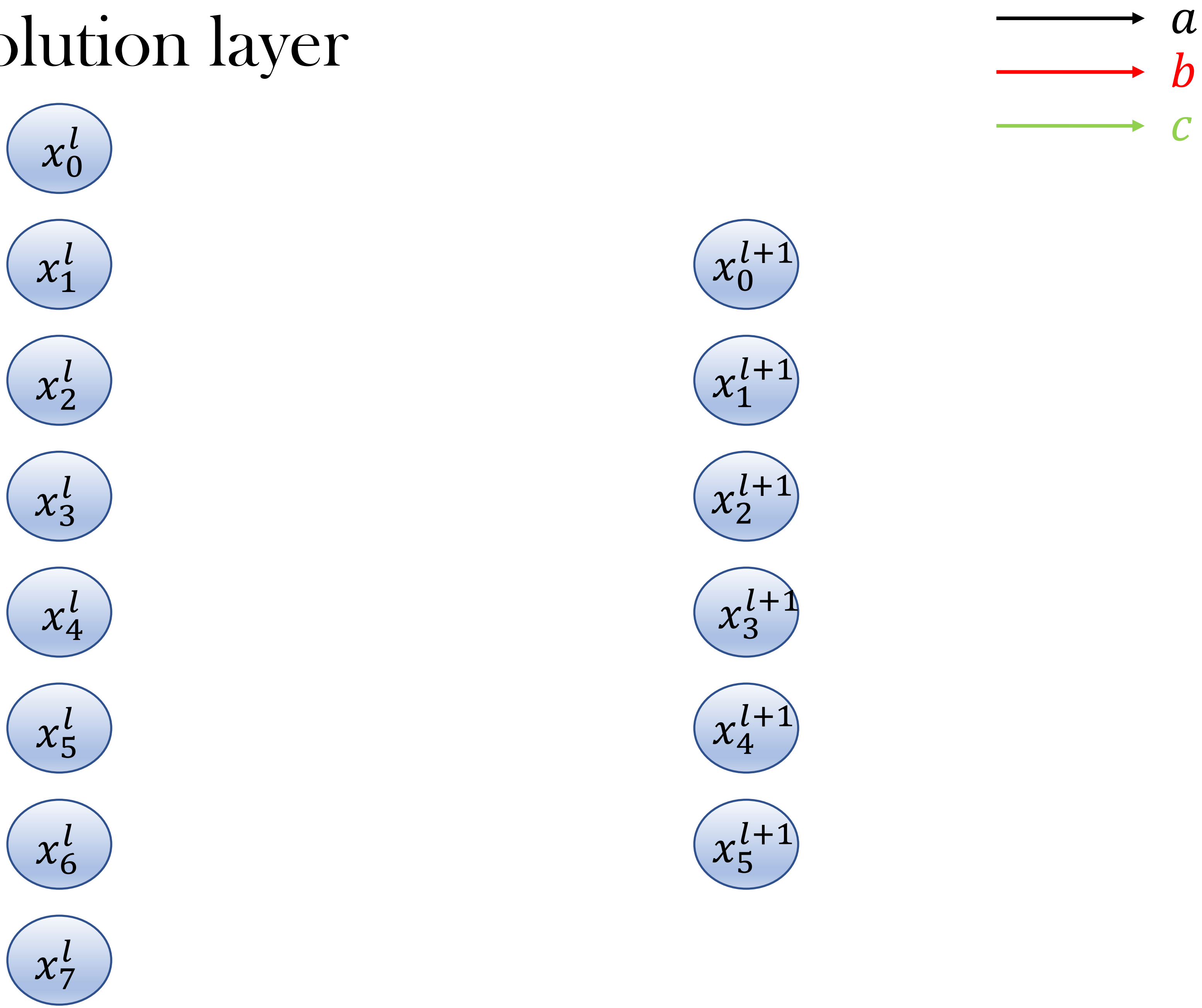
Convolution



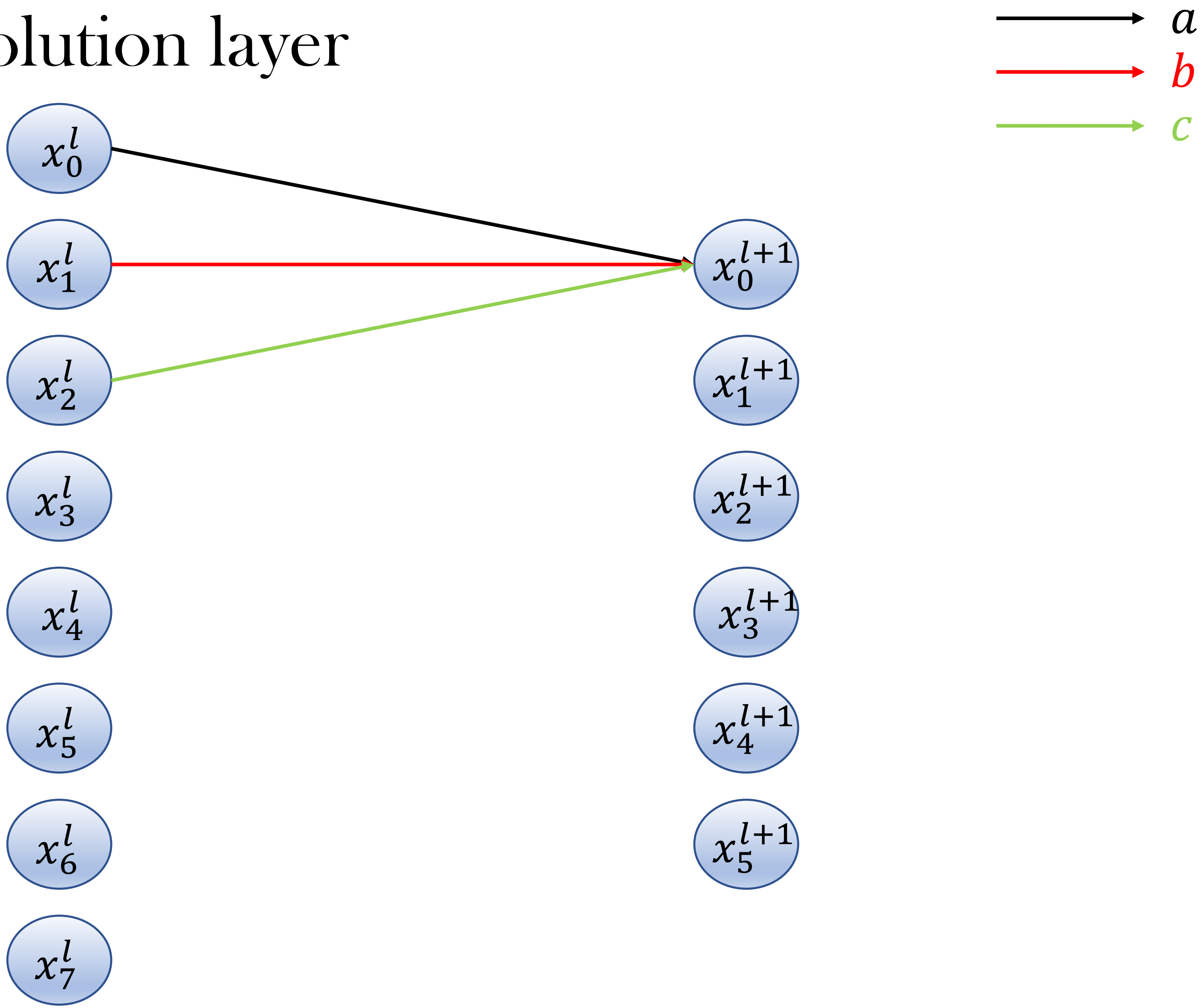


$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)\, g(t-\tau)\, d\tau$$

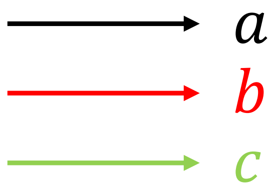
Convolution layer

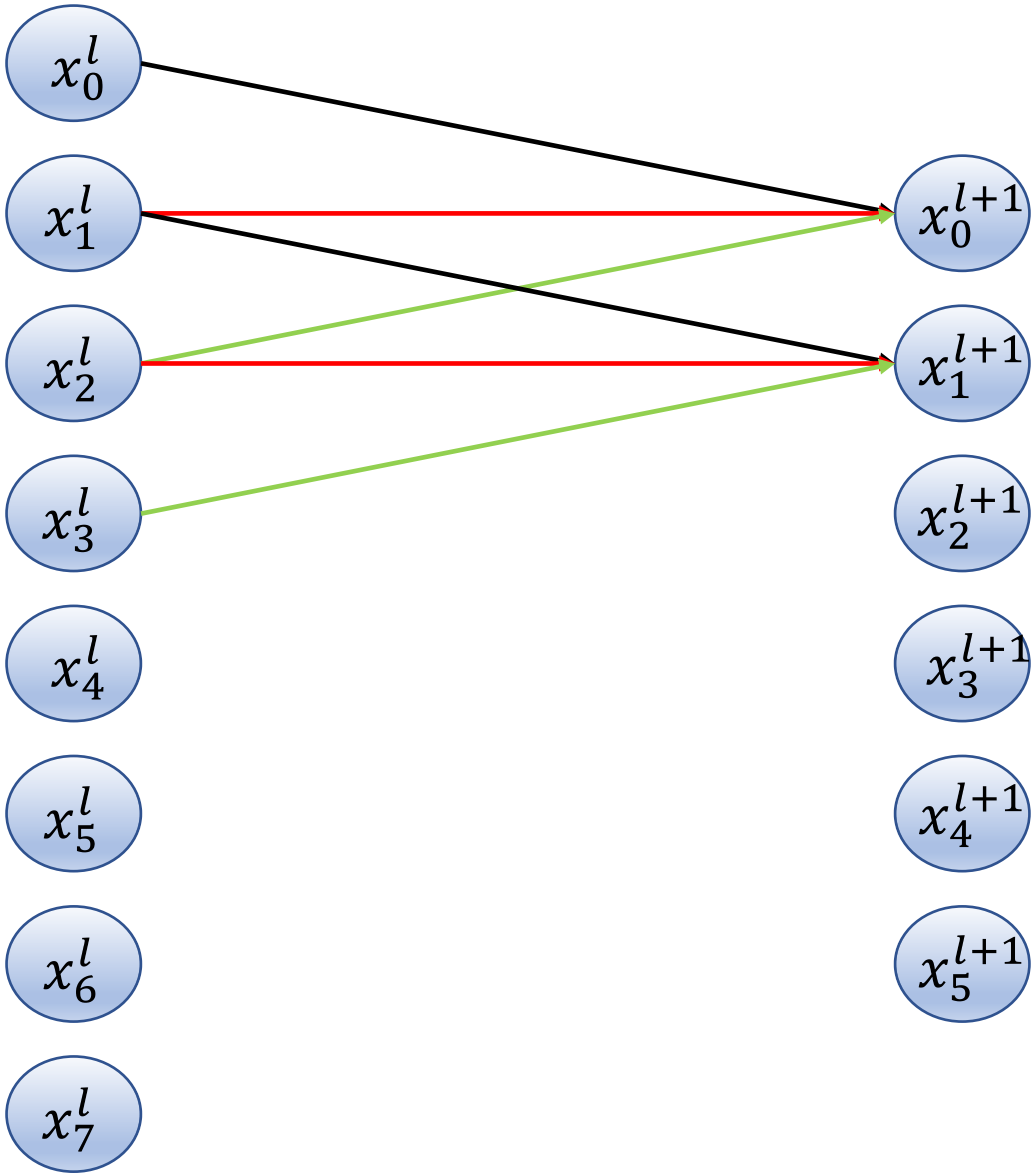


Convolution layer

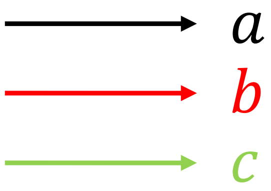


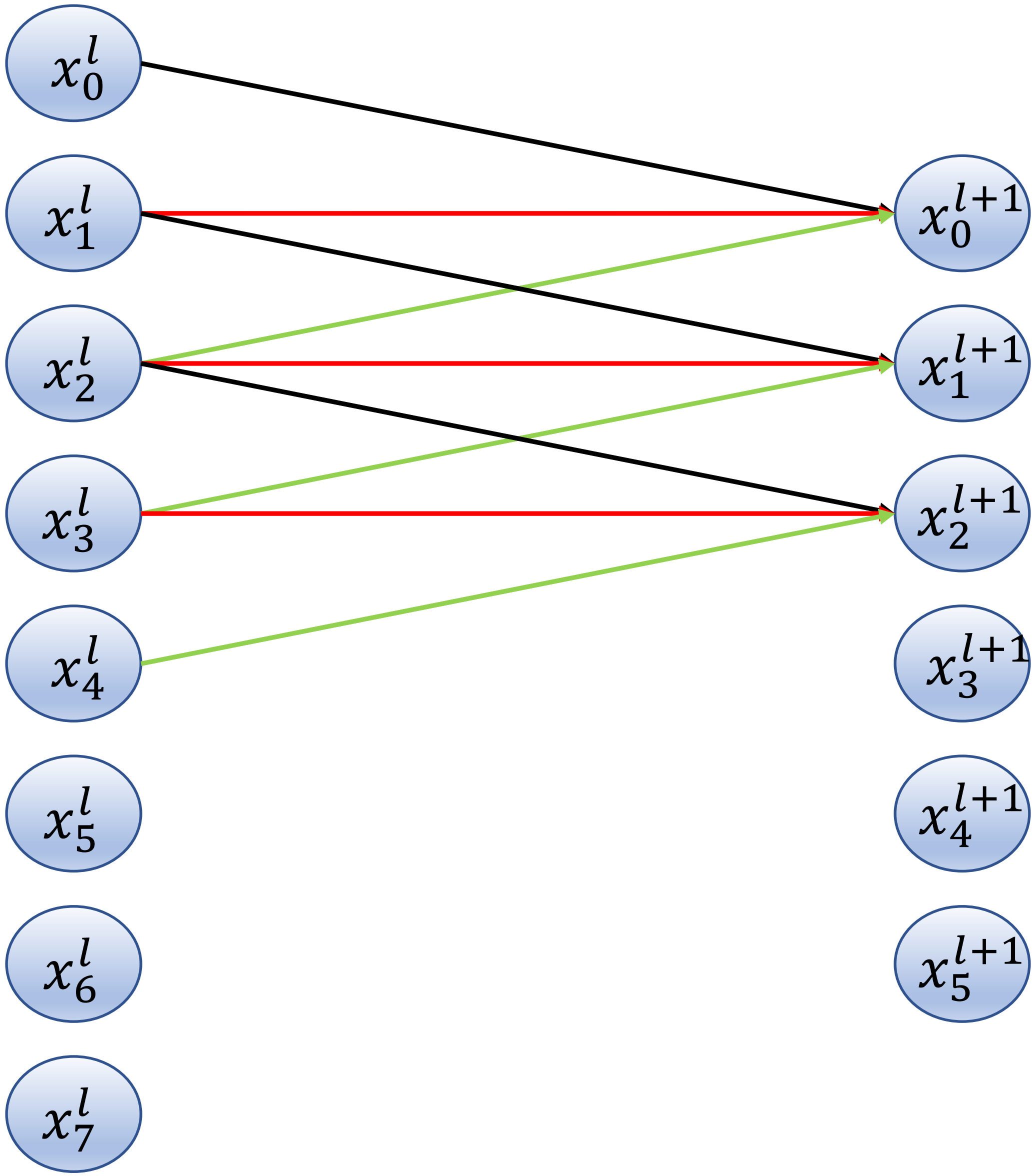
Convolution layer





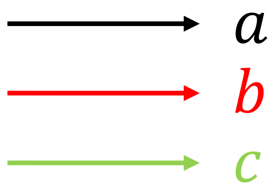
Convolution layer

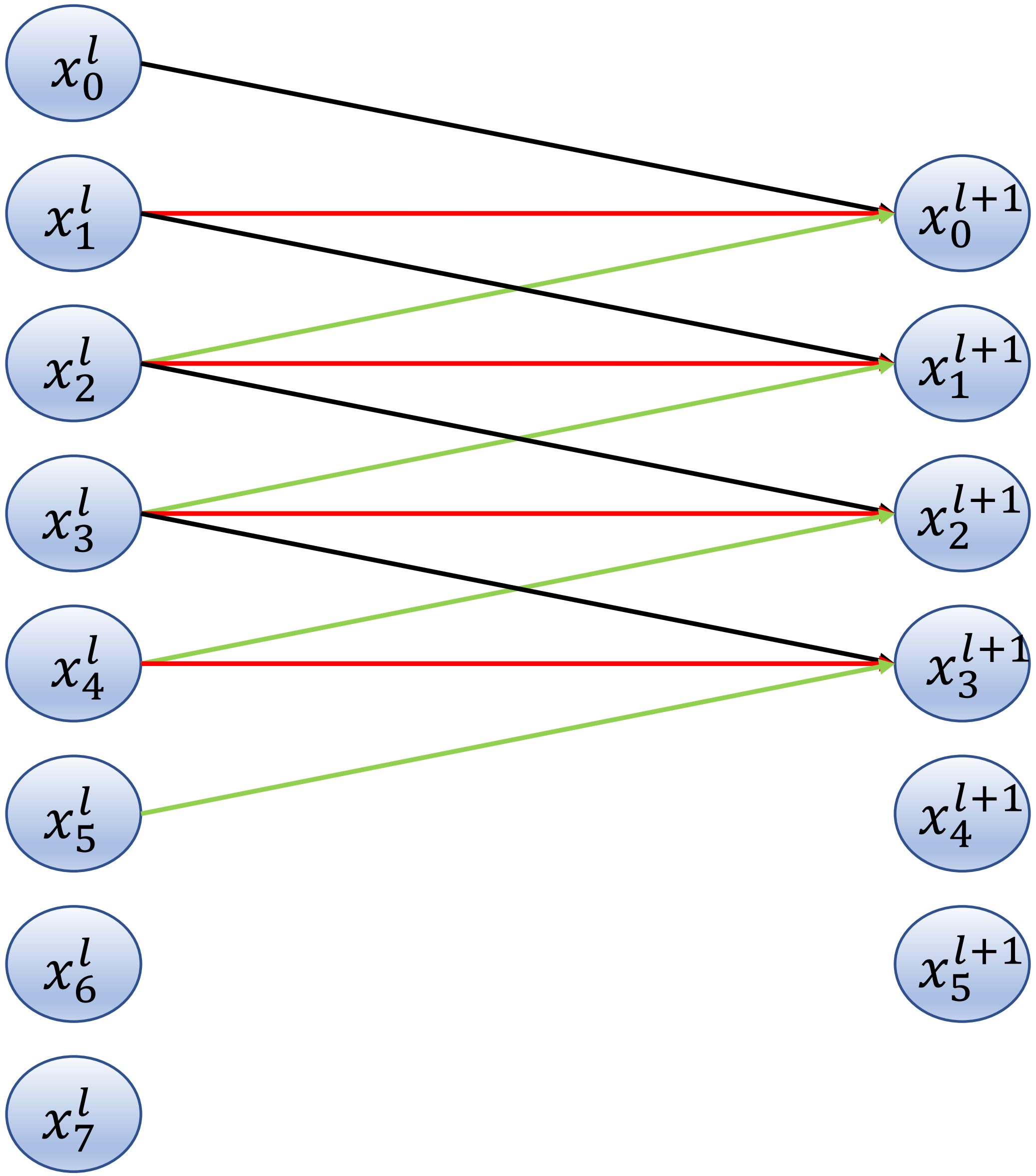




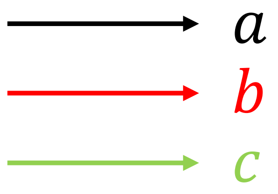
Convolution layer

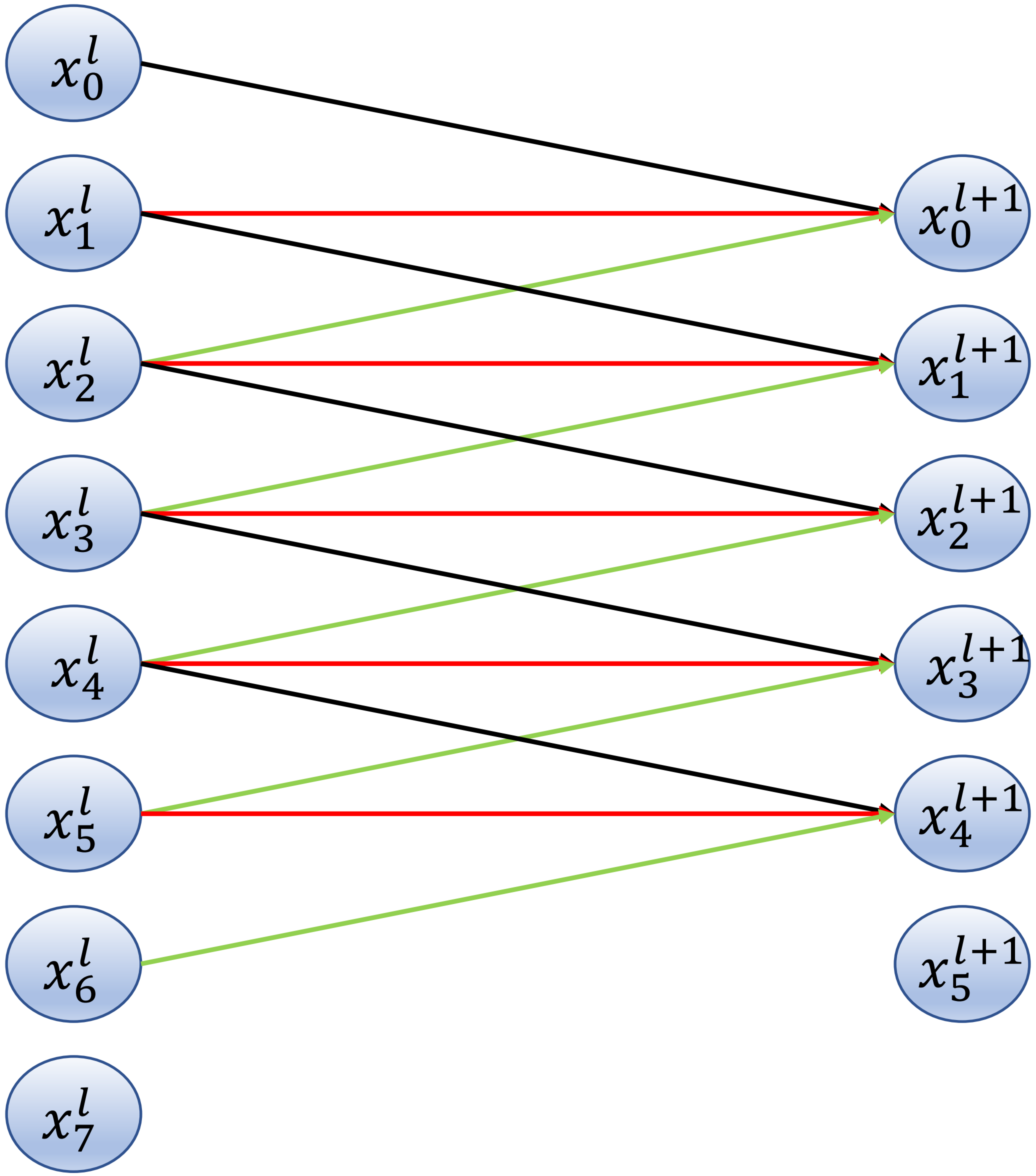
[redacted]



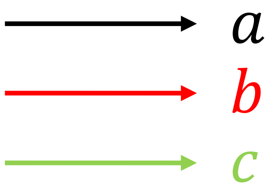


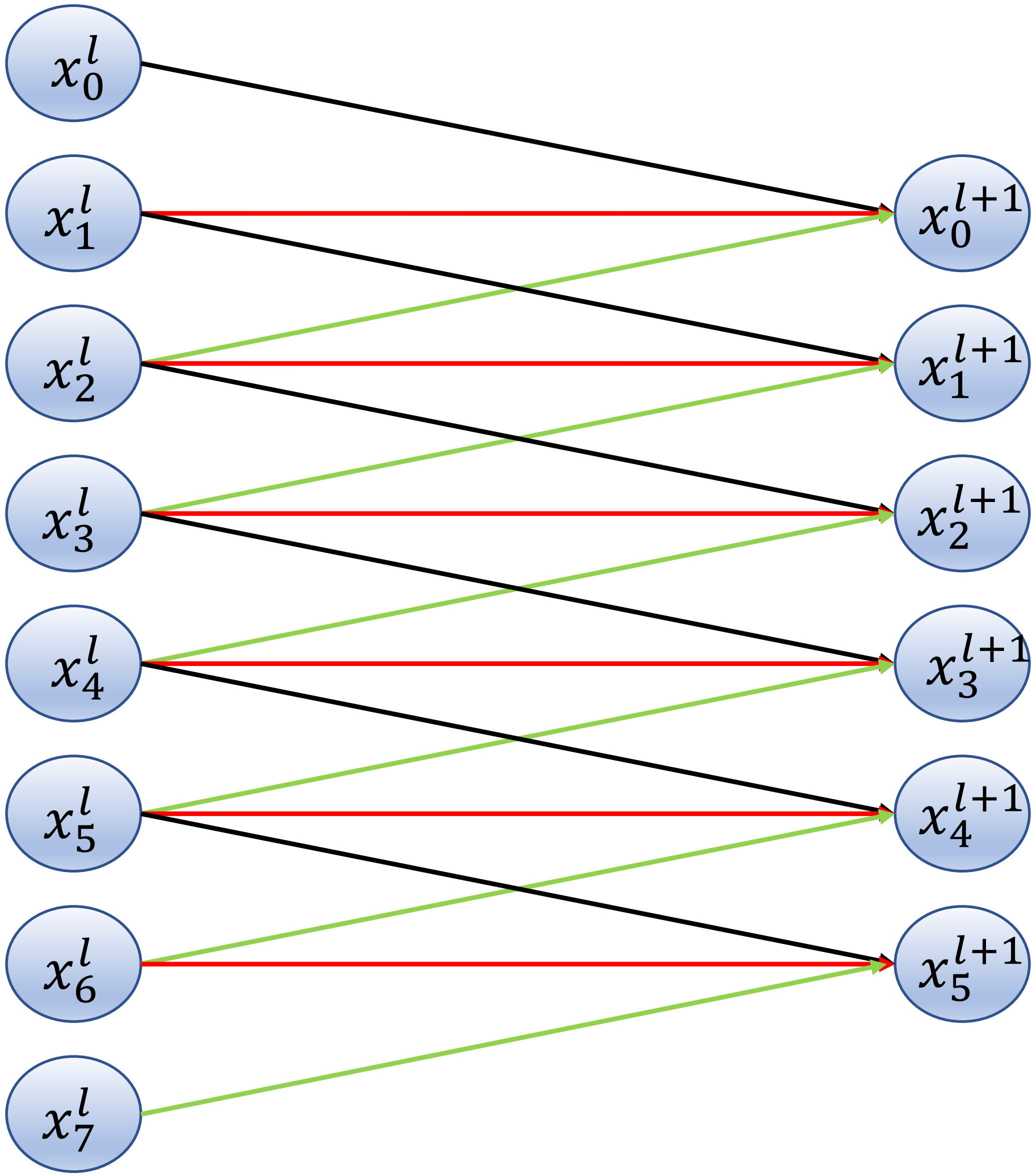
Convolution layer





Convolution layer





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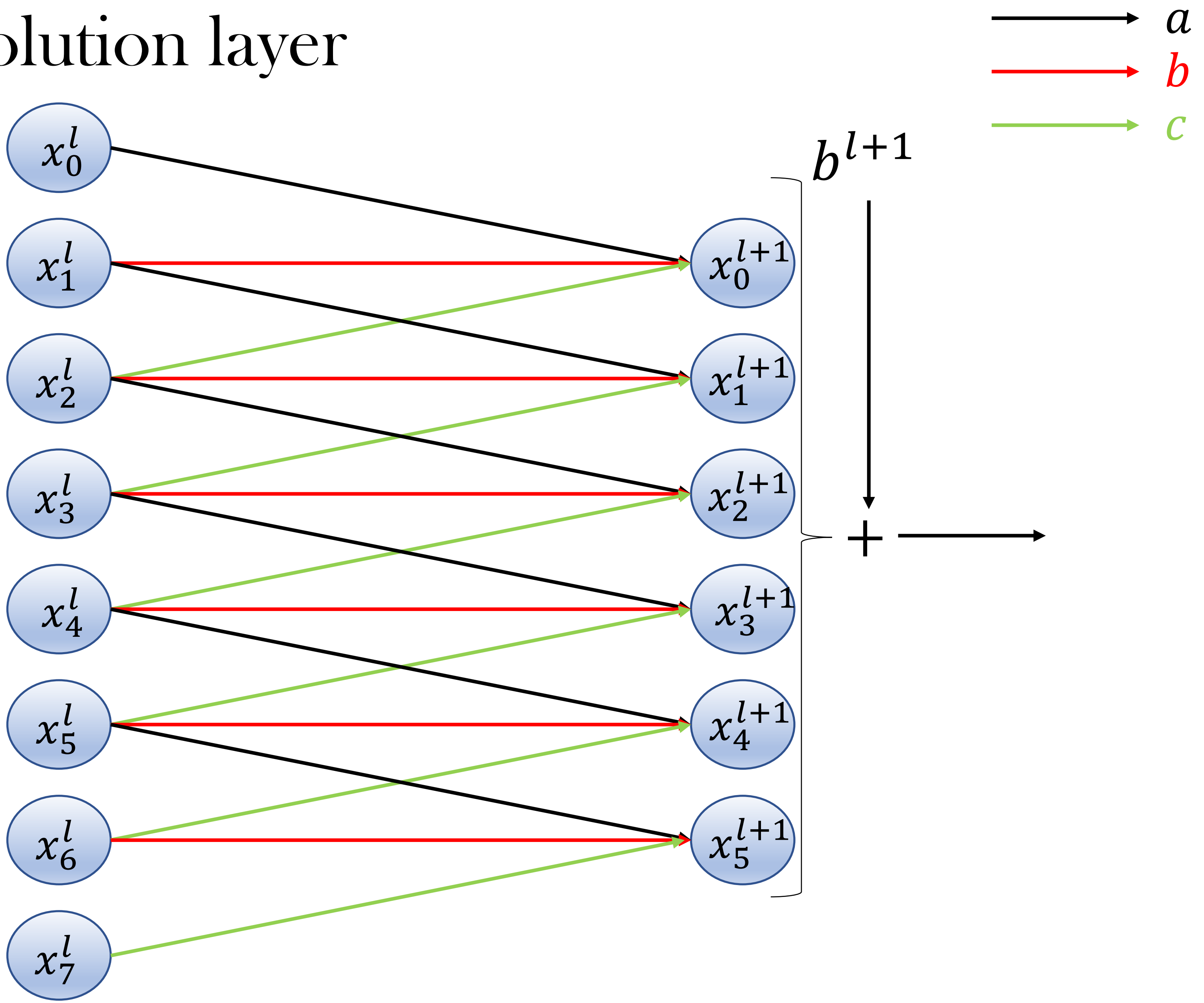

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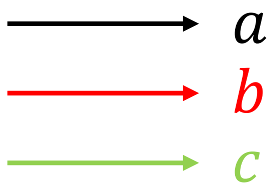
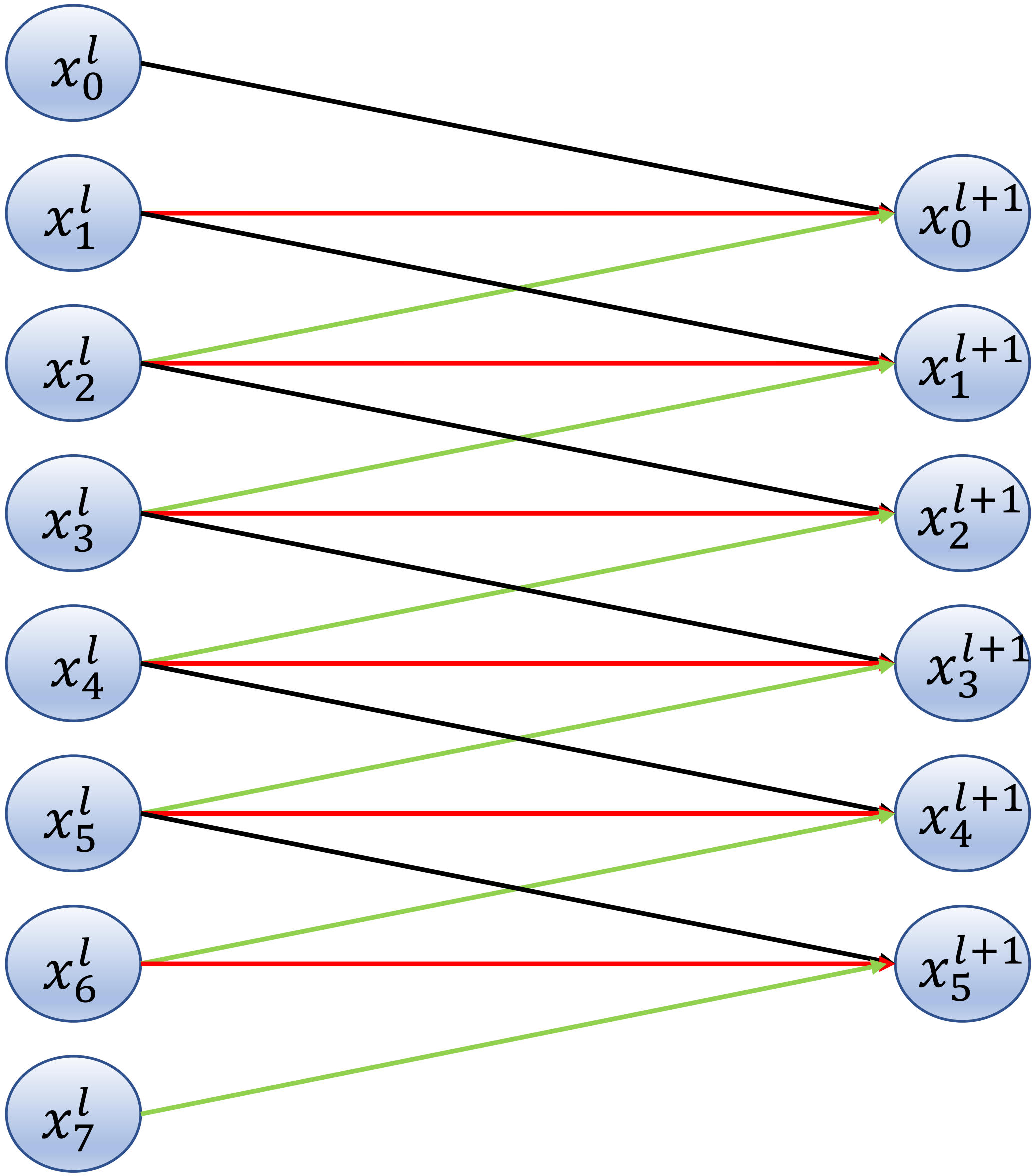
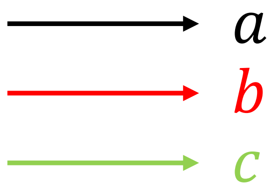
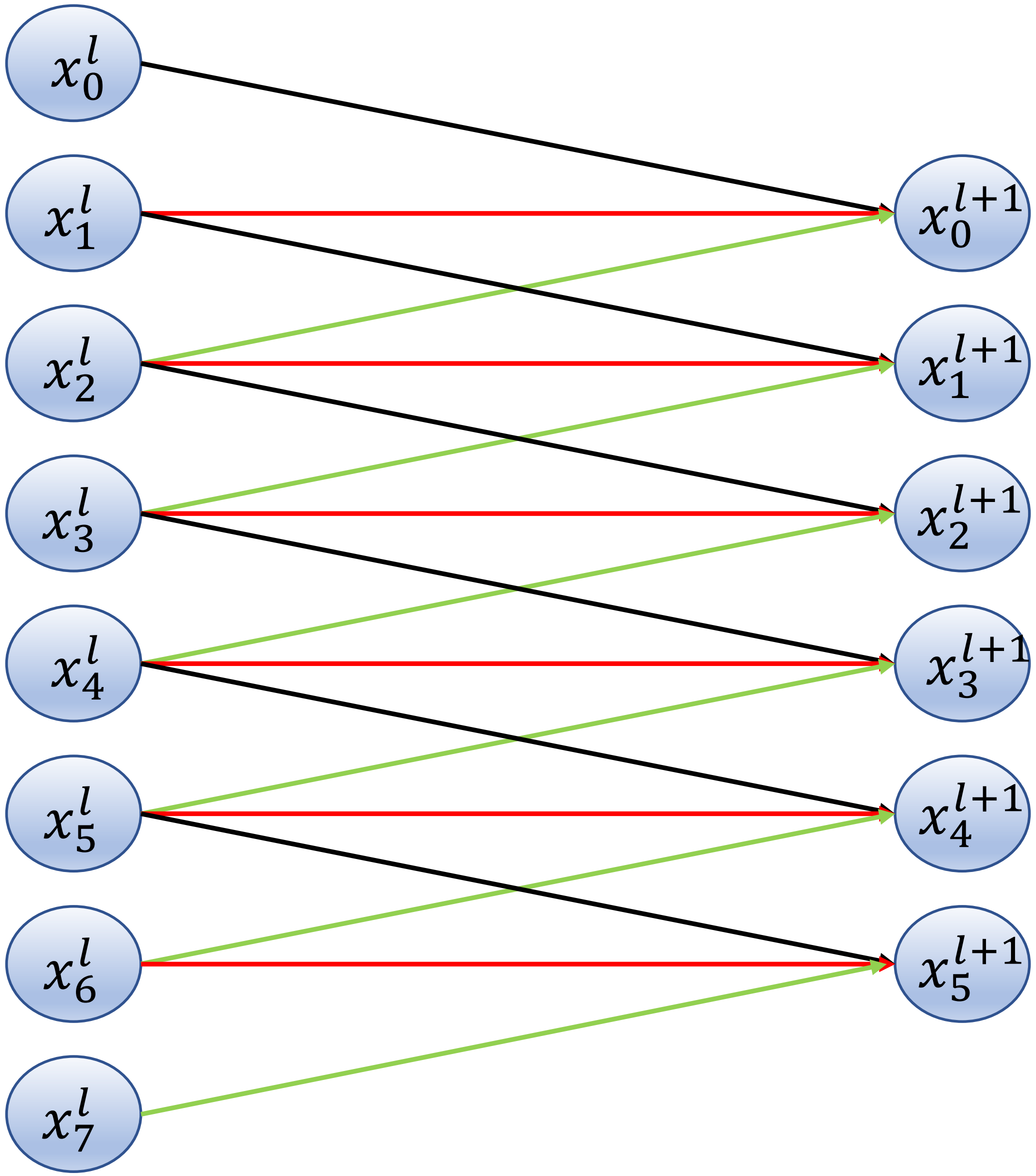




Convolution layer





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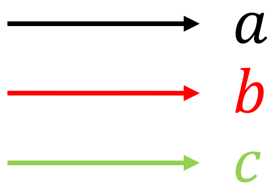

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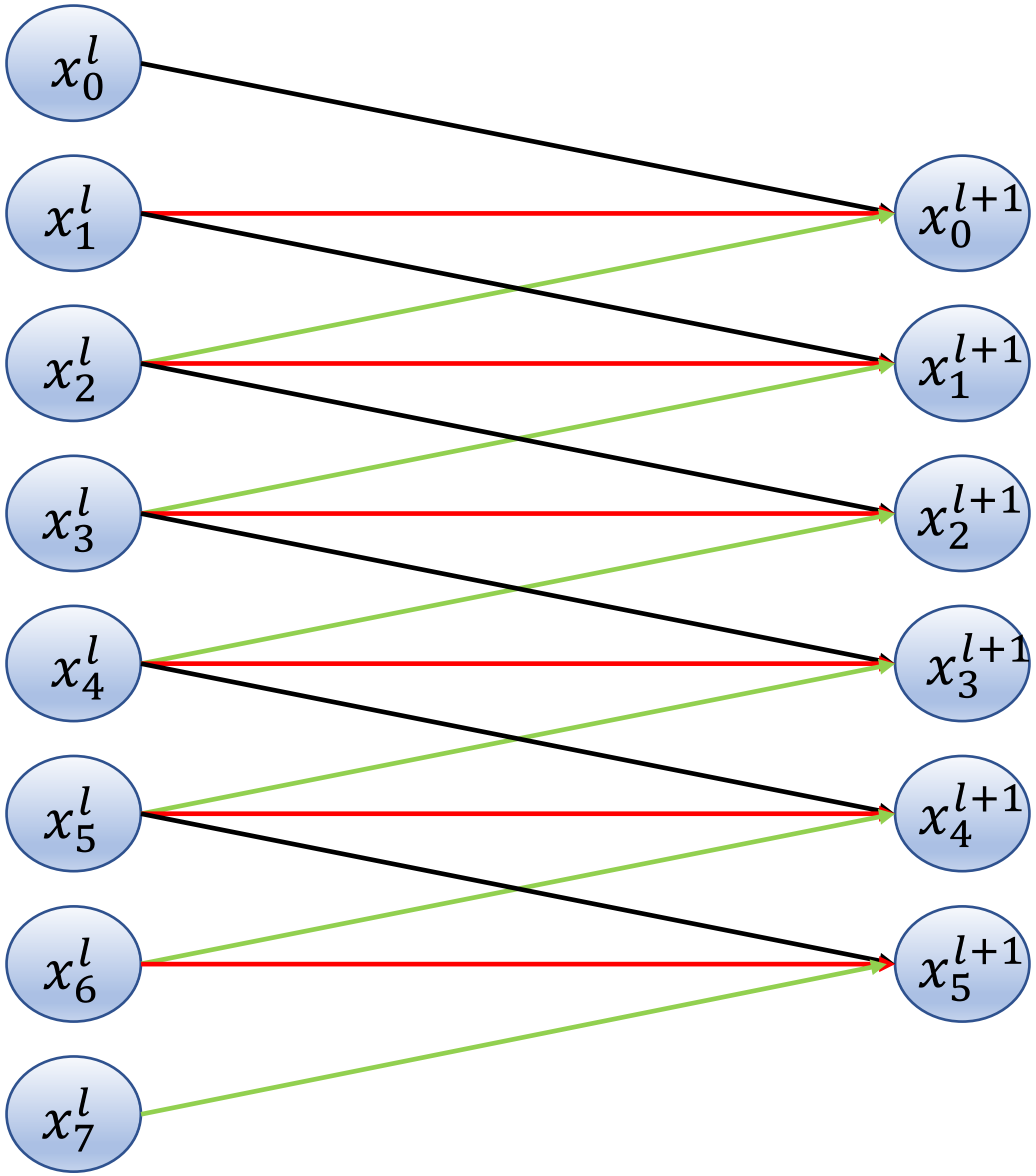
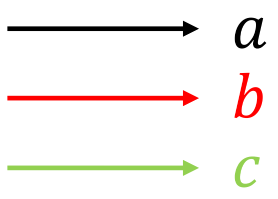
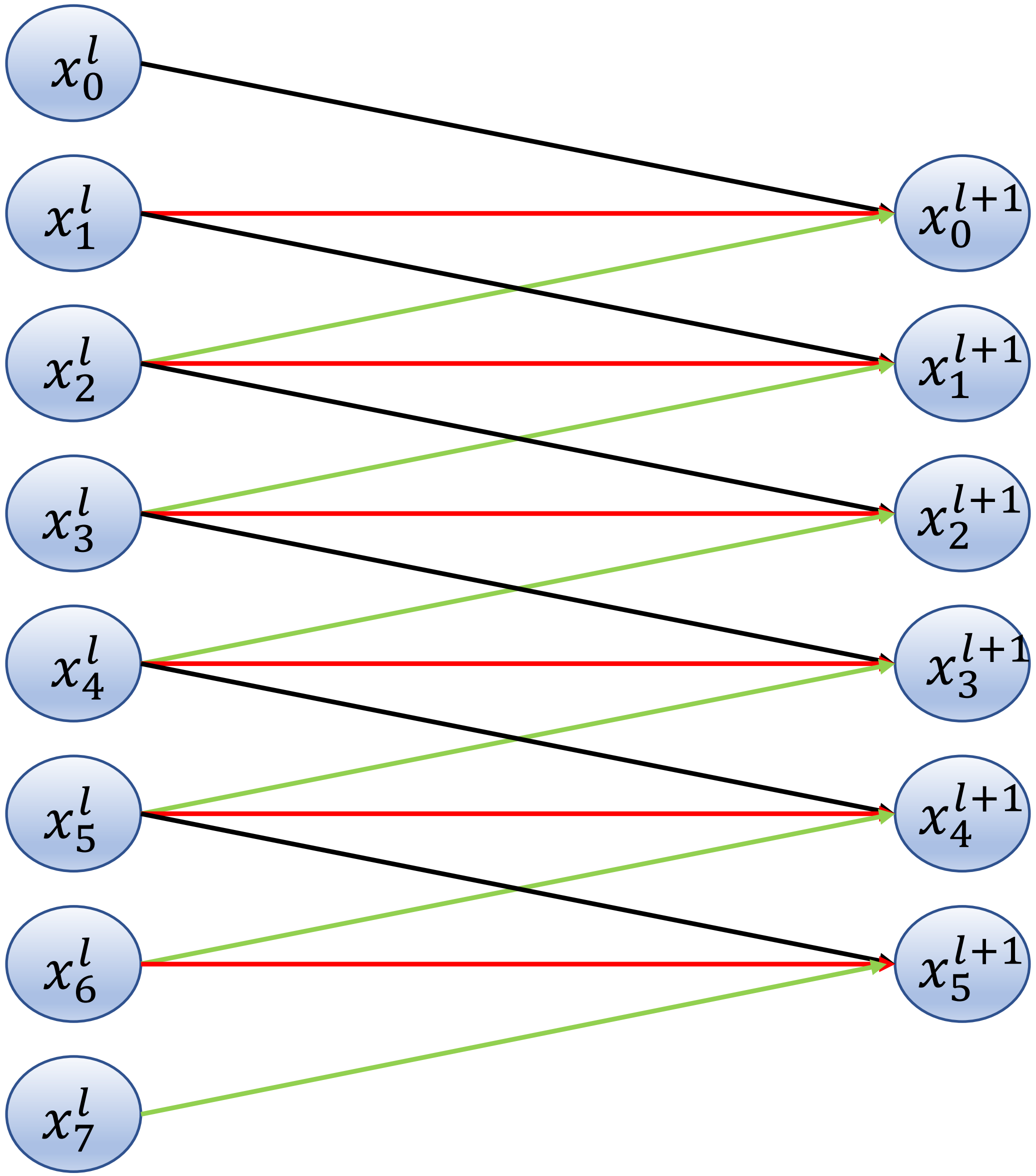


$$\begin{bmatrix} \boldsymbol{a} & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \end{bmatrix}$$

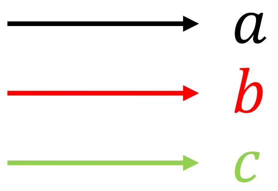
Convolution layer

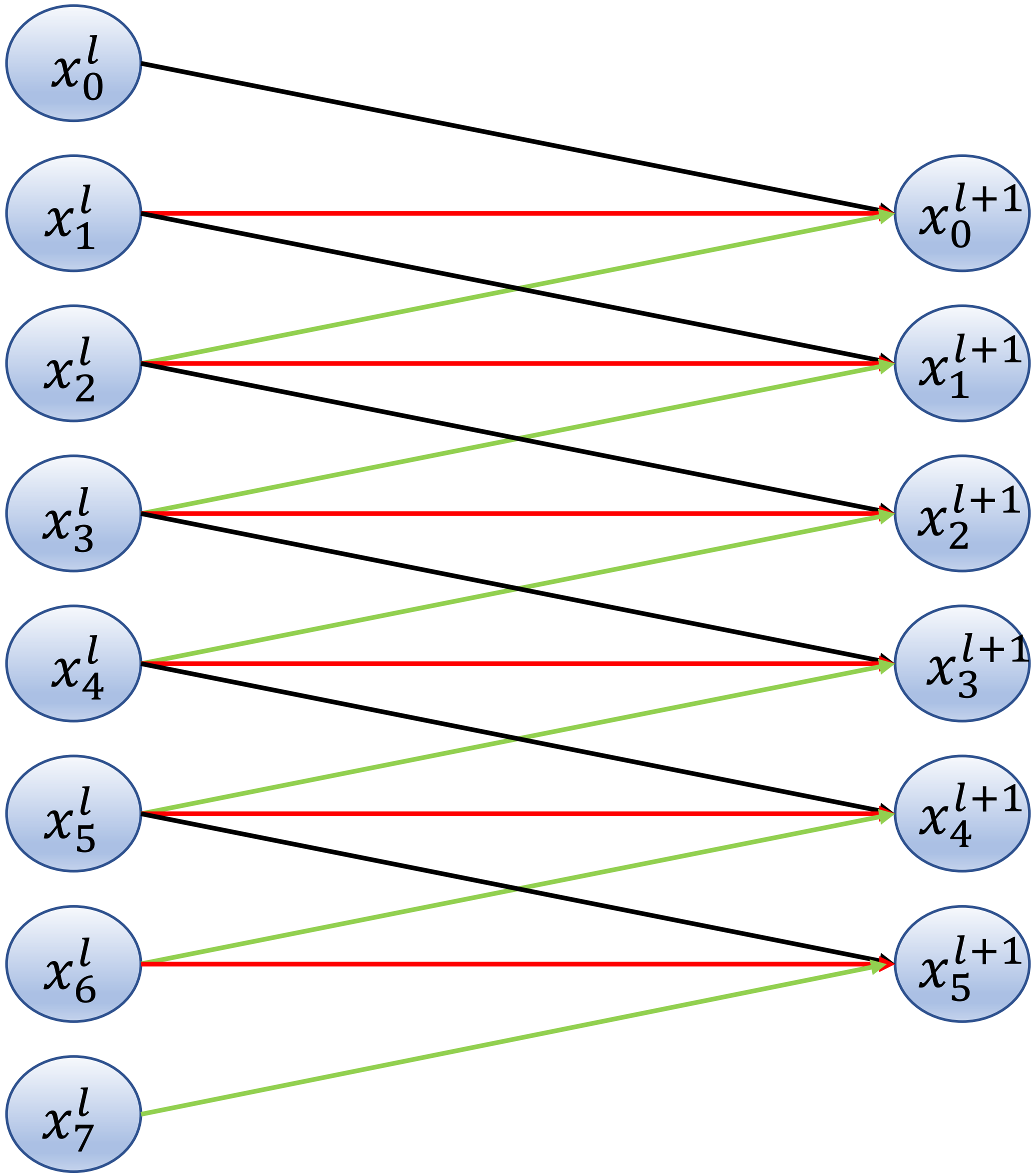




$$\begin{bmatrix} \boldsymbol{a} & \boldsymbol{b} & & & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & \end{bmatrix}$$

Convolution layer





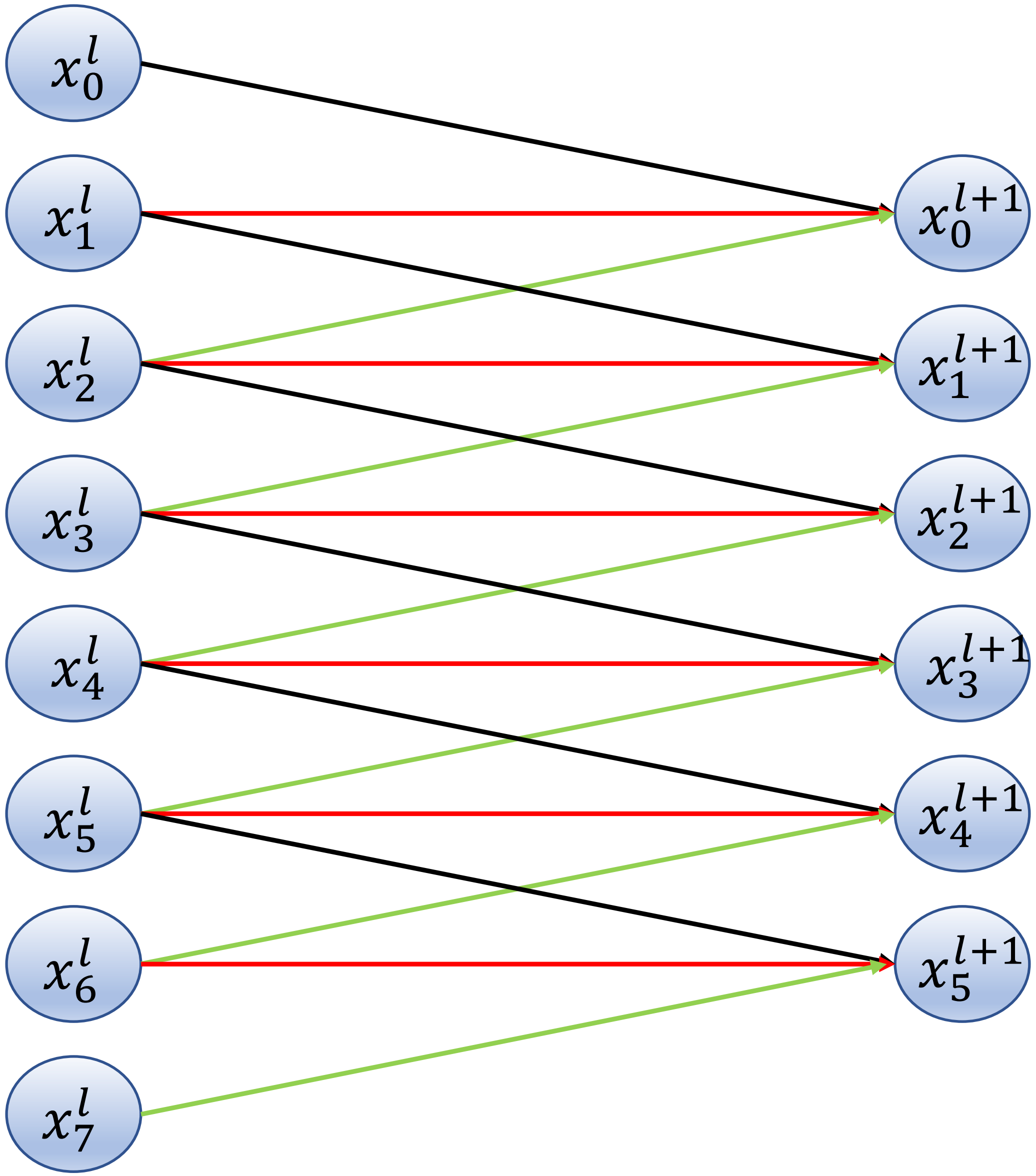
$$\begin{bmatrix} \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} & 0 & 0 & 0 & 0 & 0 \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \end{bmatrix}$$

Convolution layer

$\longrightarrow a$

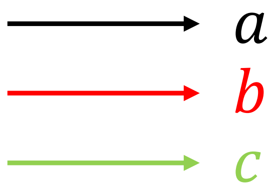
$\longrightarrow b$

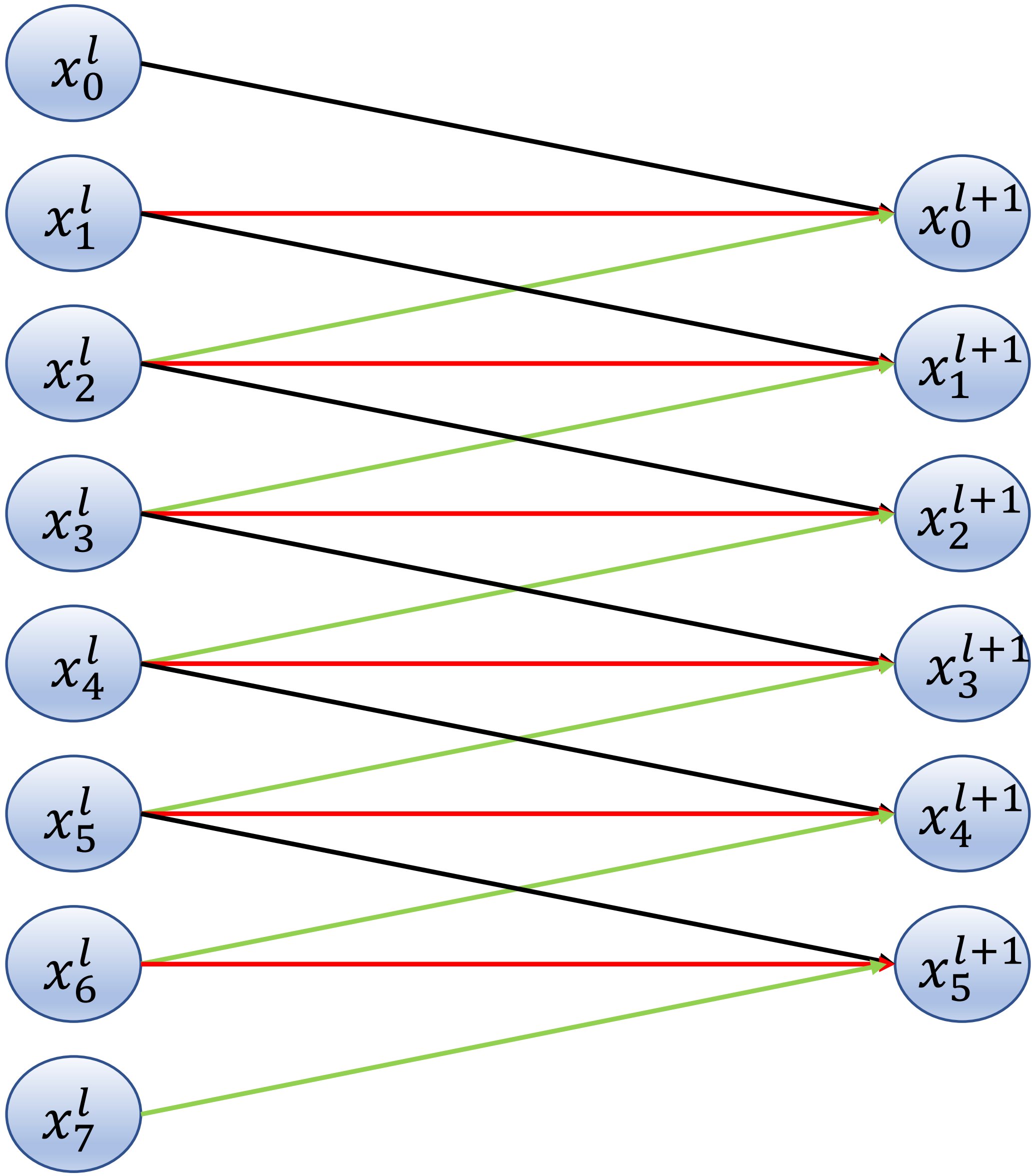
$\longrightarrow c$



$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 & 0 \\ 0 & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \end{bmatrix}$$

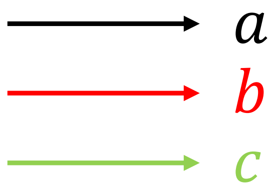
Convolution layer

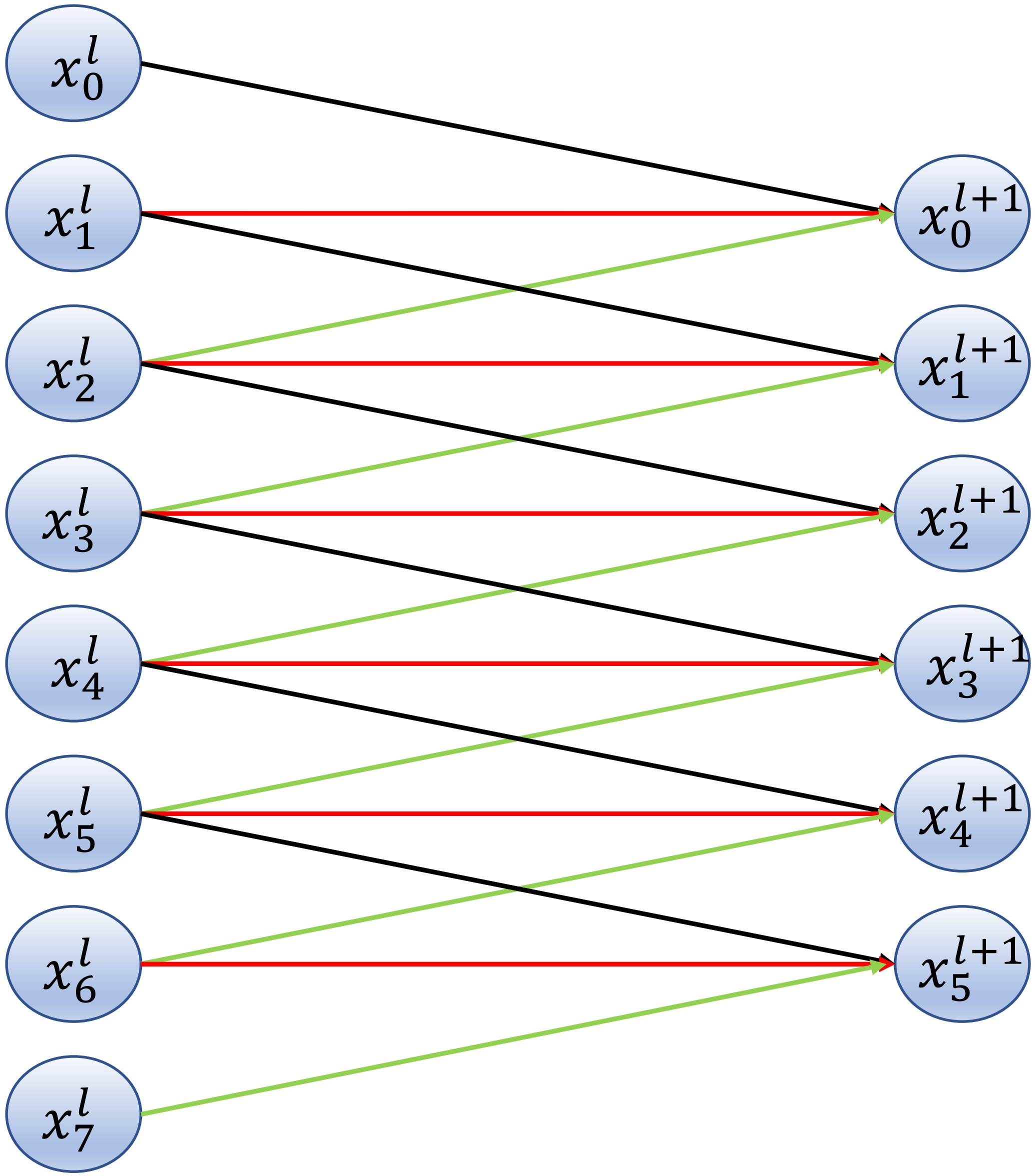




$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 & 0 \\ 0 & a & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \end{bmatrix}$$

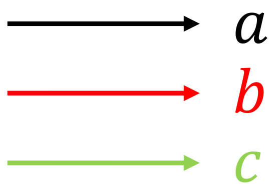
Convolution layer

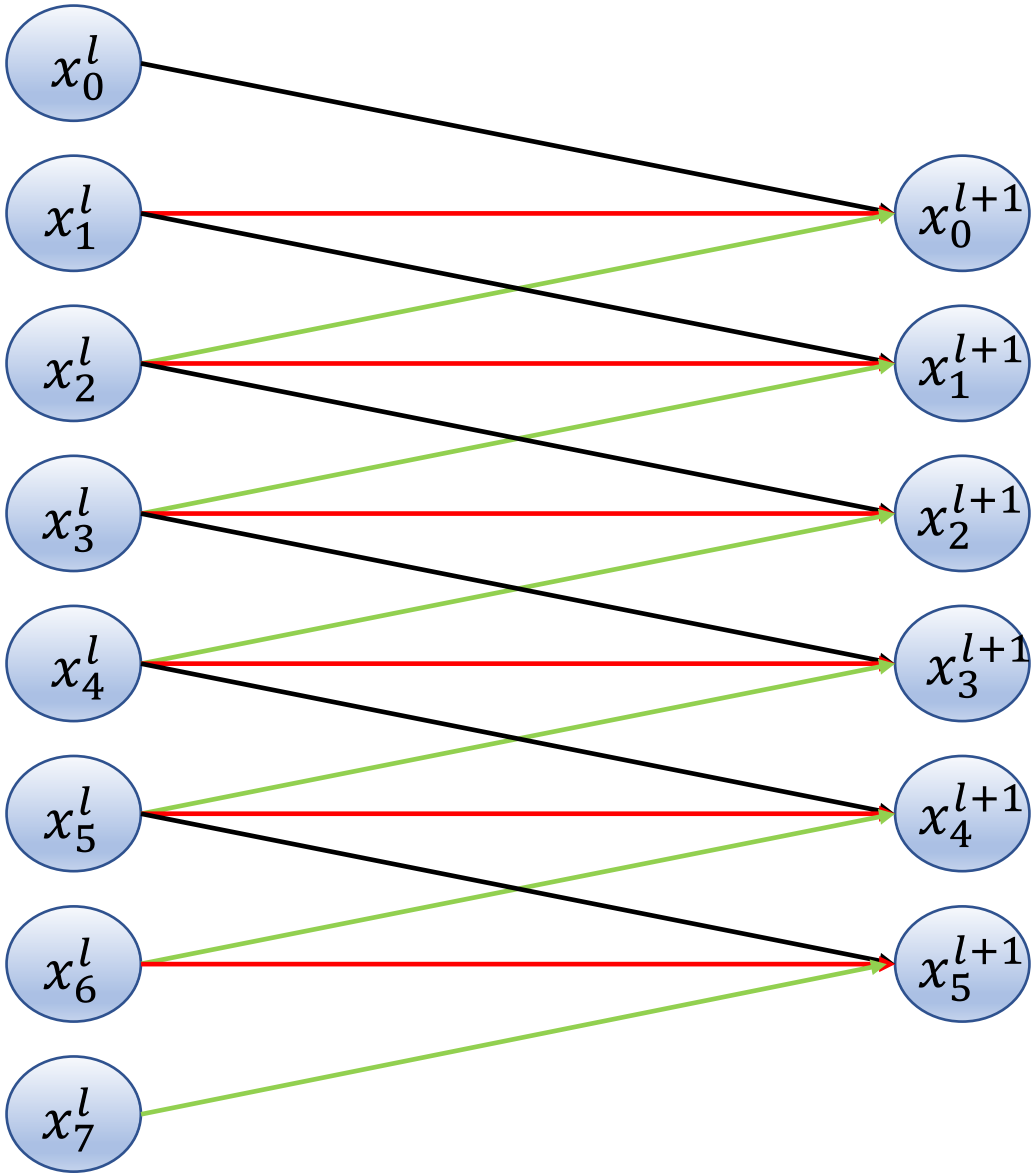




$$\begin{bmatrix} \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} & 0 & 0 & 0 & 0 & 0 \\ 0 & \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} & 0 & 0 & 0 & 0 \\ & & & & & & & \\ & & & & & & & \end{bmatrix}$$

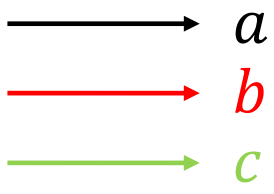
Convolution layer

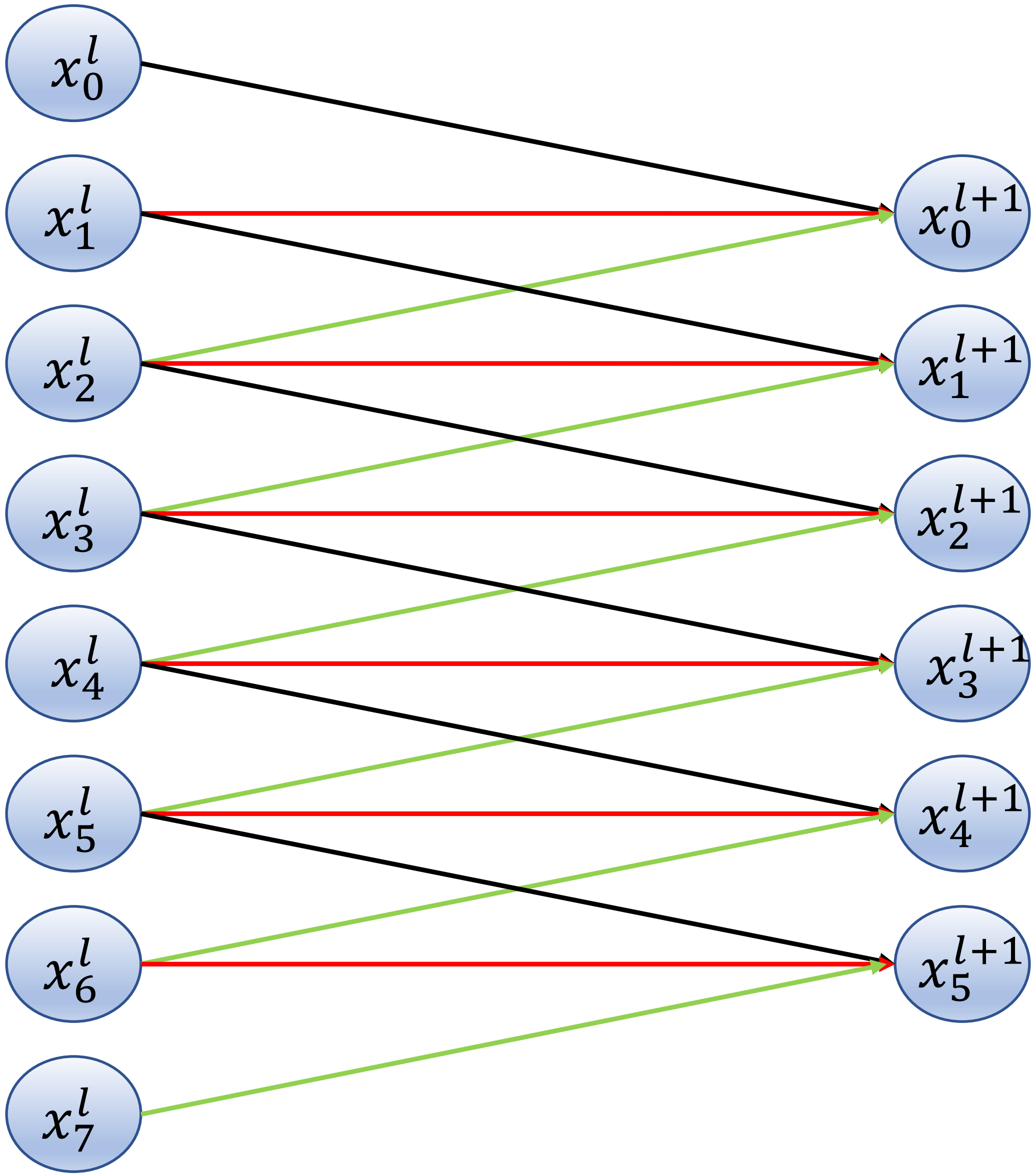




$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 & 0 \\ 0 & a & b & c & 0 & 0 & 0 & 0 \\ 0 & 0 & a & b & c & 0 & 0 & 0 \\ 0 & 0 & 0 & a & b & c & 0 & 0 \\ 0 & 0 & 0 & 0 & a & b & c & 0 \\ 0 & 0 & 0 & 0 & 0 & a & b & c \end{bmatrix}$$

Convolution layer

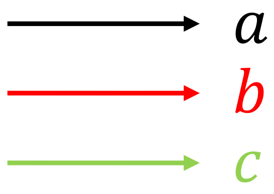


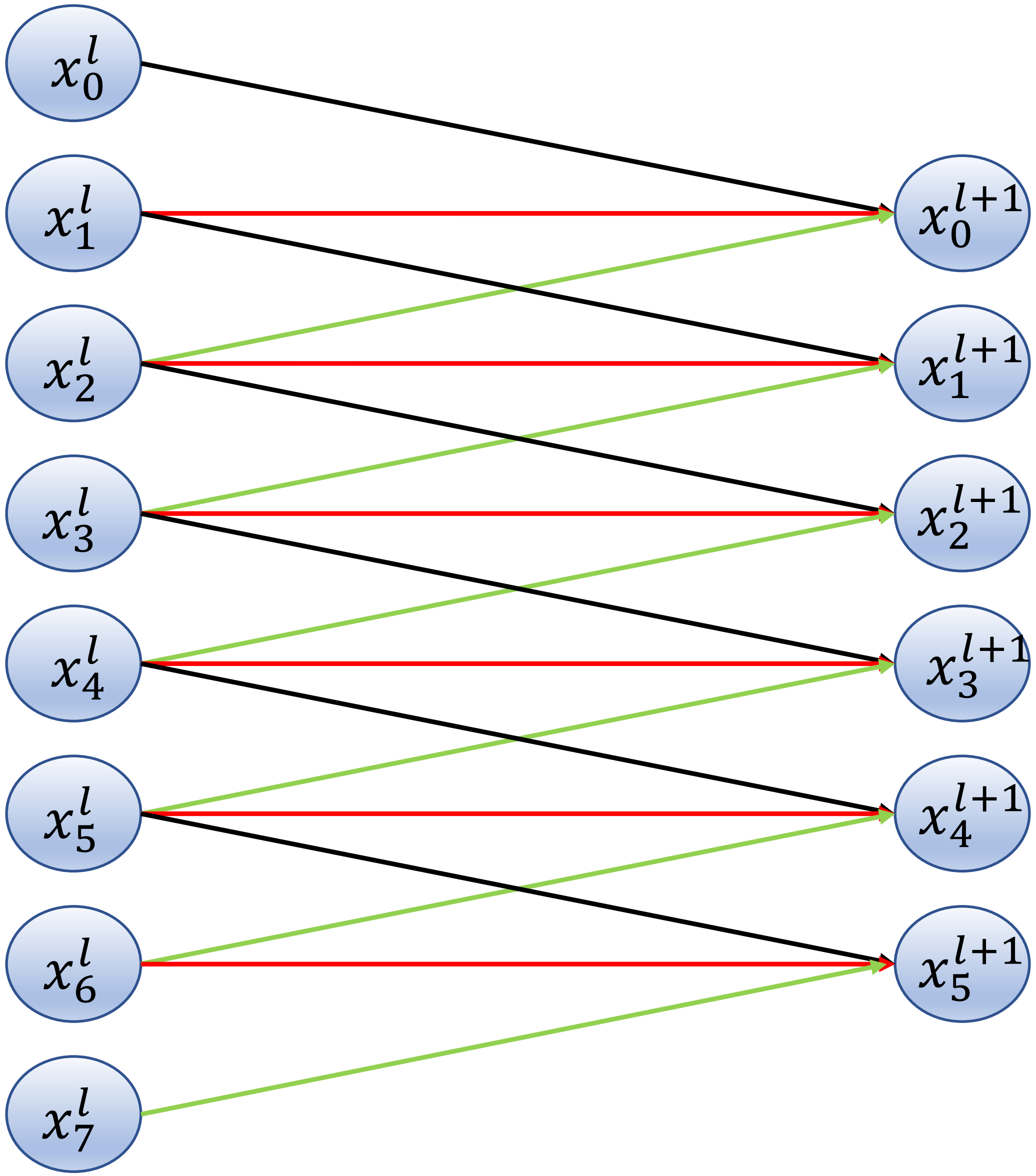


$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 & 0 \\ 0 & a & b & c & 0 & 0 & 0 & 0 \\ 0 & 0 & a & b & c & 0 & 0 & 0 \\ 0 & 0 & 0 & a & b & c & 0 & 0 \\ 0 & 0 & 0 & 0 & a & b & c & 0 \\ 0 & 0 & 0 & 0 & 0 & a & b & c \end{bmatrix}$$

Toeplitz matrix

Convolution layer



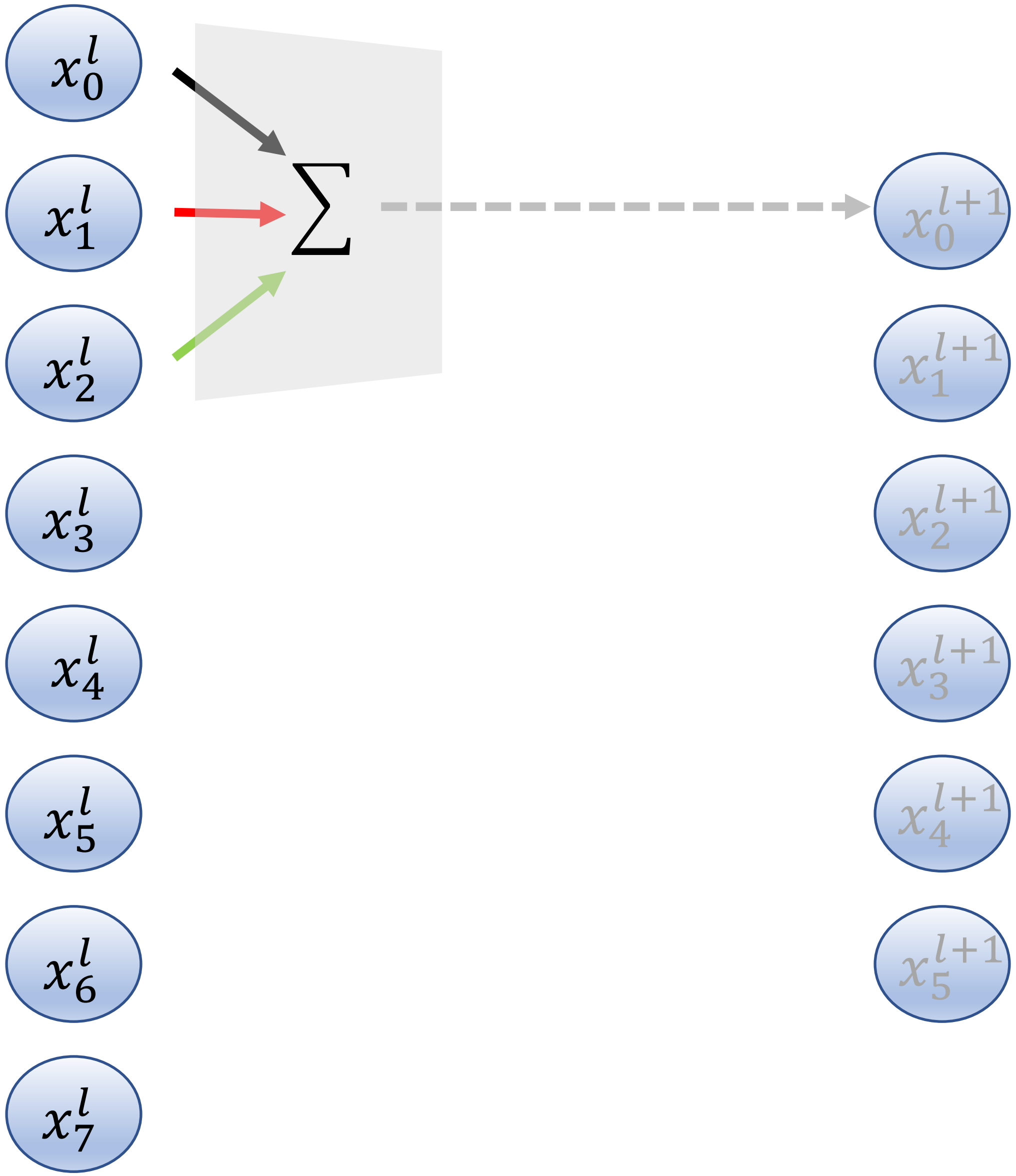


$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 & 0 \\ 0 & a & b & c & 0 & 0 & 0 & 0 \\ 0 & 0 & a & b & c & 0 & 0 & 0 \\ 0 & 0 & 0 & a & b & c & 0 & 0 \\ 0 & 0 & 0 & 0 & a & b & c & 0 \\ 0 & 0 & 0 & 0 & 0 & a & b & c \end{bmatrix}$$

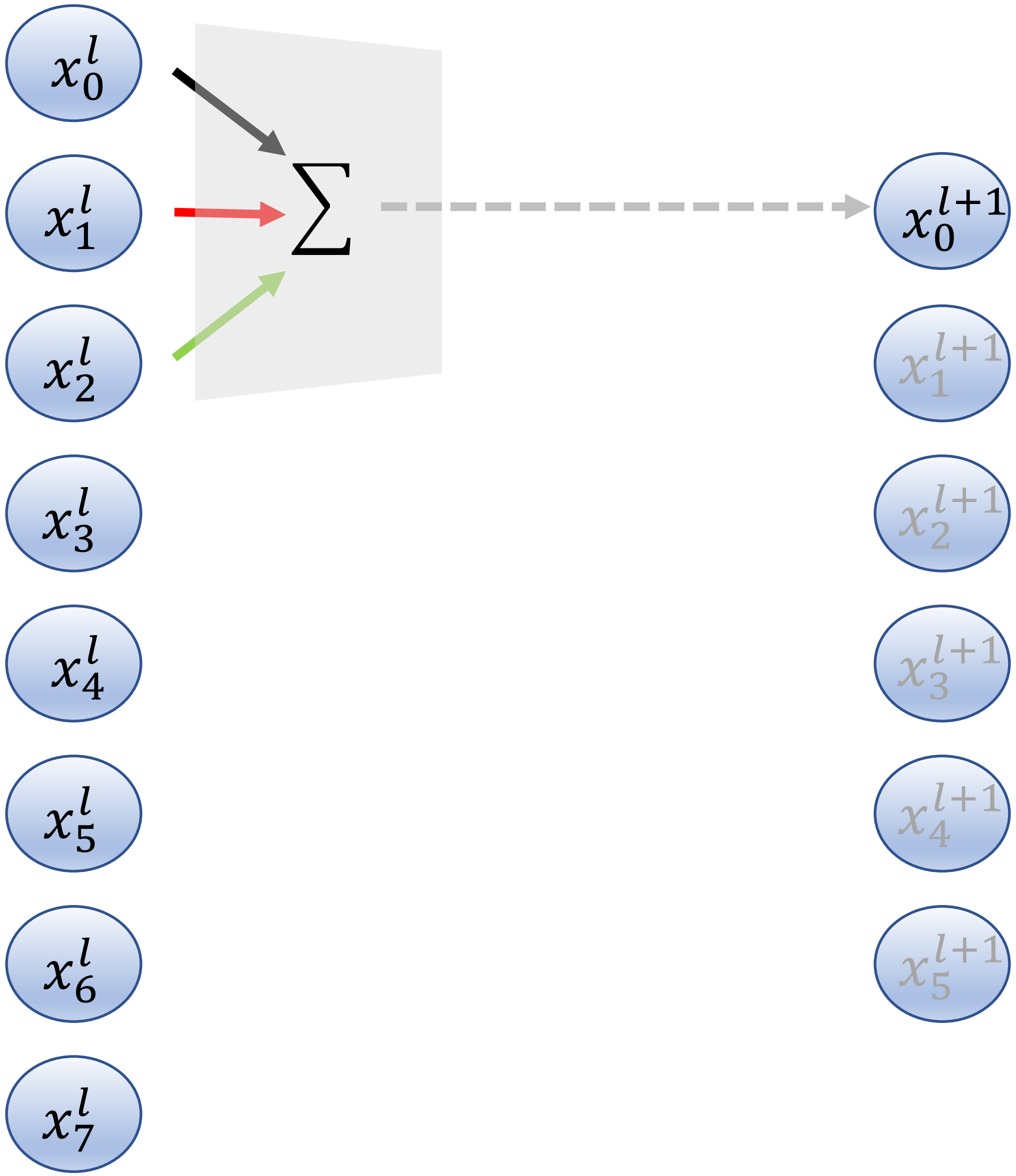
Special case of Linear Layer

Toeplitz matrix

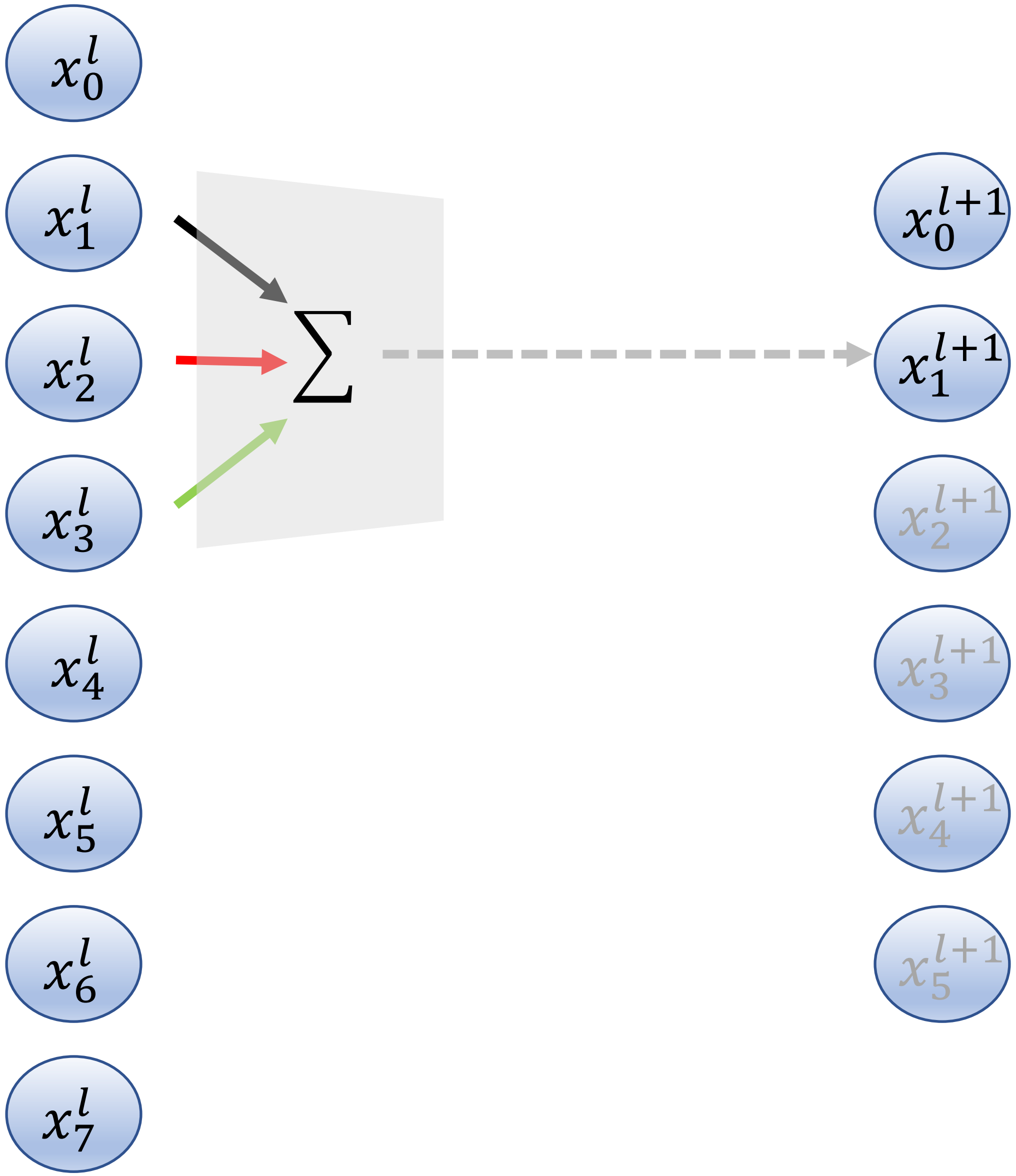
Convolution Filter



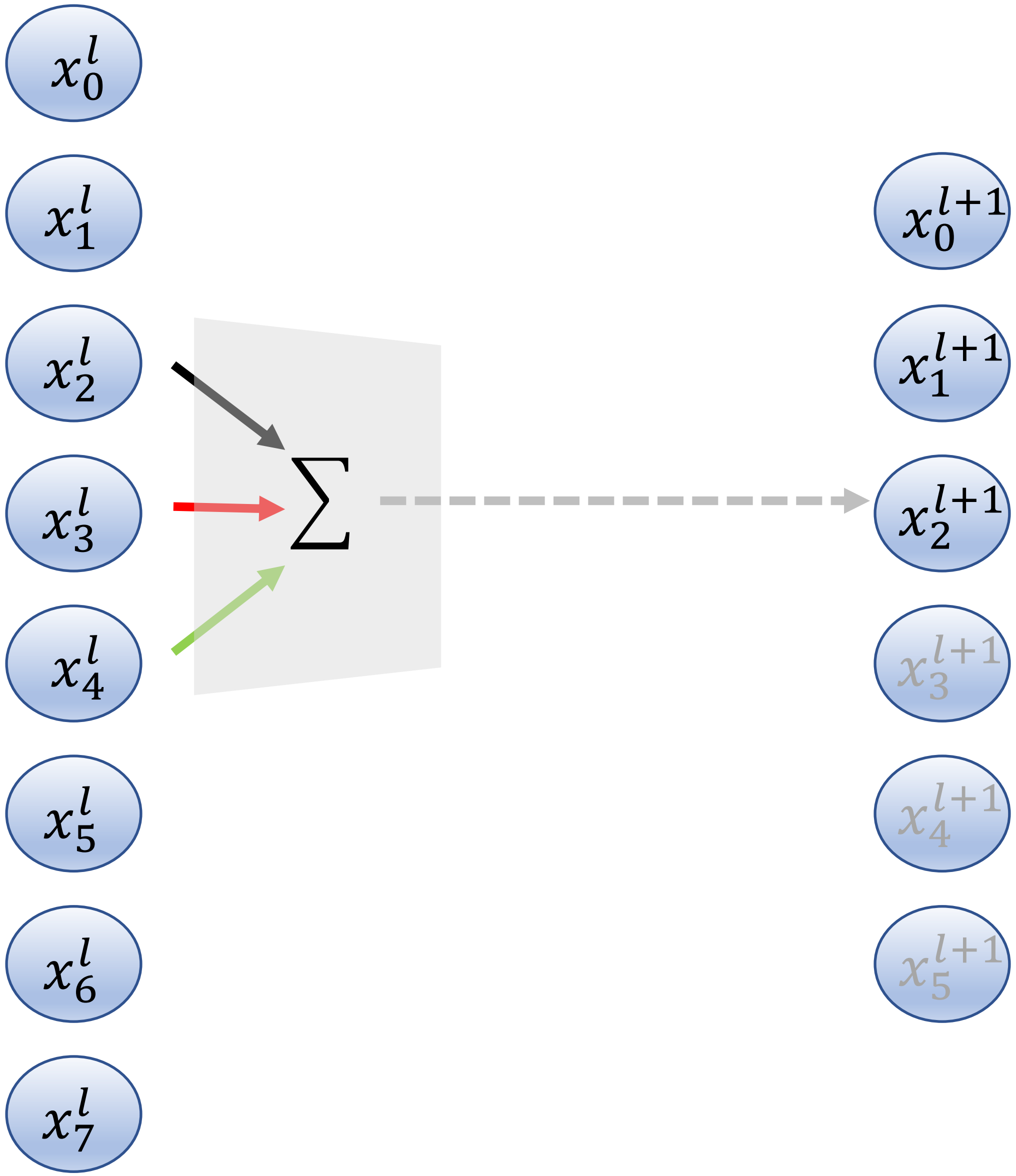
Convolution Filter



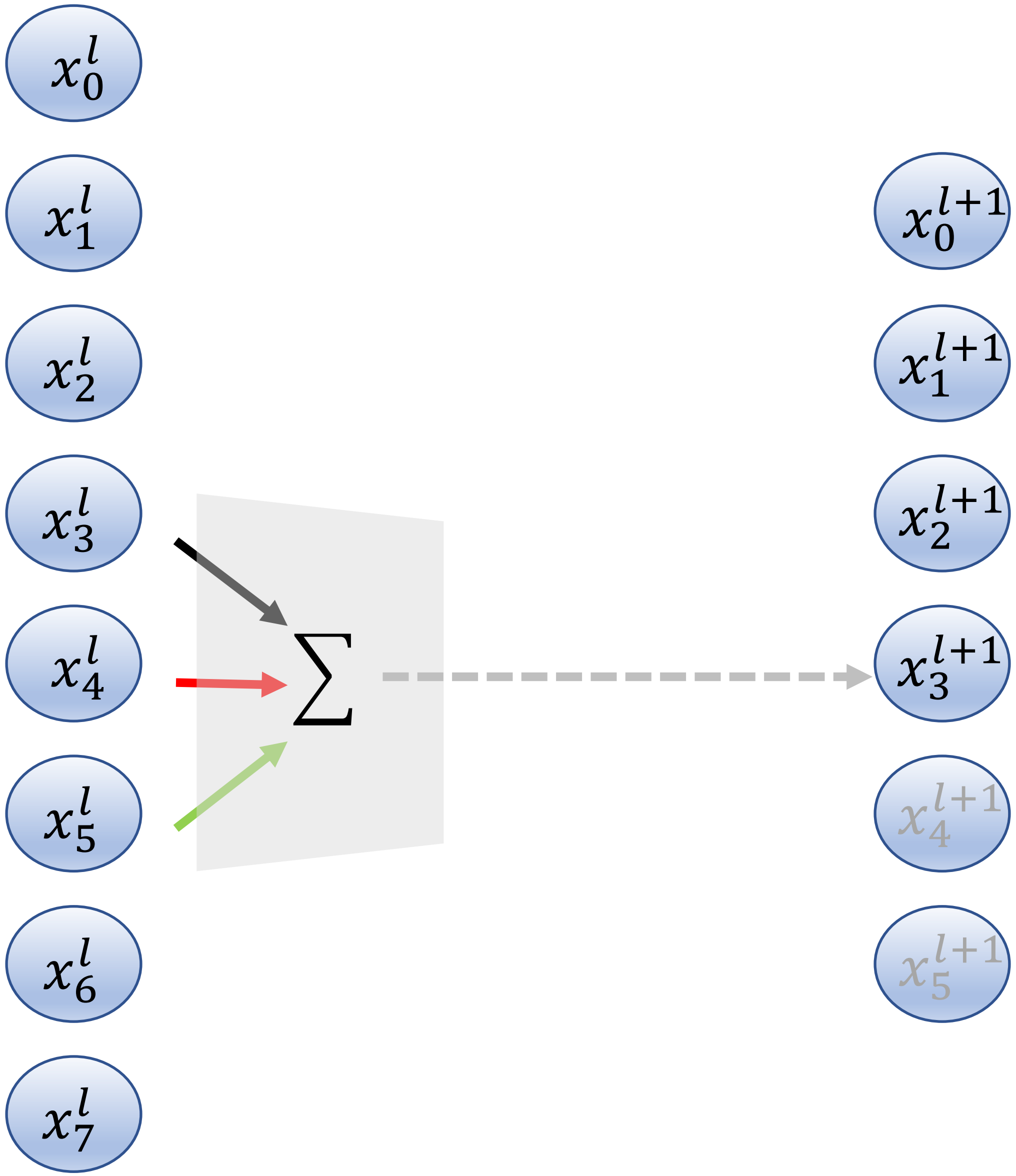
Convolution Filter



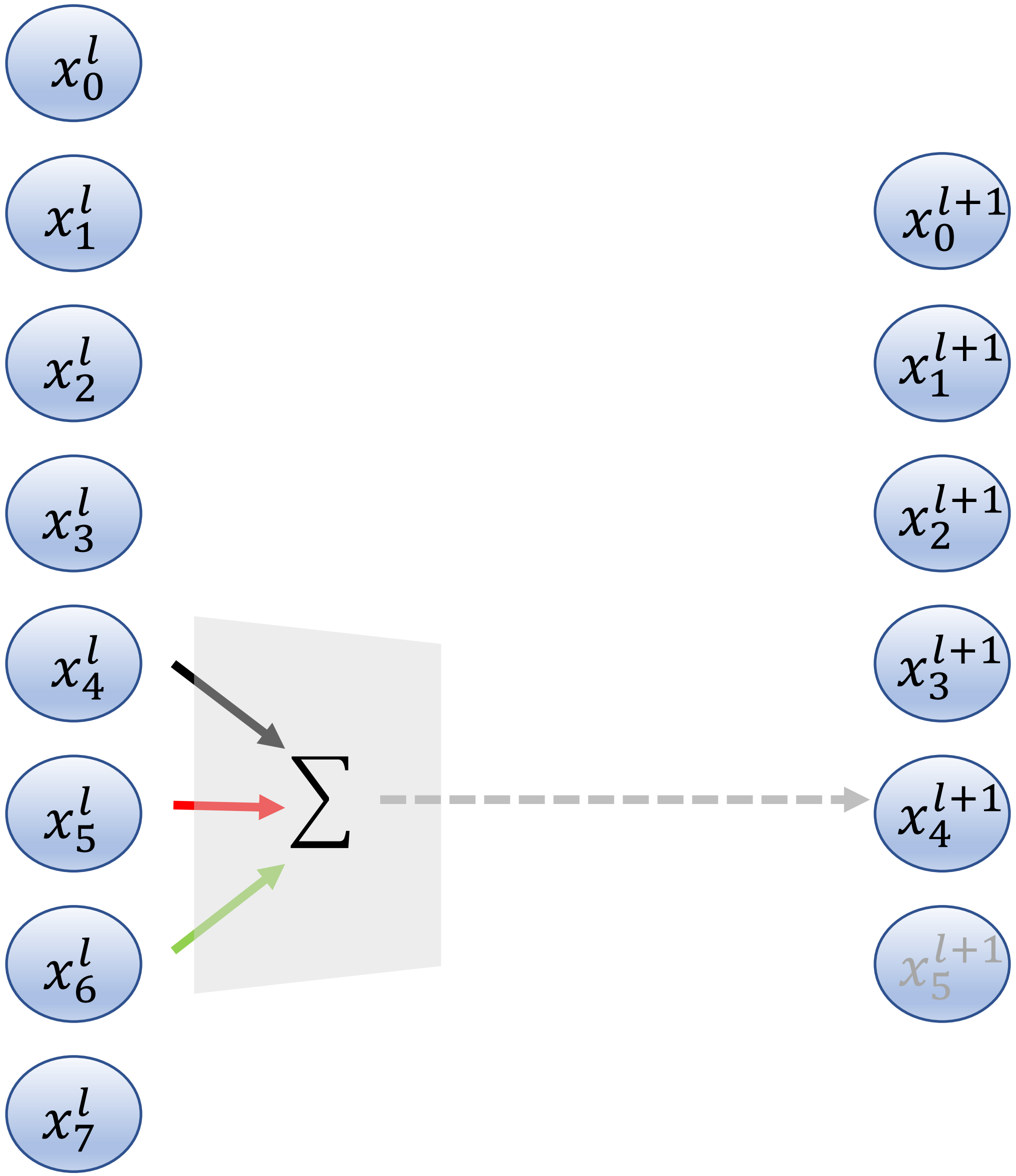
Convolution Filter



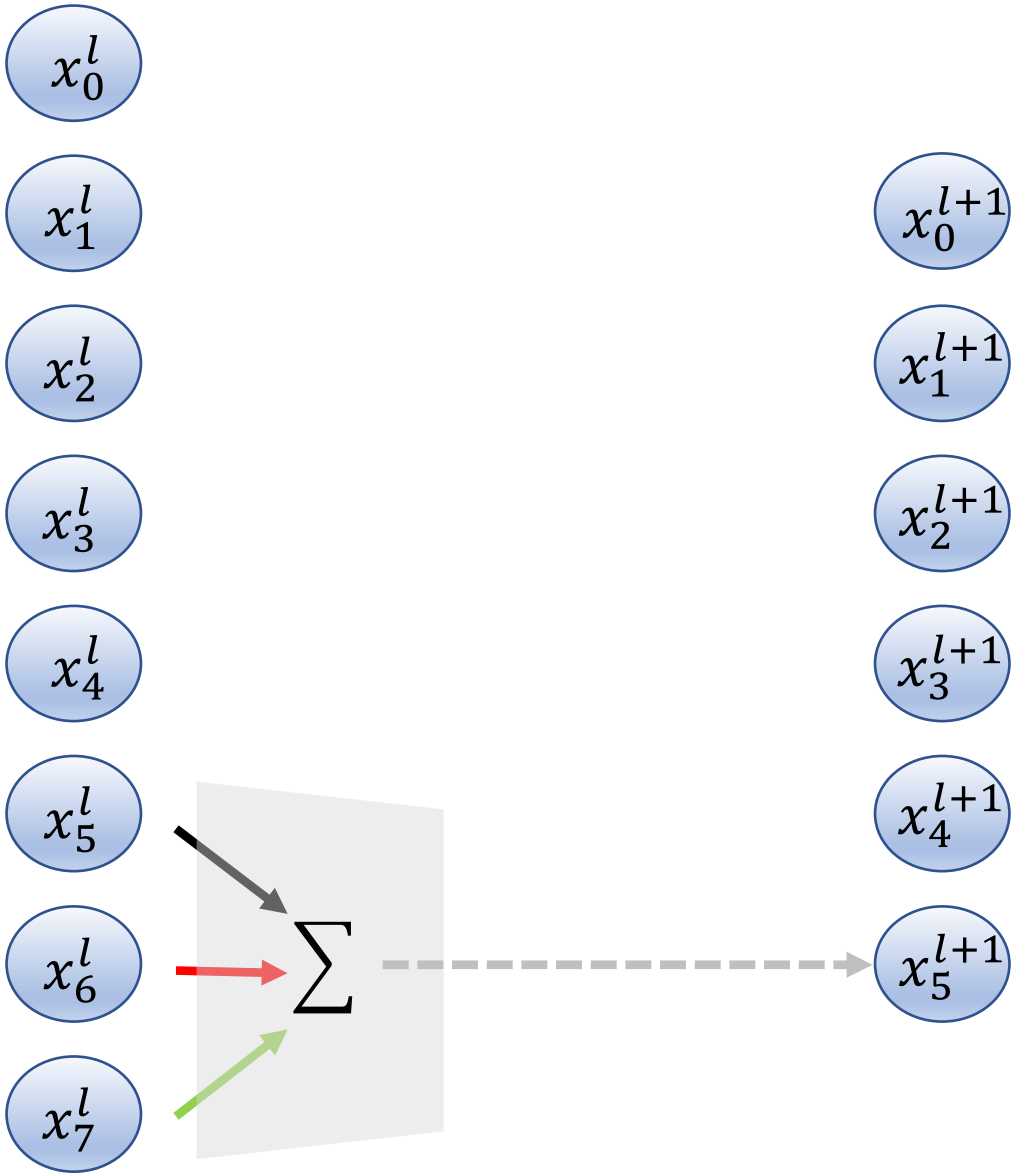
Convolution Filter



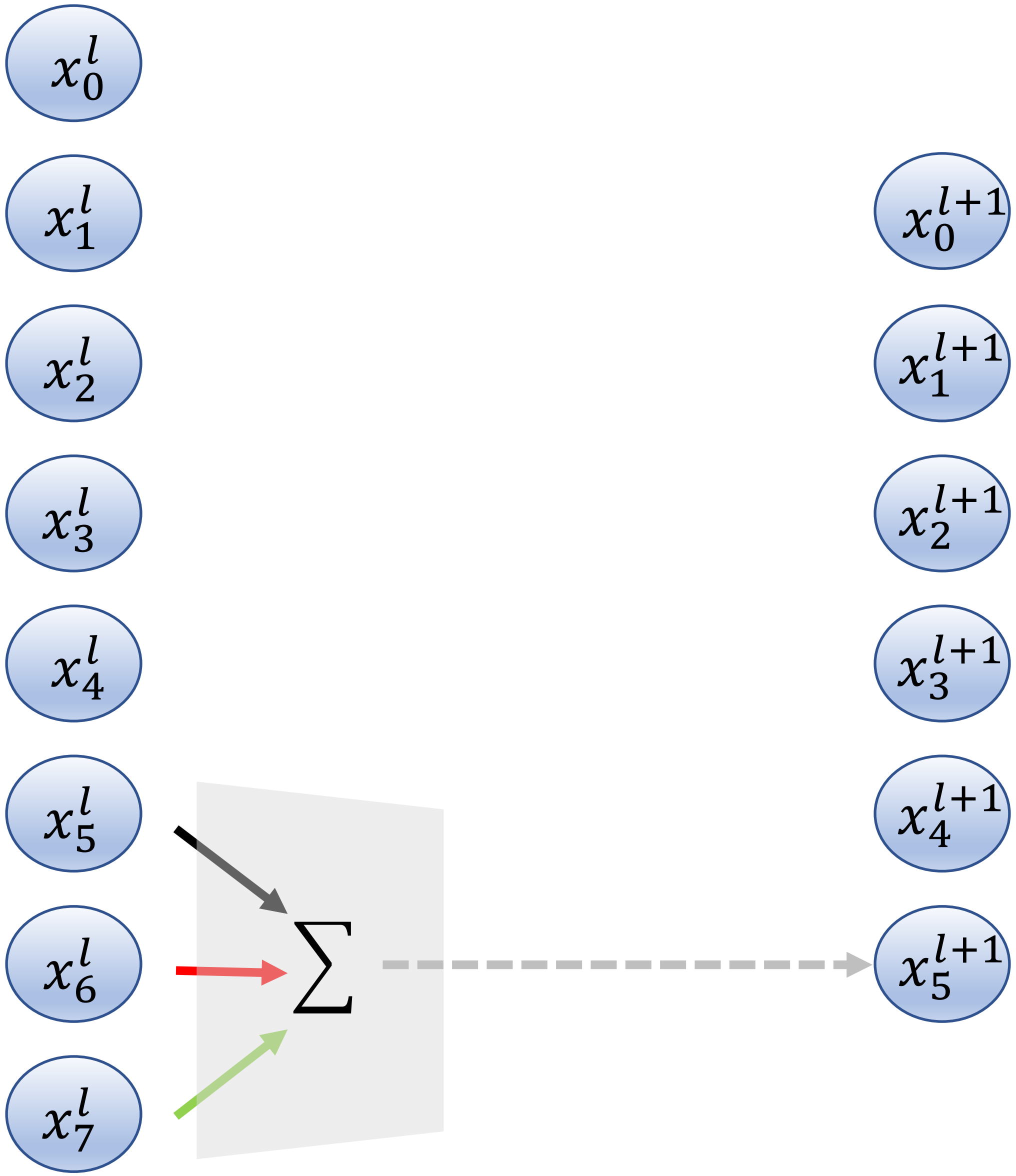
Convolution Filter



Convolution Filter

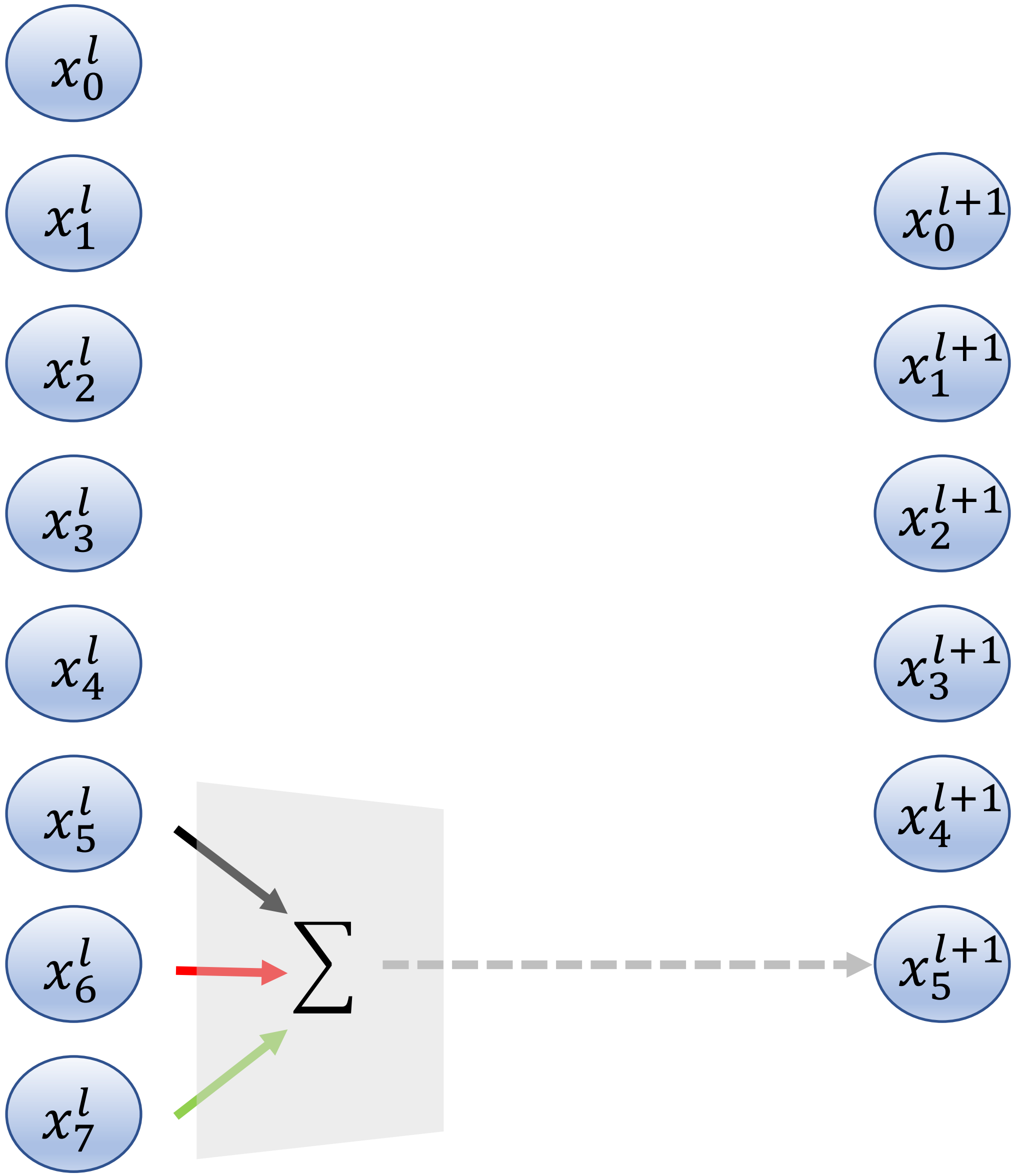


Convolution Filter



Q: Given input size N and filter size K, find output size.

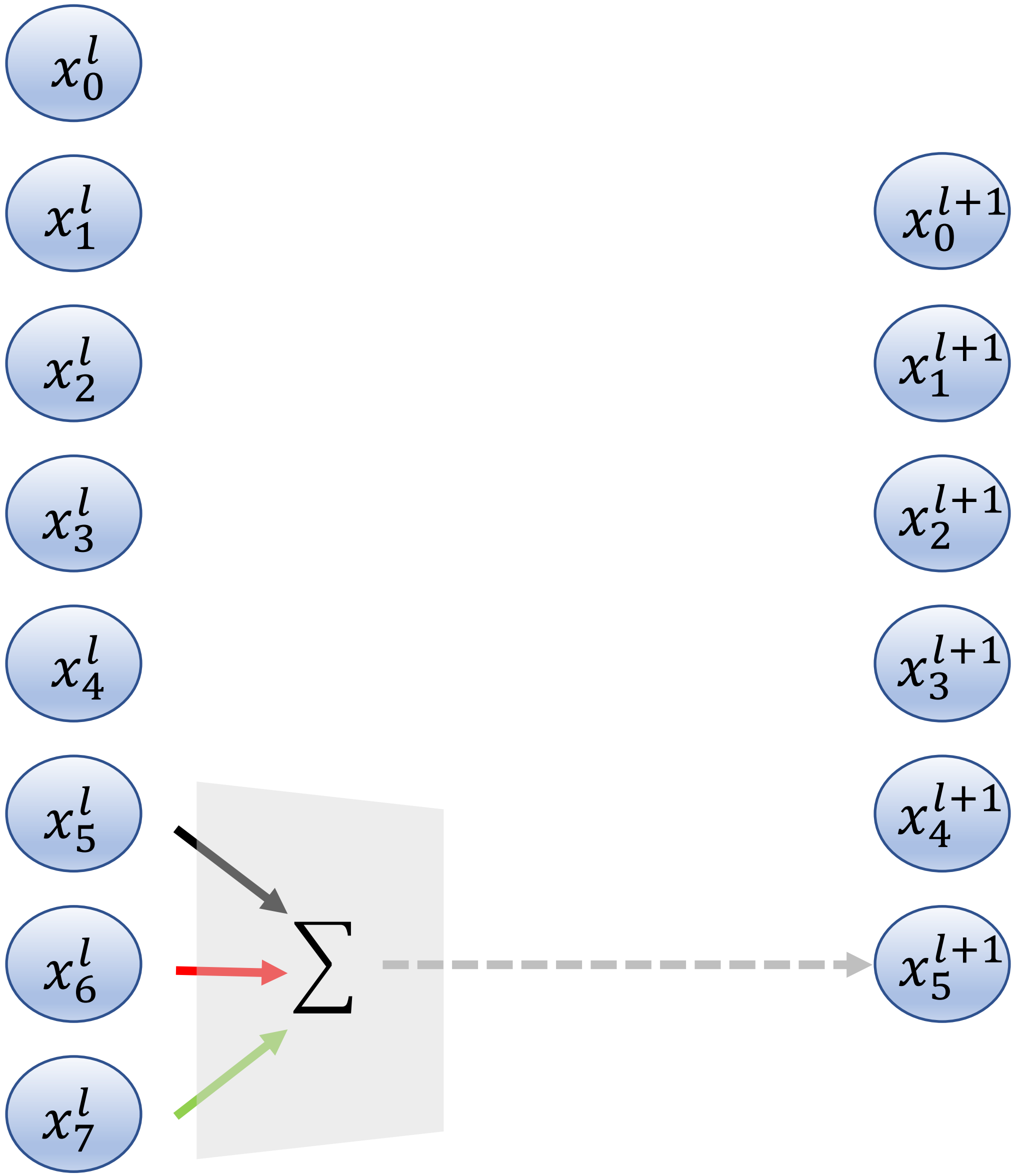
Convolution Filter



Q: Given input size N and filter size K, find output size.

A: $N - K + 1$

Convolution Filter

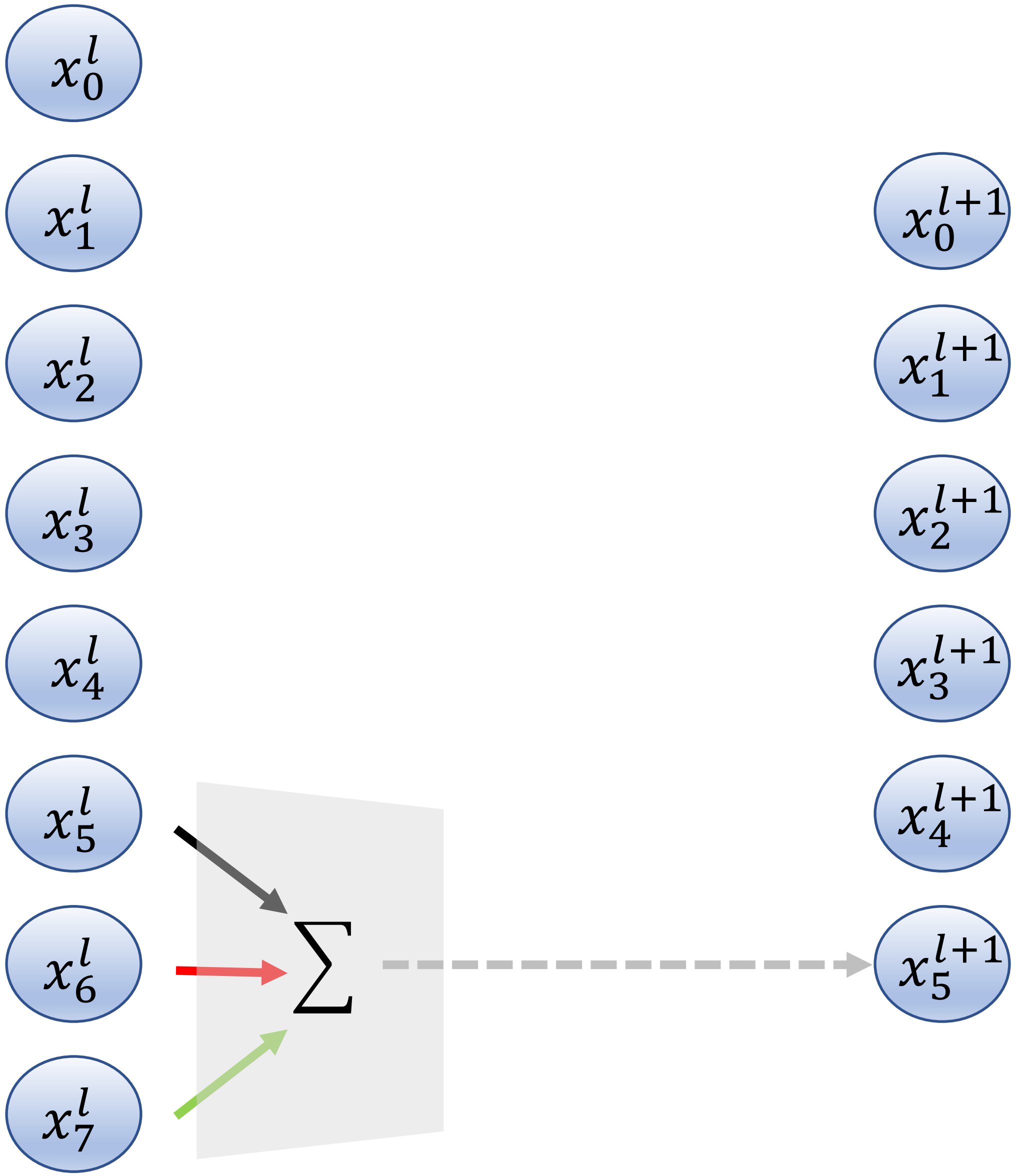


Q: Given input size N and filter size K, find output size.

A: $N - K + 1$

Q: is this a convolution?

Convolution Filter

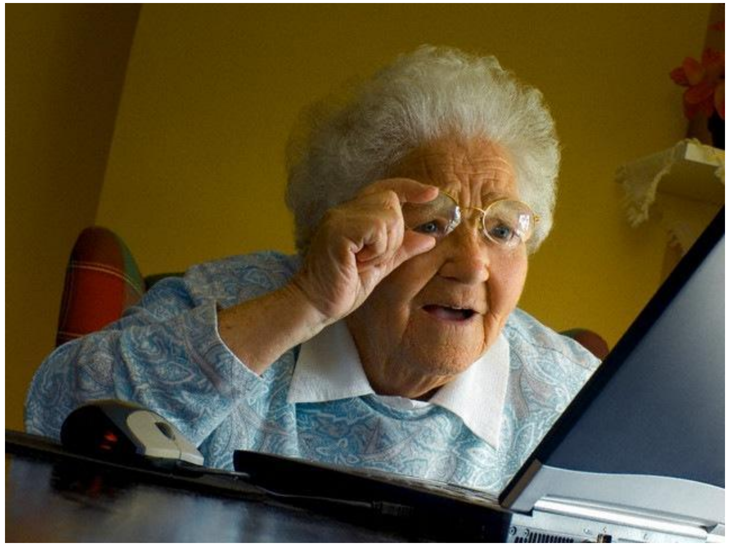


Q: Given input size N and filter size K, find output size.

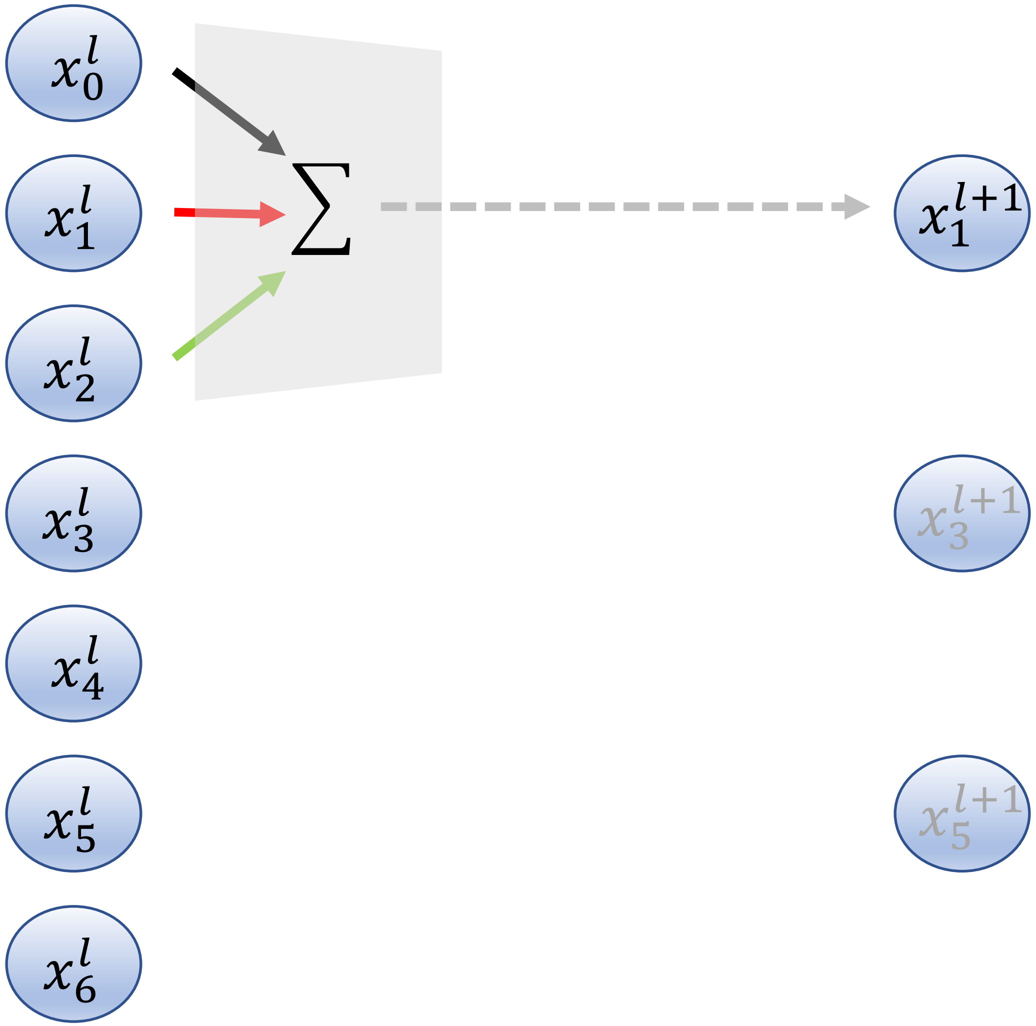
A: $N - K + 1$

Q: is this a convolution?

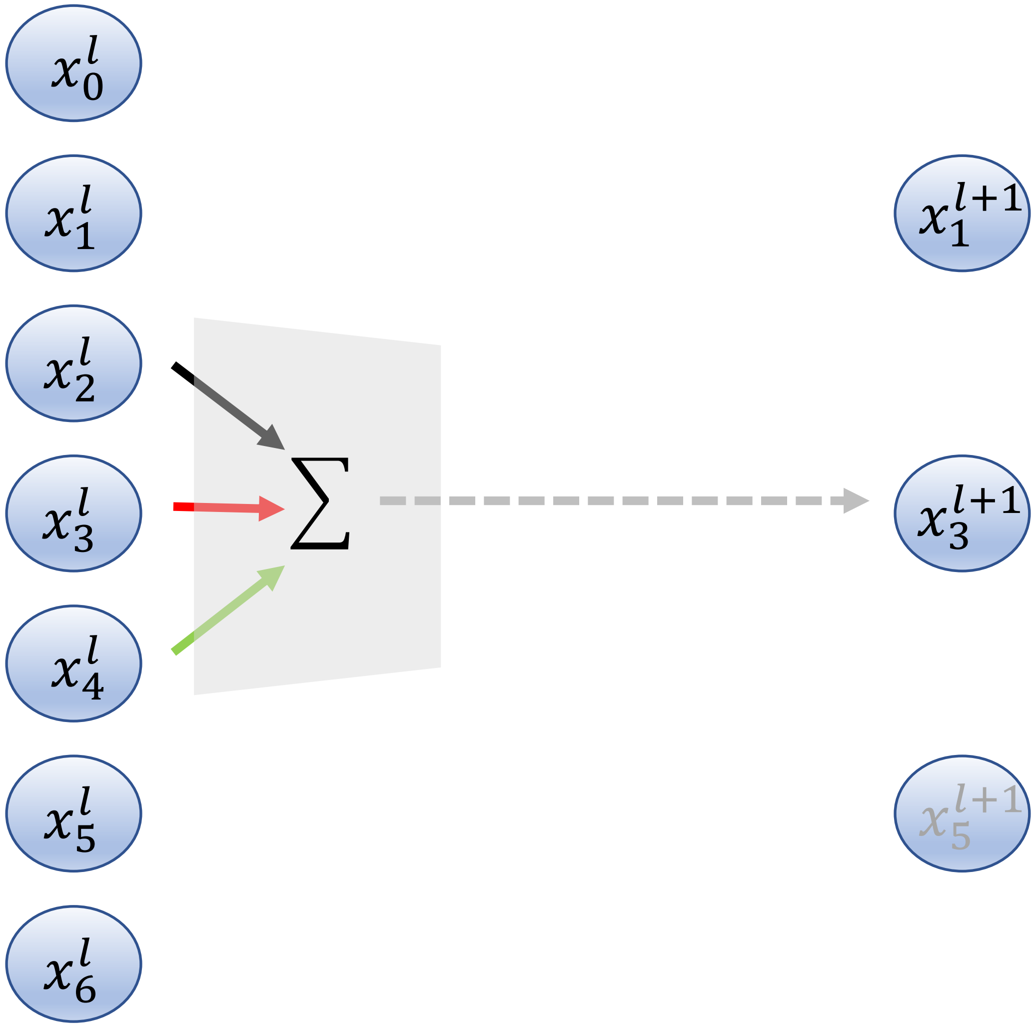
A: Yes, but with the flipped filter.
This is cross-correlation.



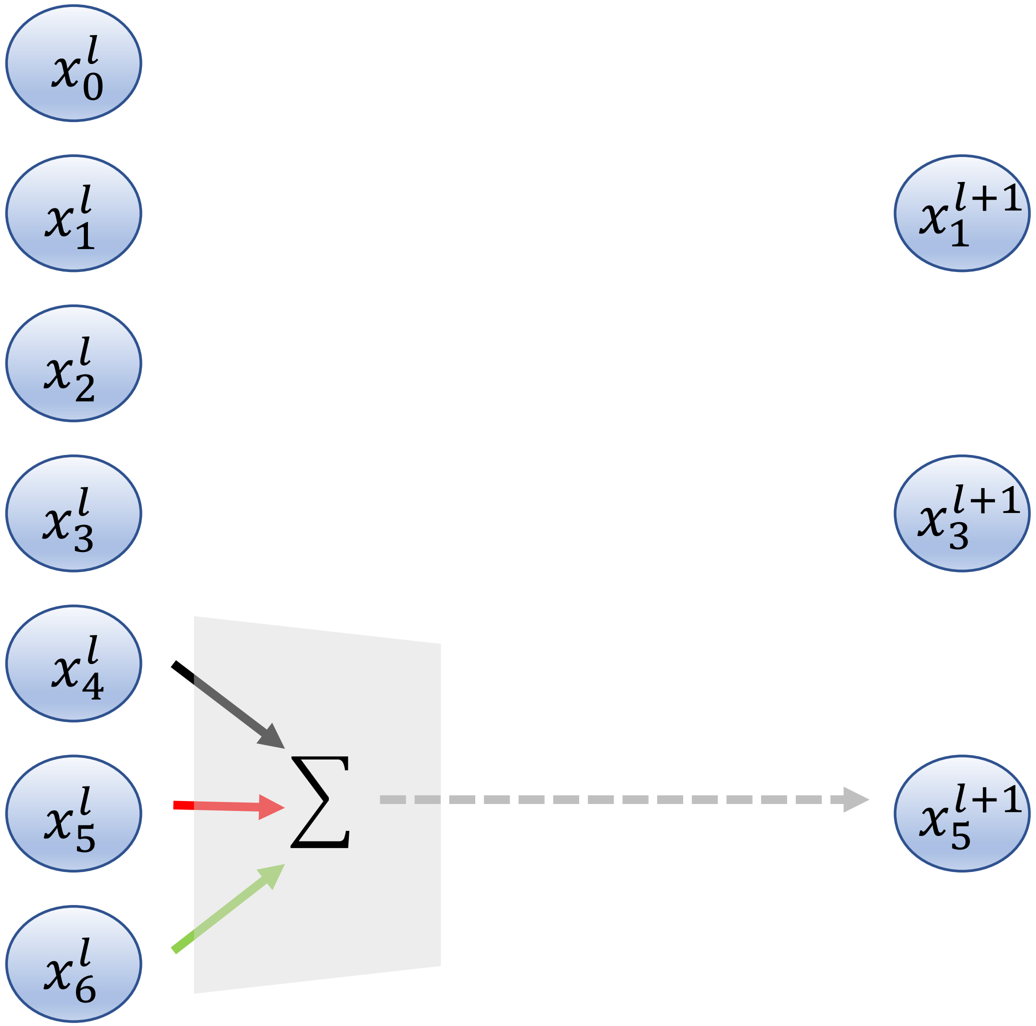
Stride



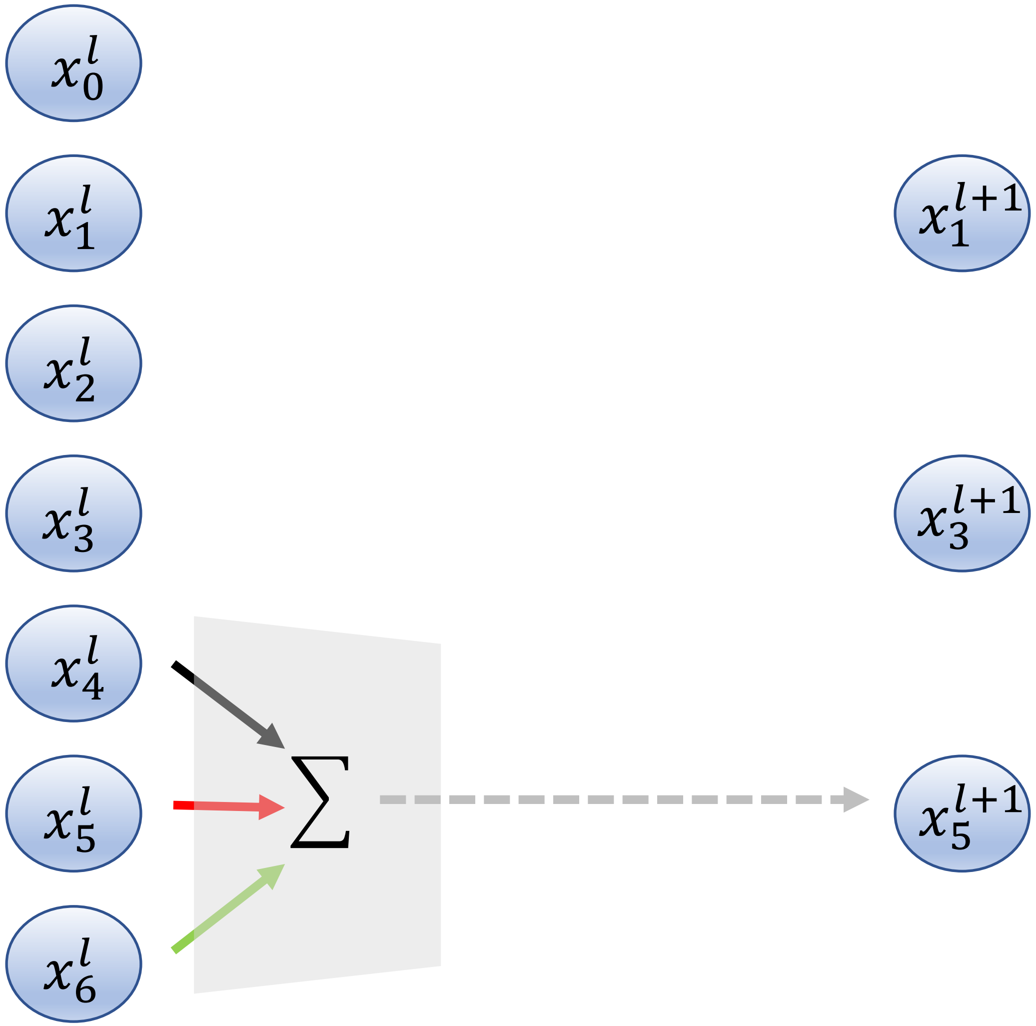
Stride



Stride

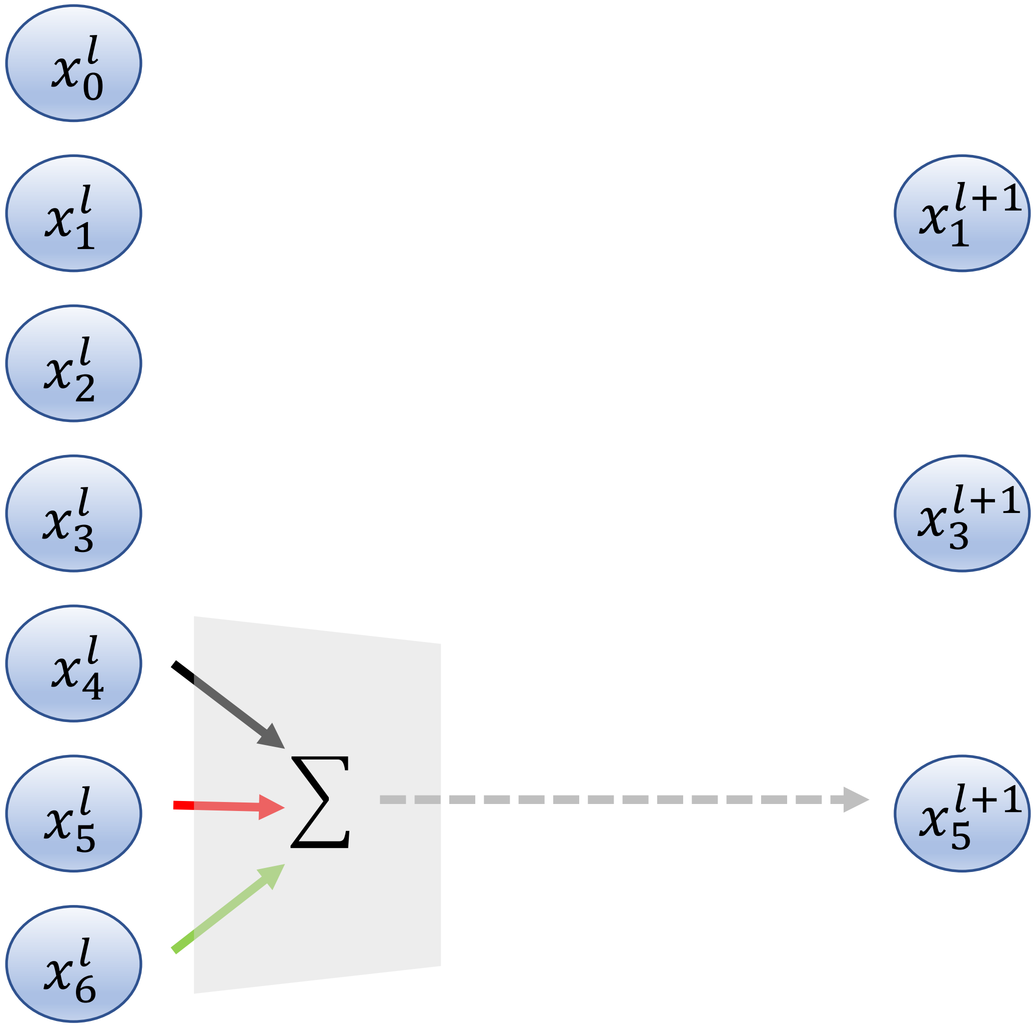


Stride



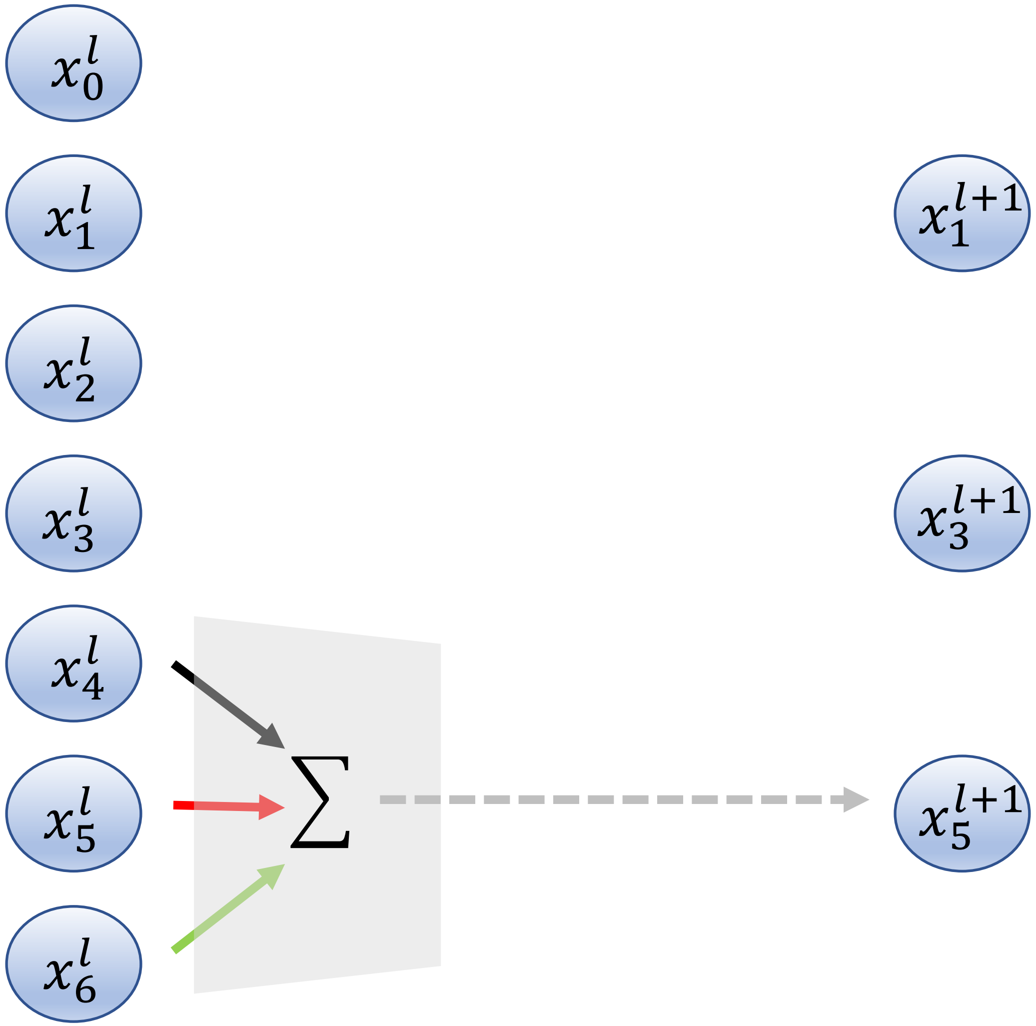
$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 \\ 0 & a & b & c & 0 & 0 & 0 \\ 0 & 0 & a & b & c & 0 & 0 \\ 0 & 0 & 0 & a & b & c & 0 \\ 0 & 0 & 0 & 0 & a & b & c \\ 0 & 0 & 0 & 0 & 0 & a & b \end{bmatrix}$$

Stride



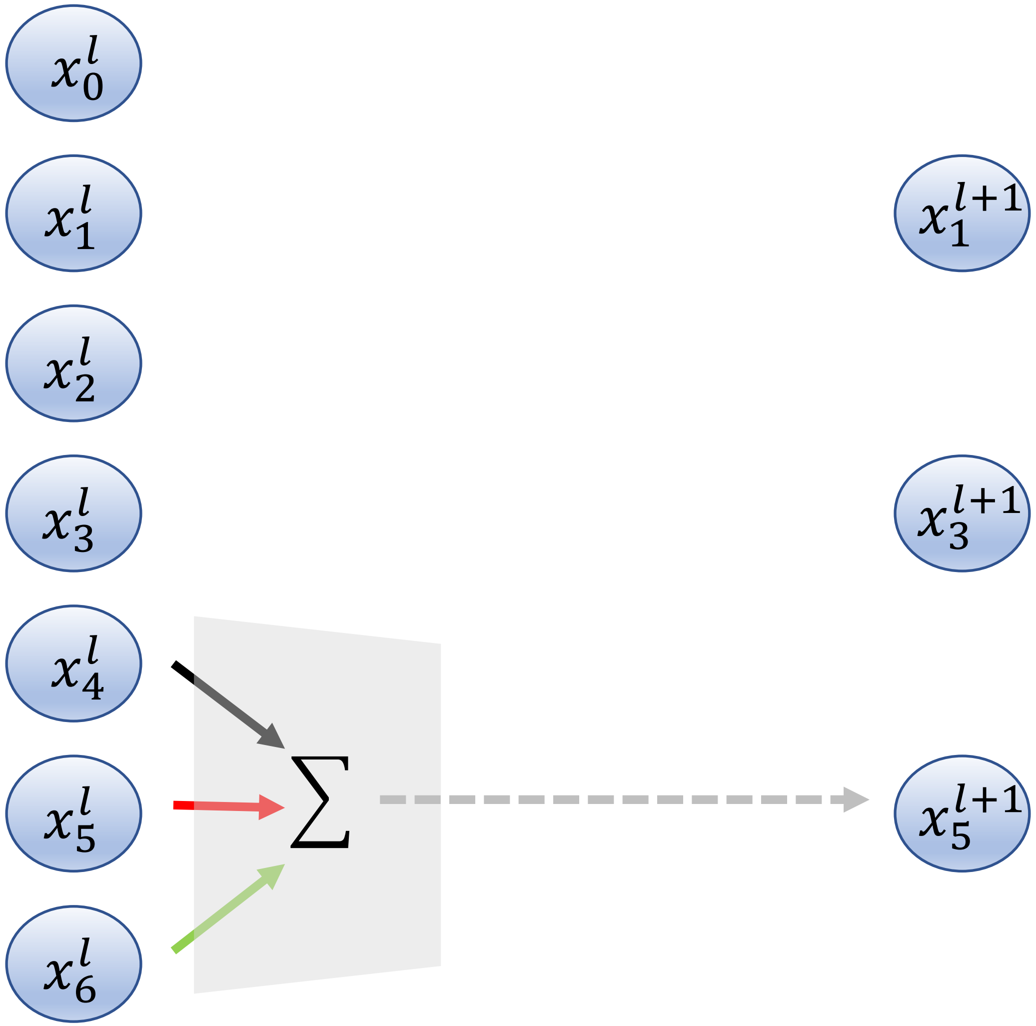
$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 \\ 0 & a & b & c & 0 & 0 & 0 \\ 0 & 0 & a & b & c & 0 & 0 \\ 0 & 0 & 0 & a & b & c & 0 \\ 0 & 0 & 0 & 0 & a & b & c \\ 0 & 0 & 0 & 0 & 0 & a & b \end{bmatrix}$$

Stride



$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 \\ 0 & 0 & a & b & c & 0 & 0 \\ 0 & 0 & 0 & 0 & a & b & c \end{bmatrix}$$

Stride

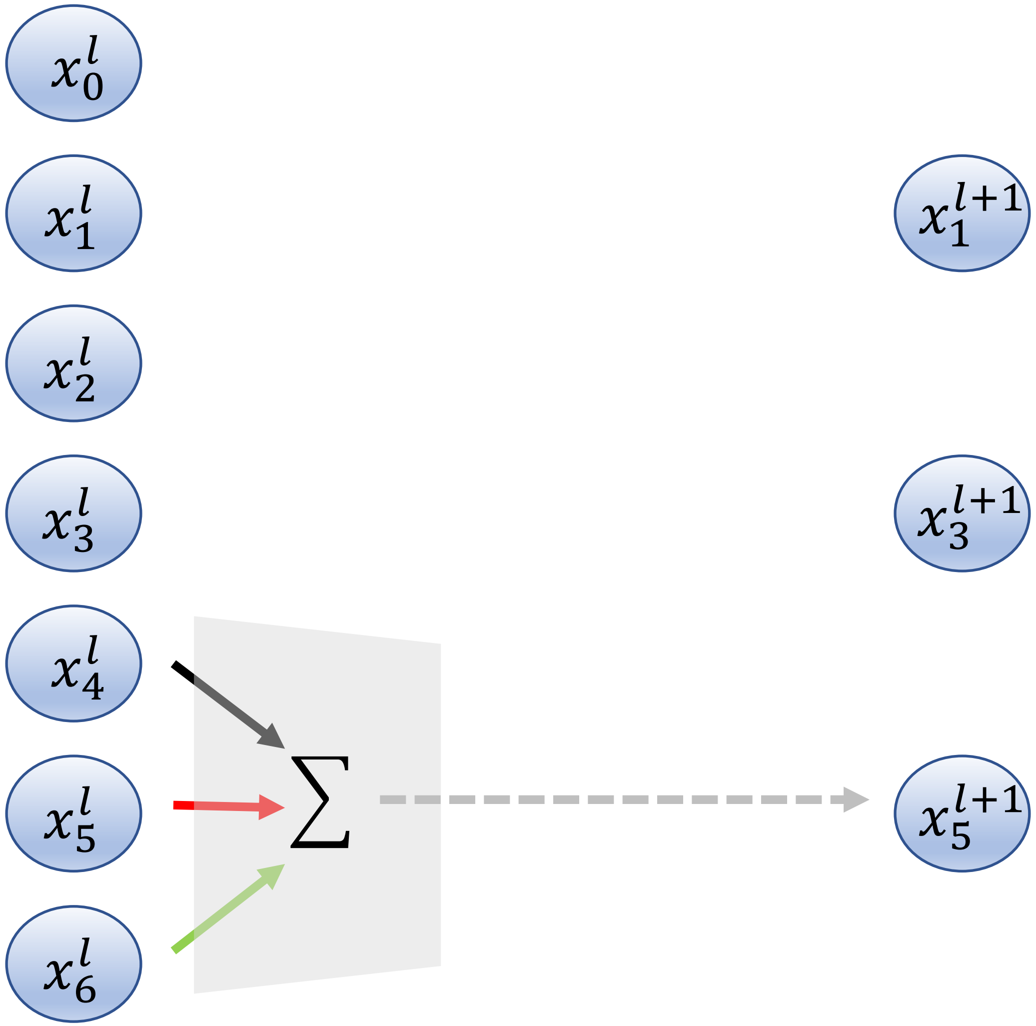


$$\begin{bmatrix} \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} & 0 & 0 & 0 & 0 \\ 0 & 0 & \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} & 0 & 0 \\ 0 & 0 & 0 & 0 & \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} \end{bmatrix}$$

Q: Given input size N, filter size K and stride S , find output size.

Stride

[redacted]

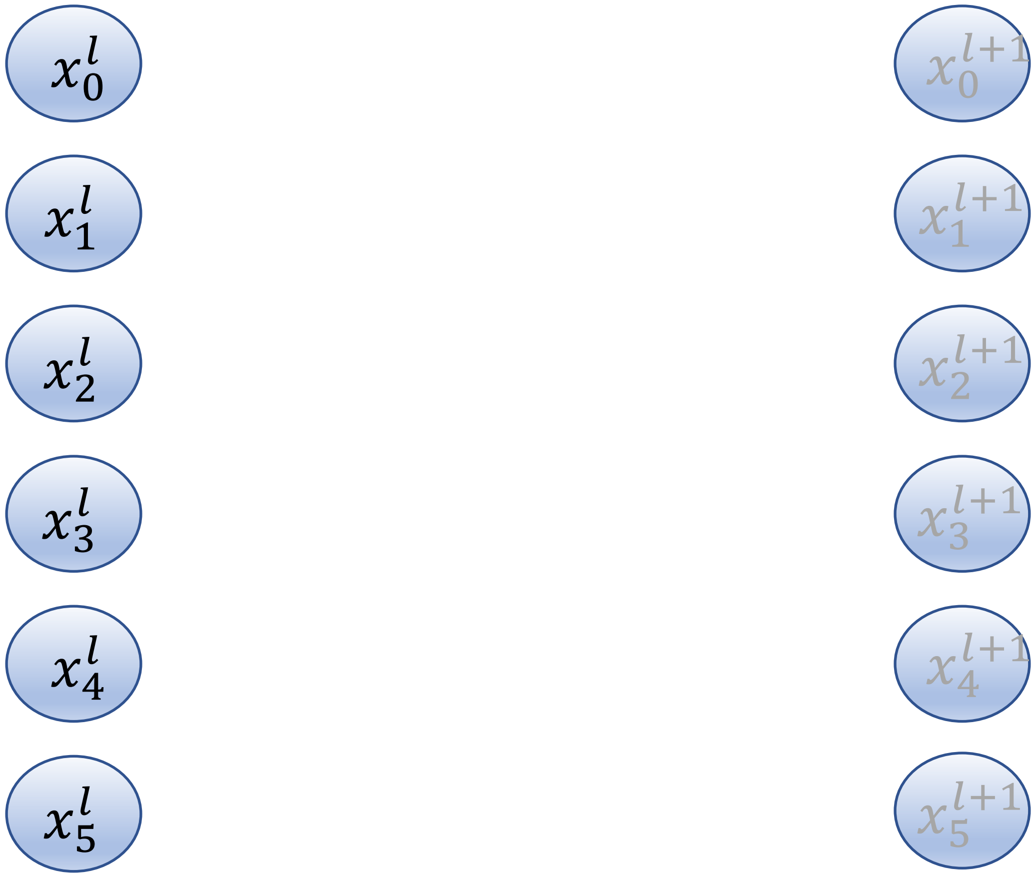


$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 \\ 0 & 0 & a & b & c & 0 & 0 \\ 0 & 0 & 0 & 0 & a & b & c \end{bmatrix}$$

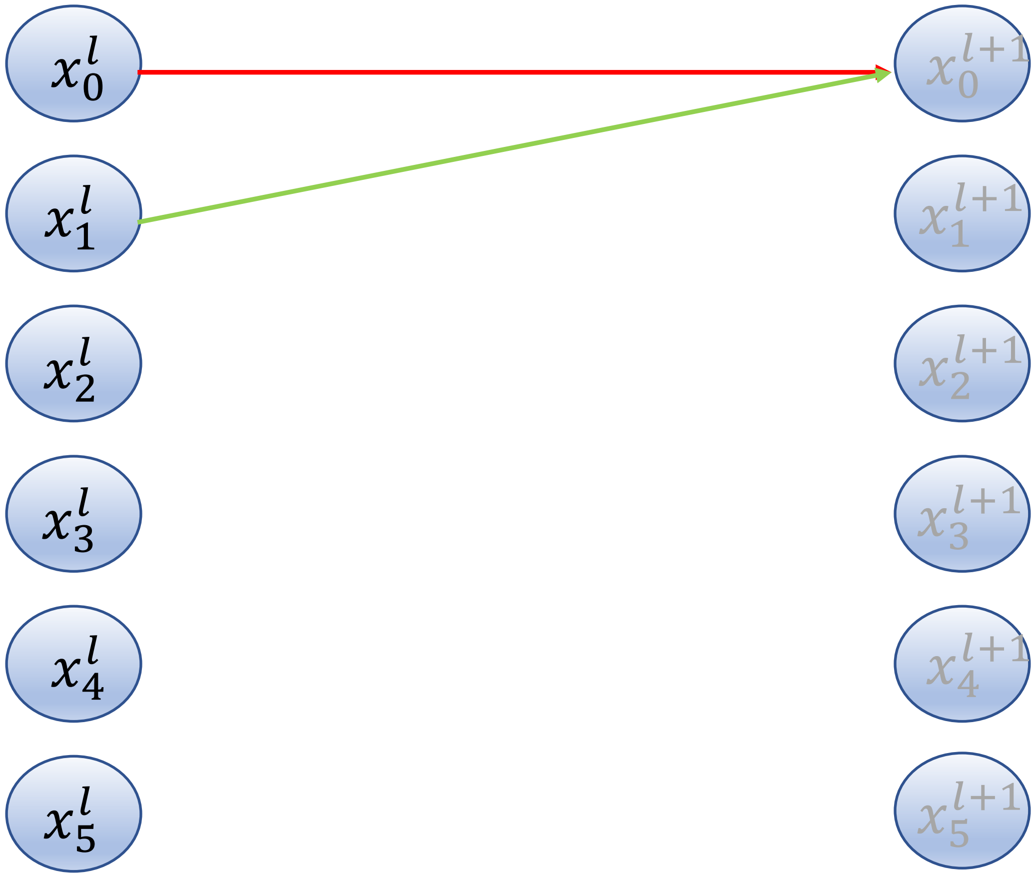
Q: Given input size N, filter size K and stride S , find output size.

A: $\left\lfloor \frac{N-K}{S} + 1 \right\rfloor$

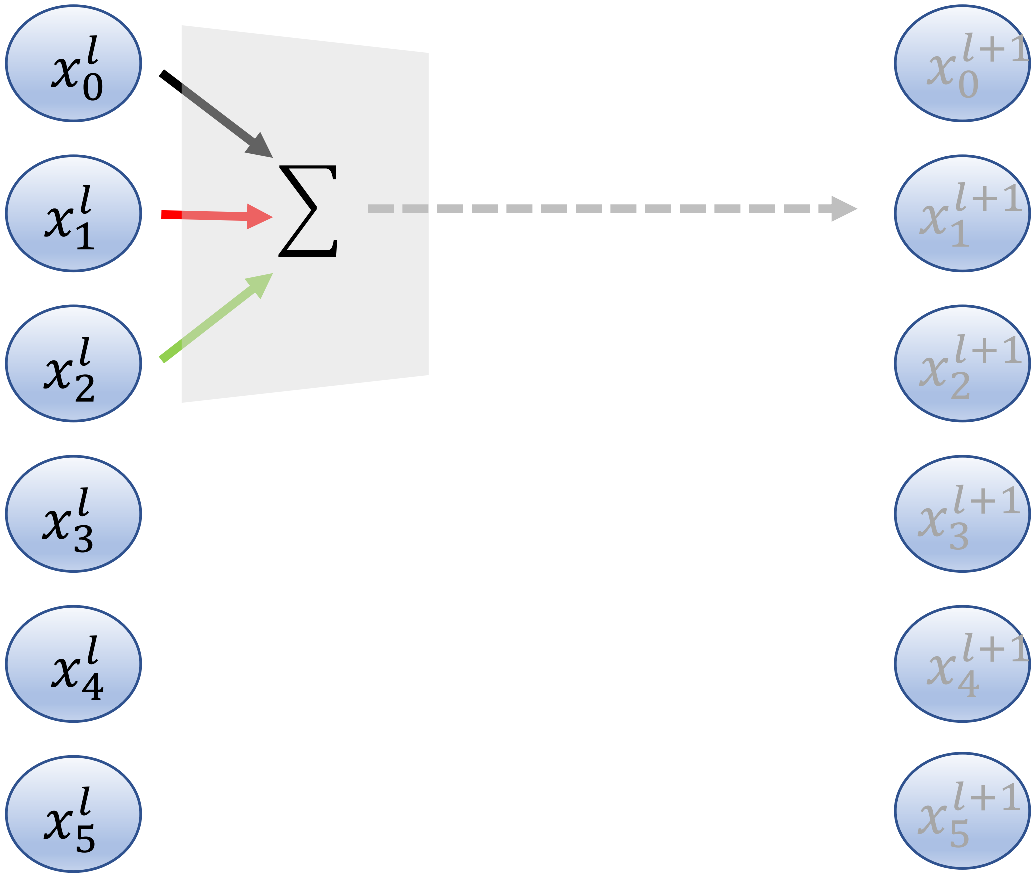
Padding



Padding



Padding



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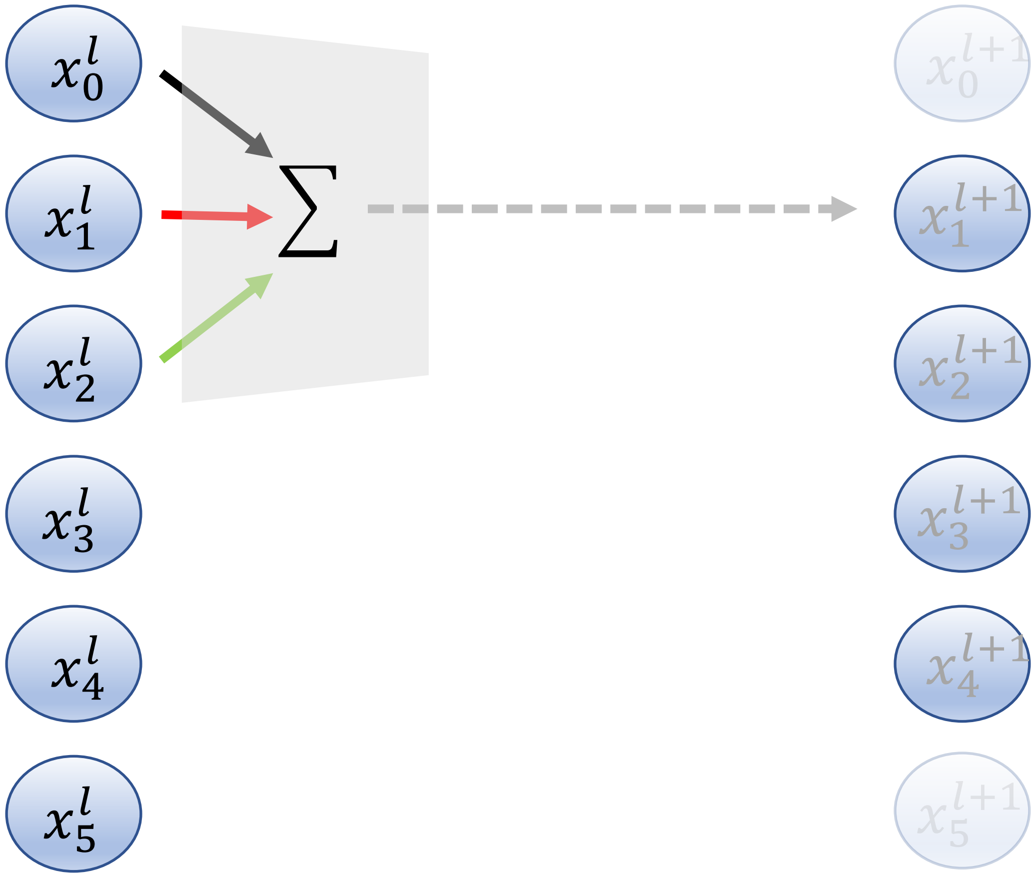

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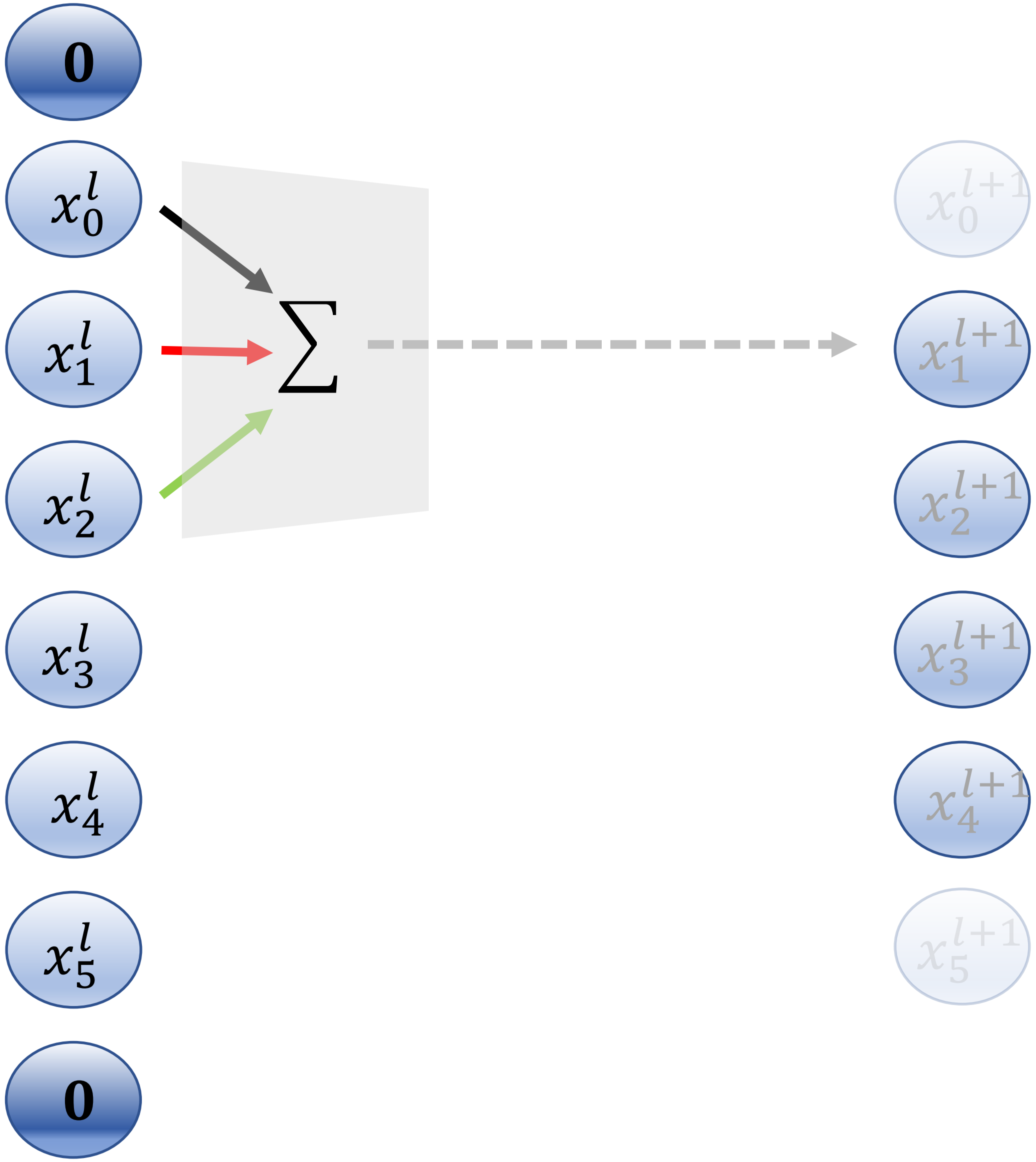

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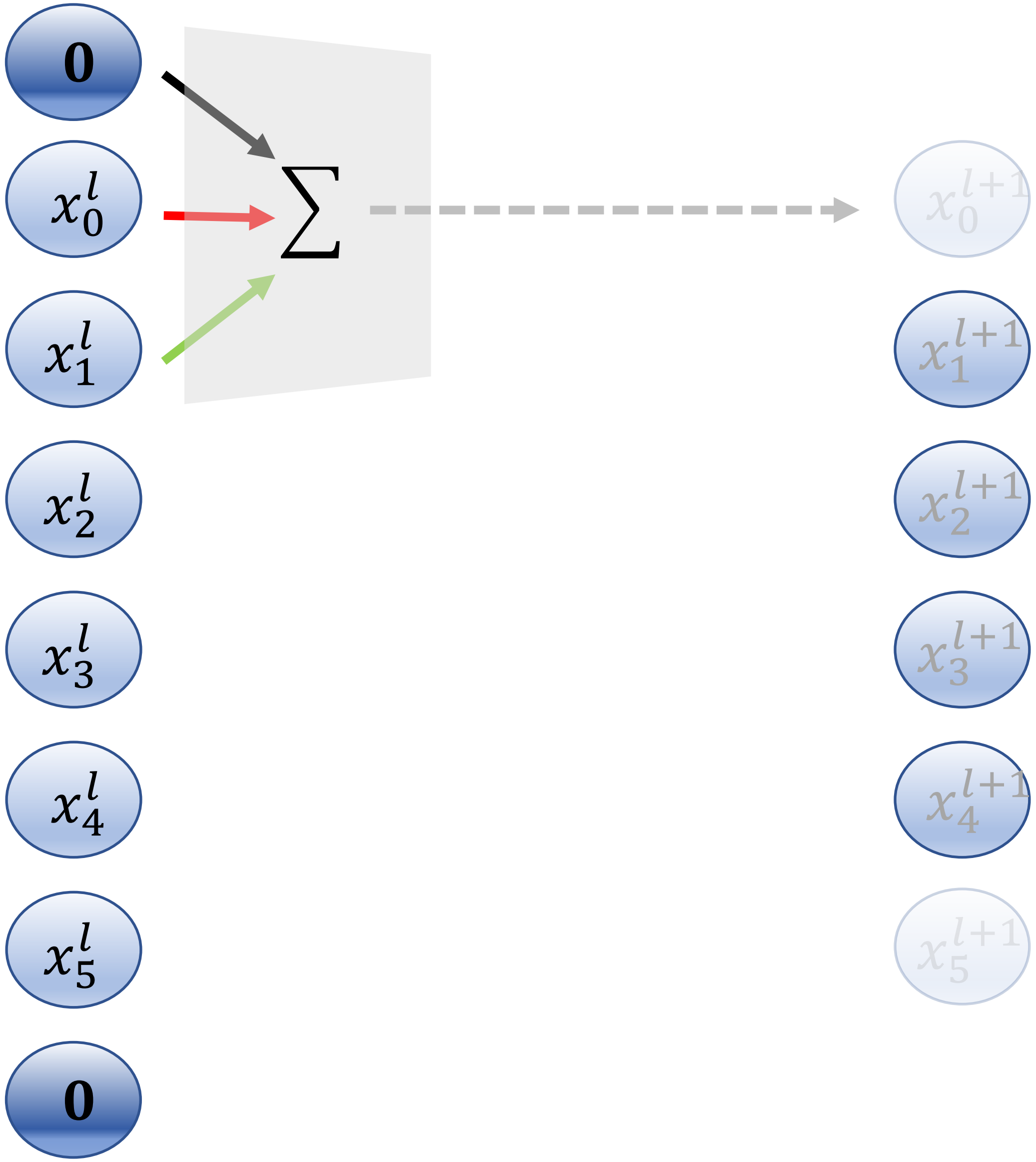

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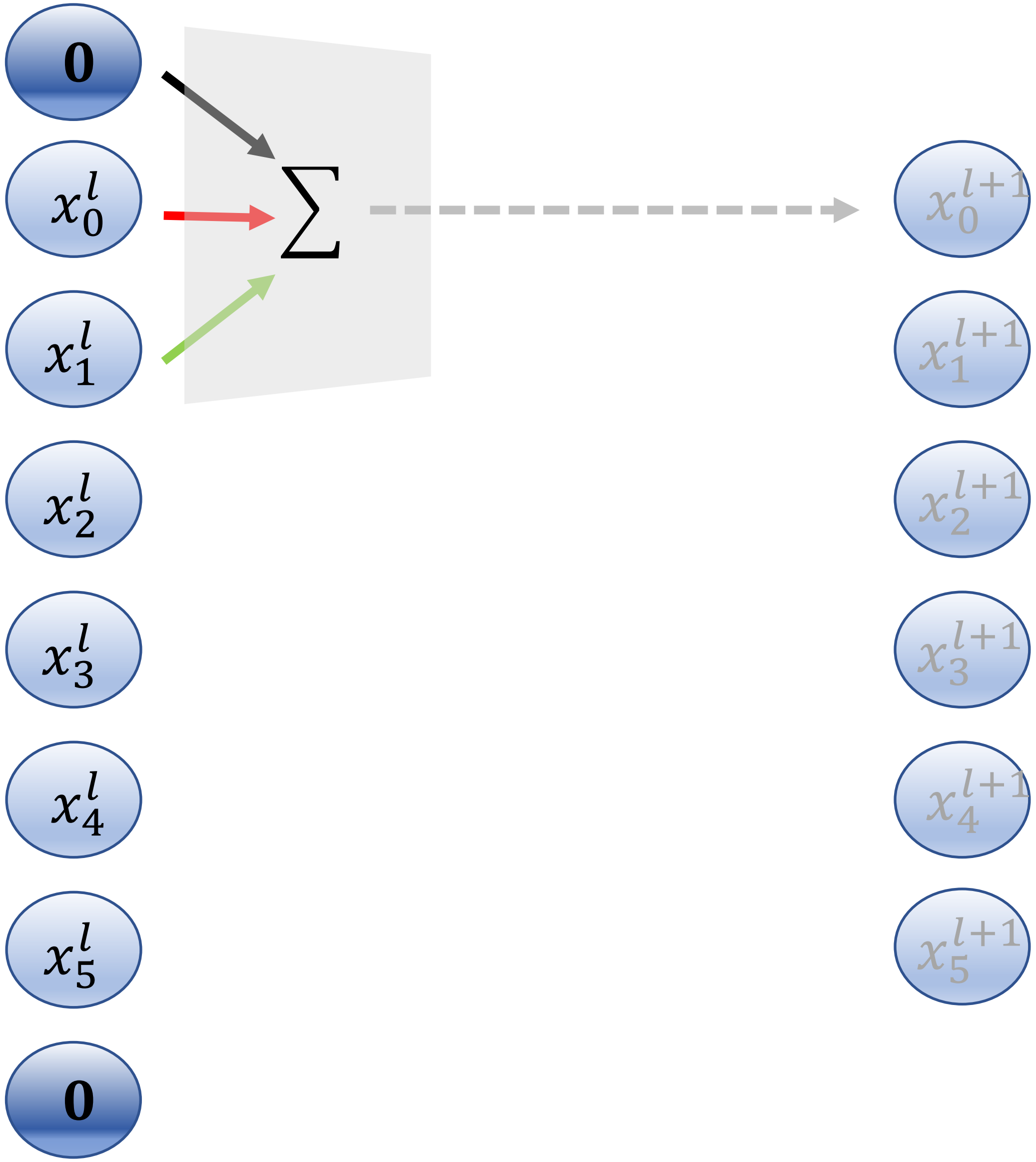

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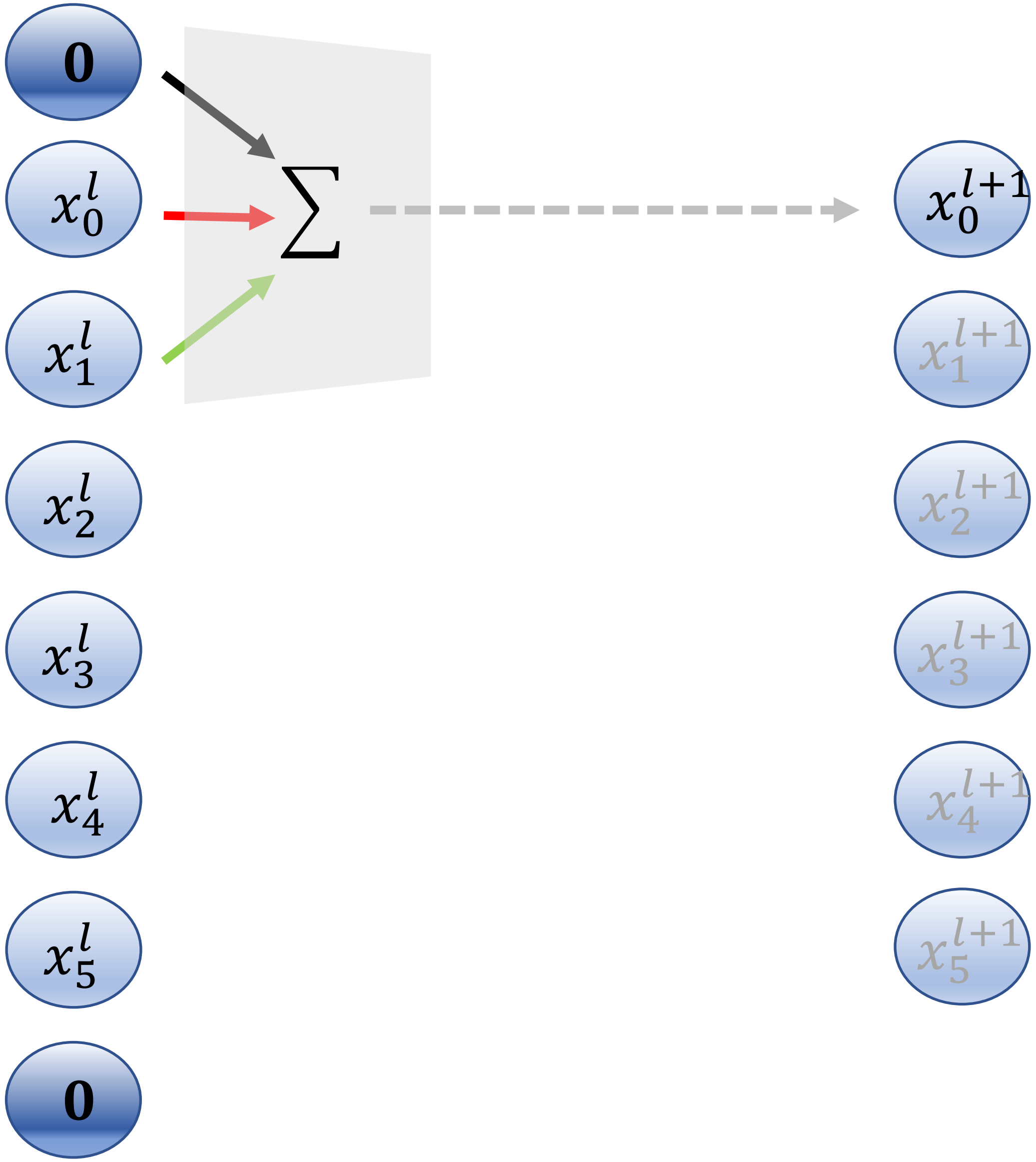

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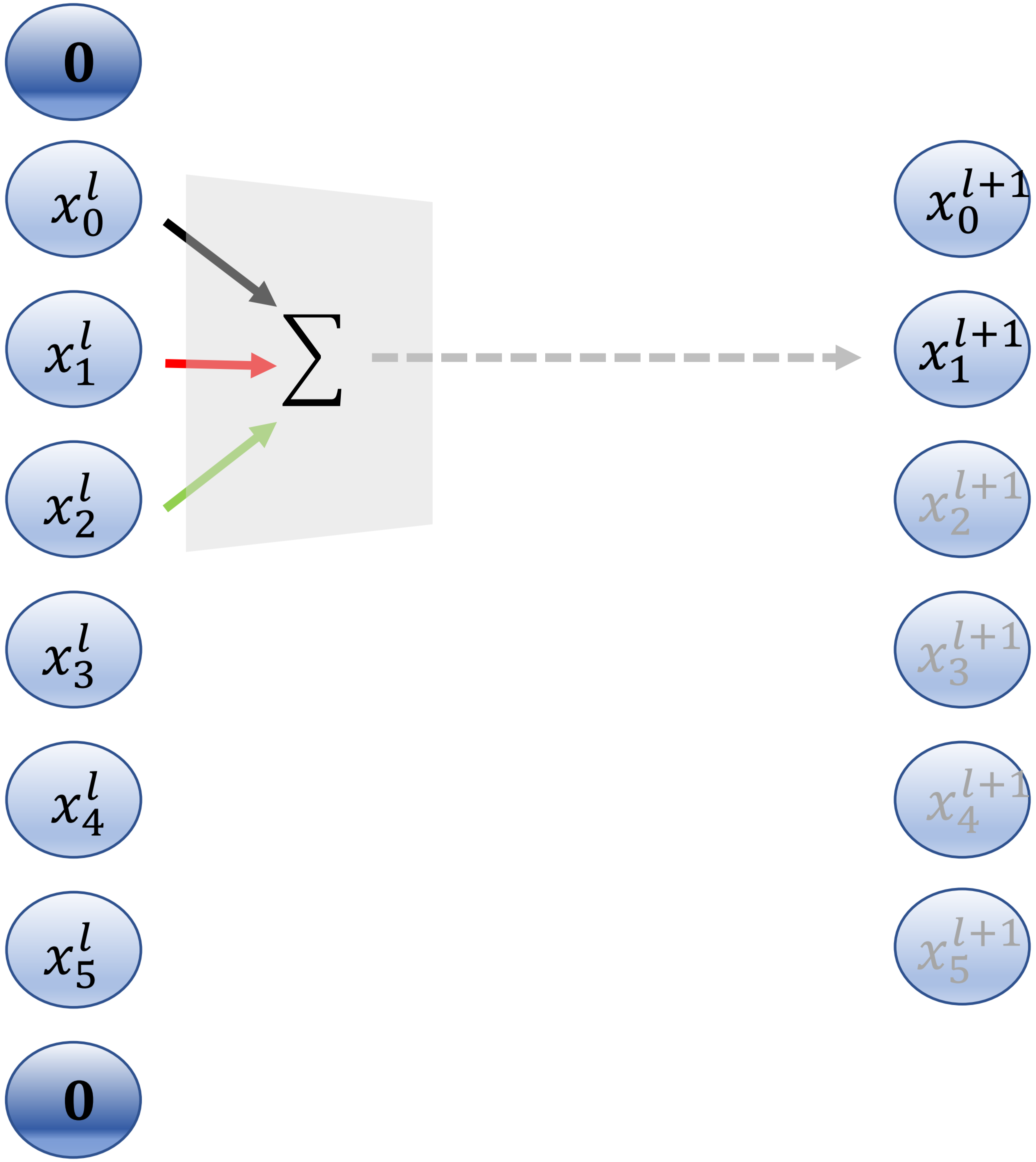

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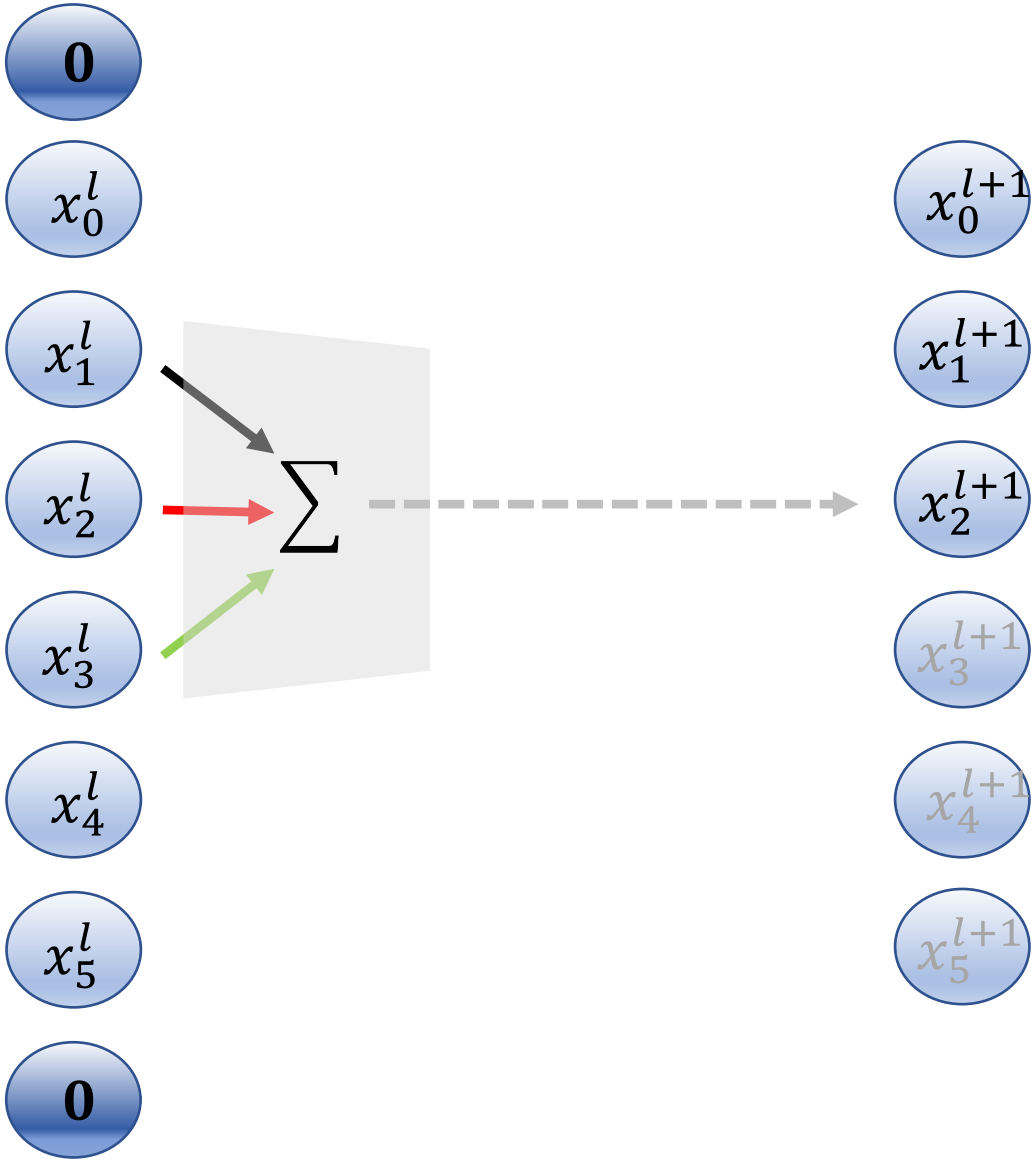

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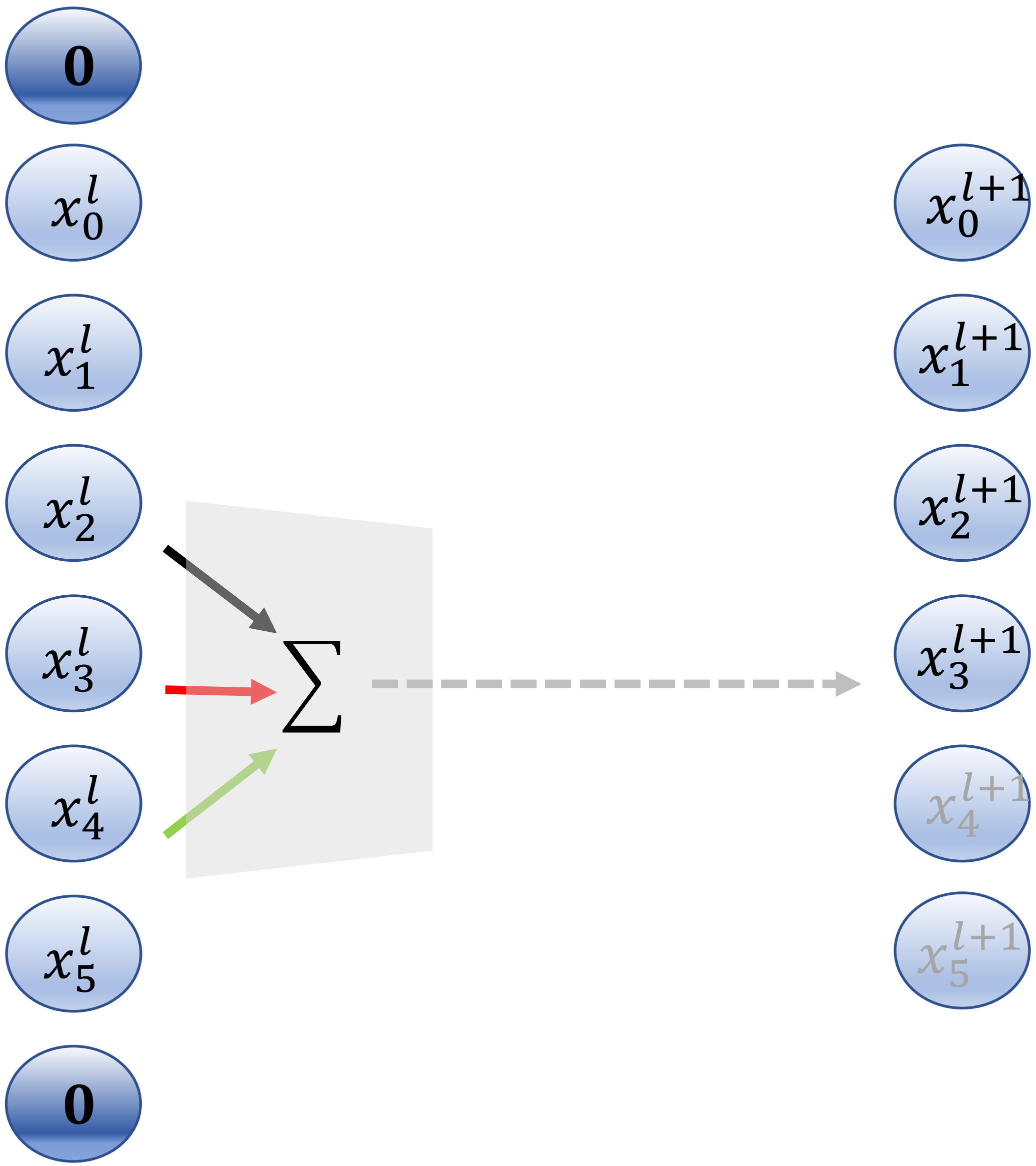

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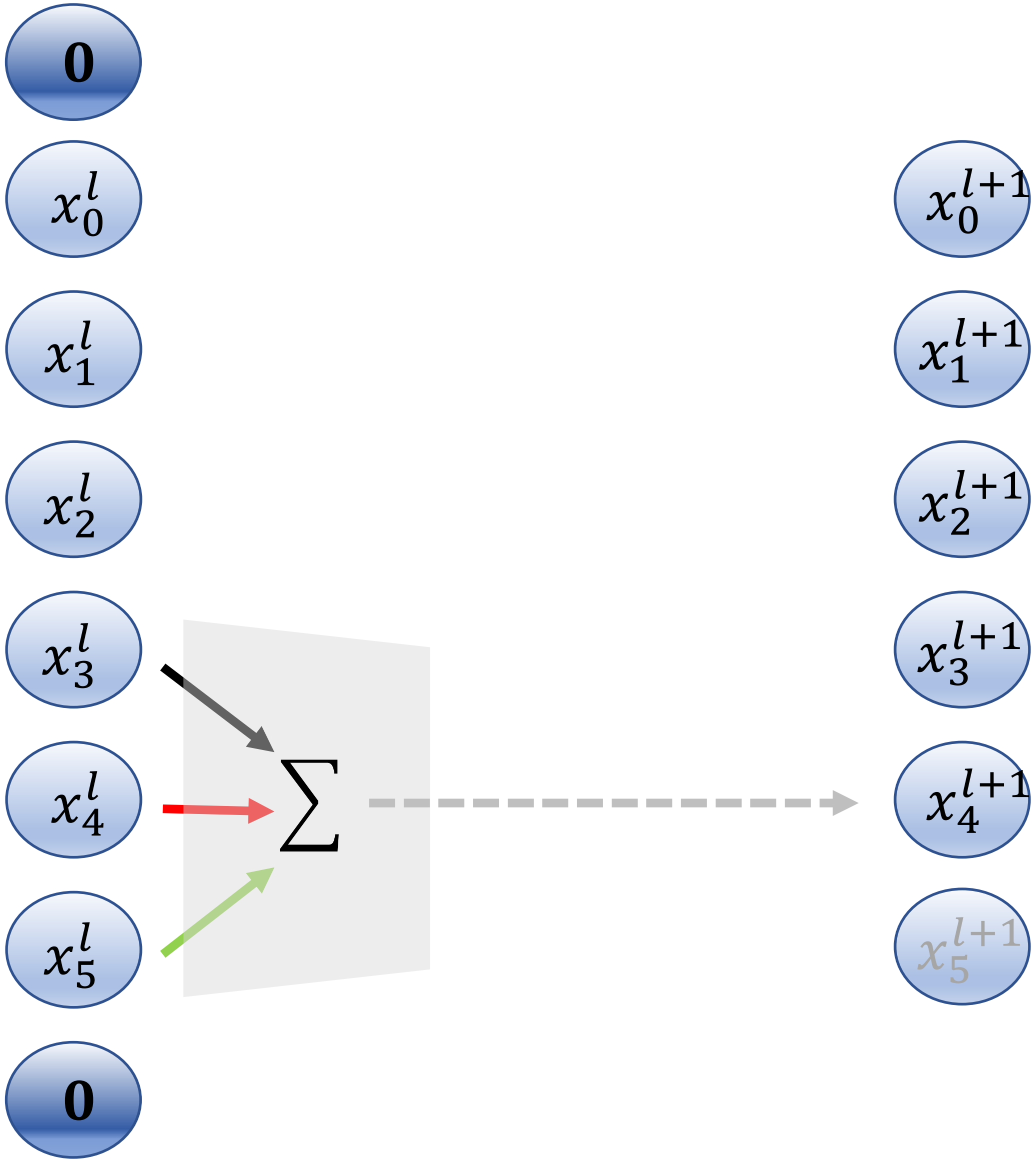

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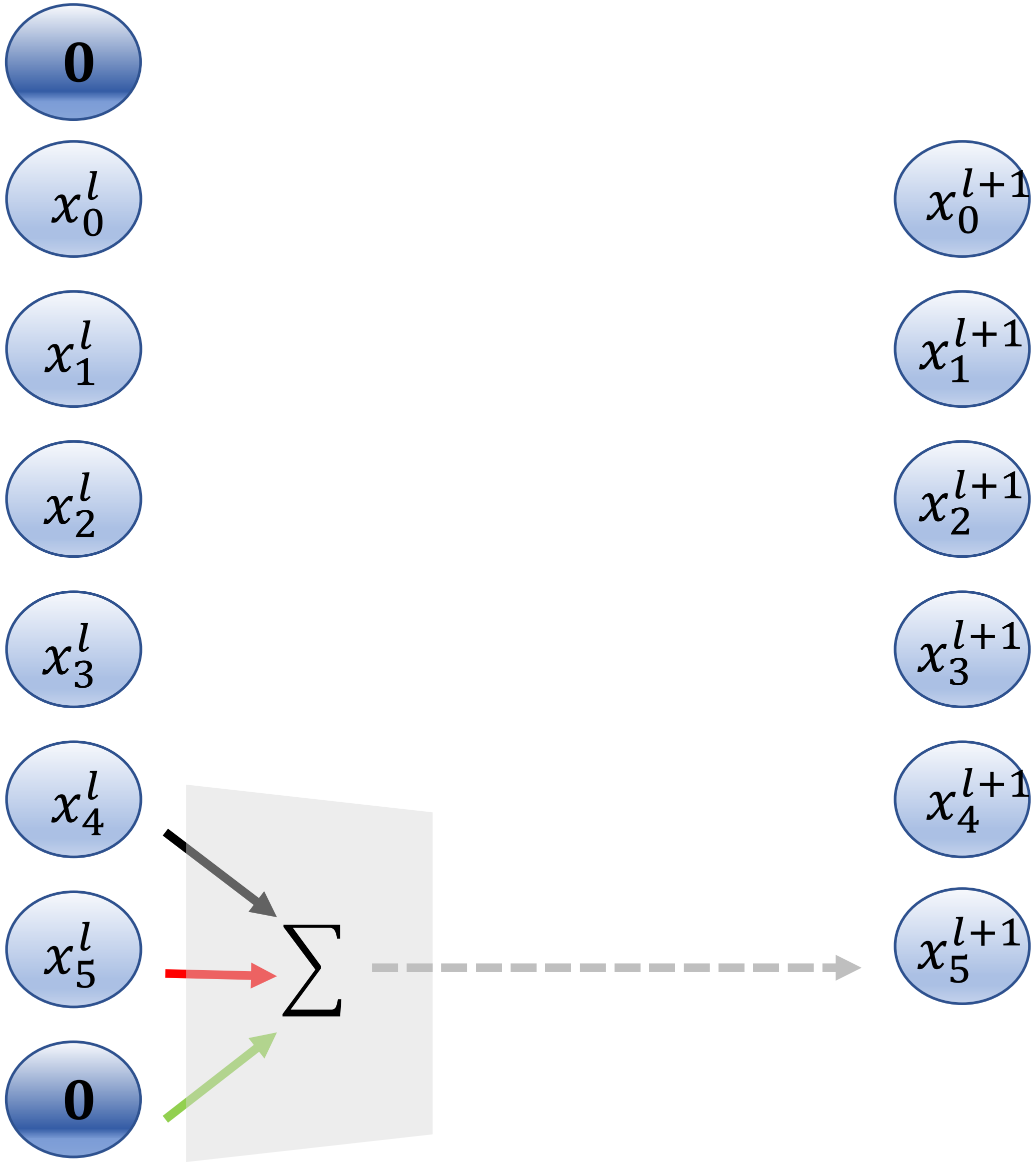
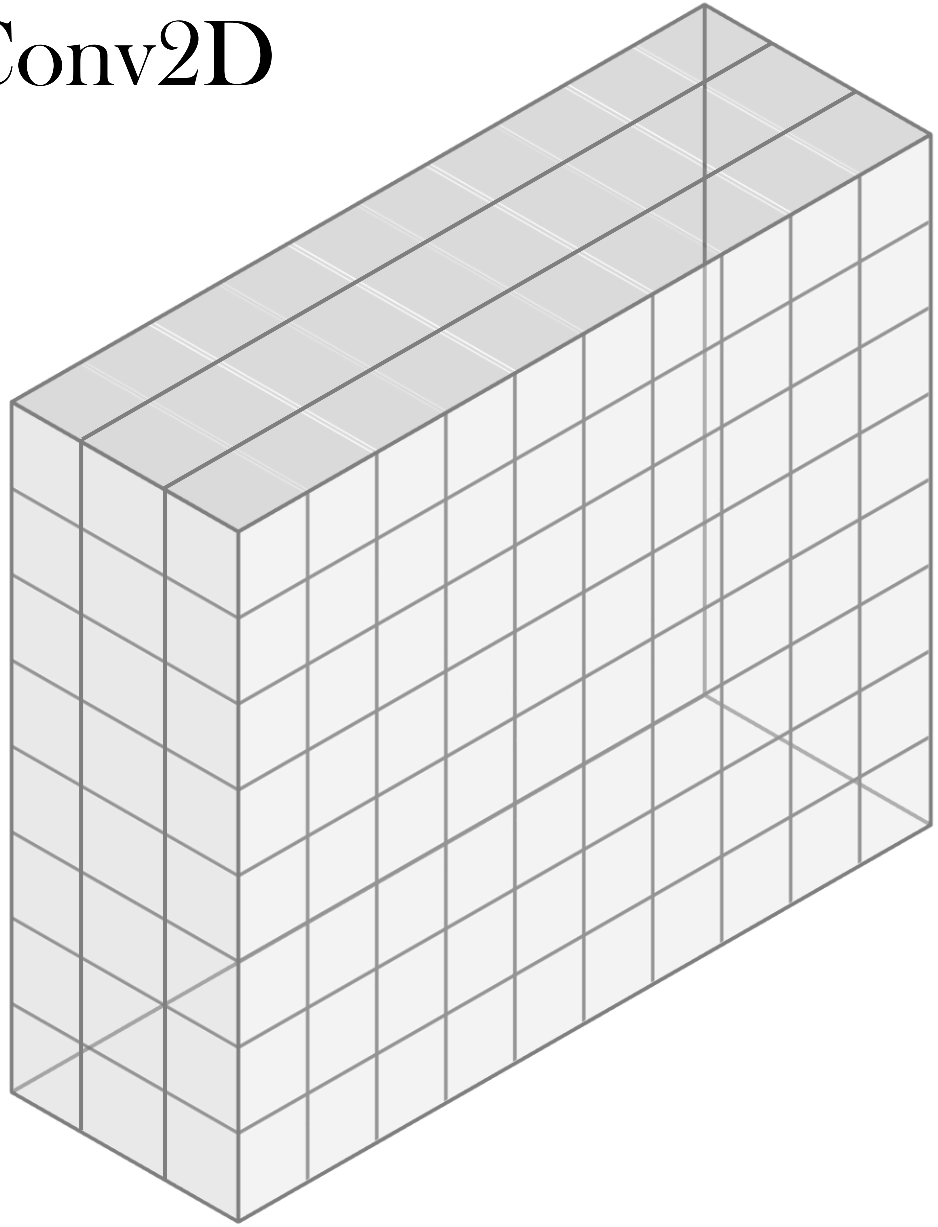
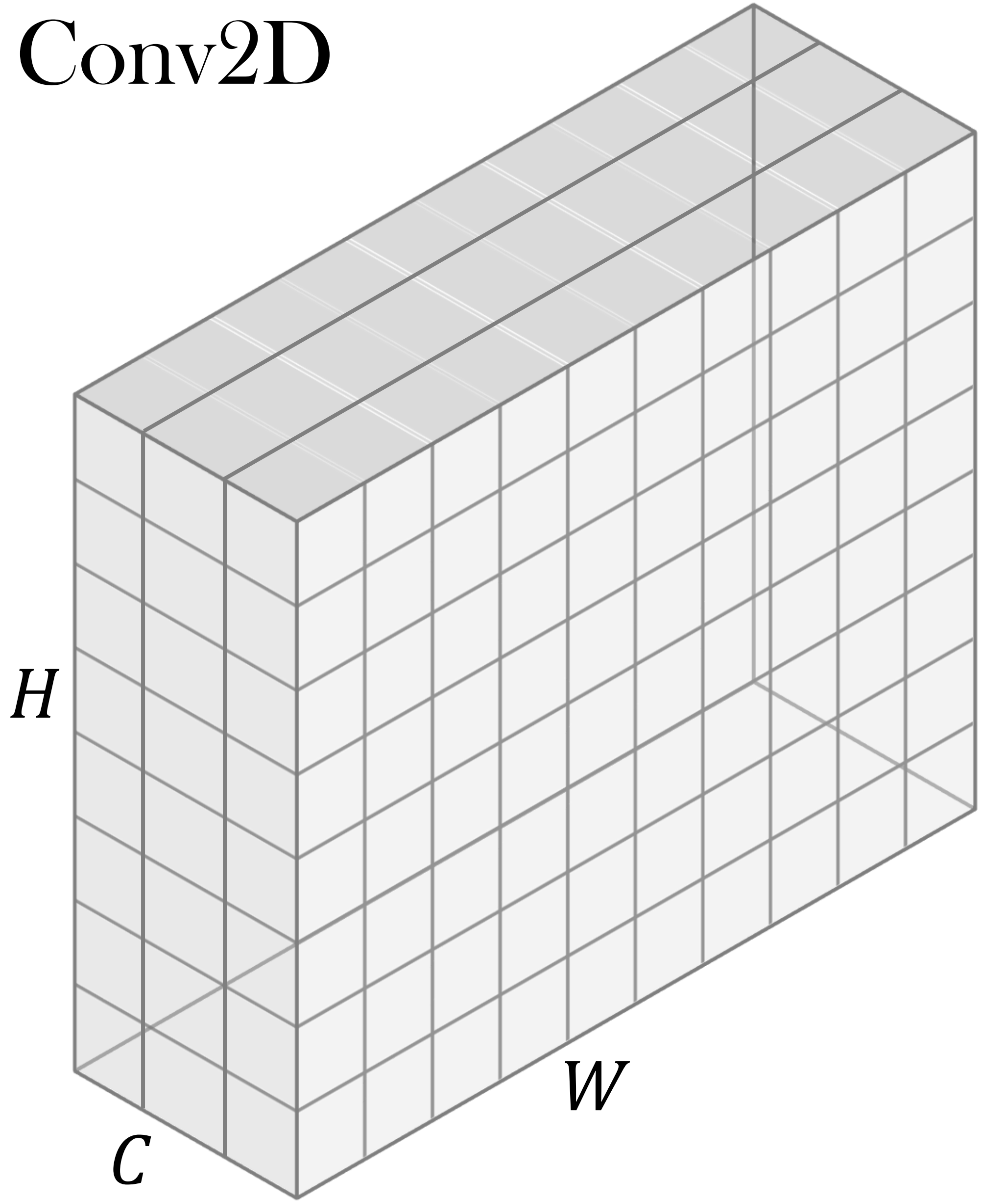


Conv2D

Conv2D

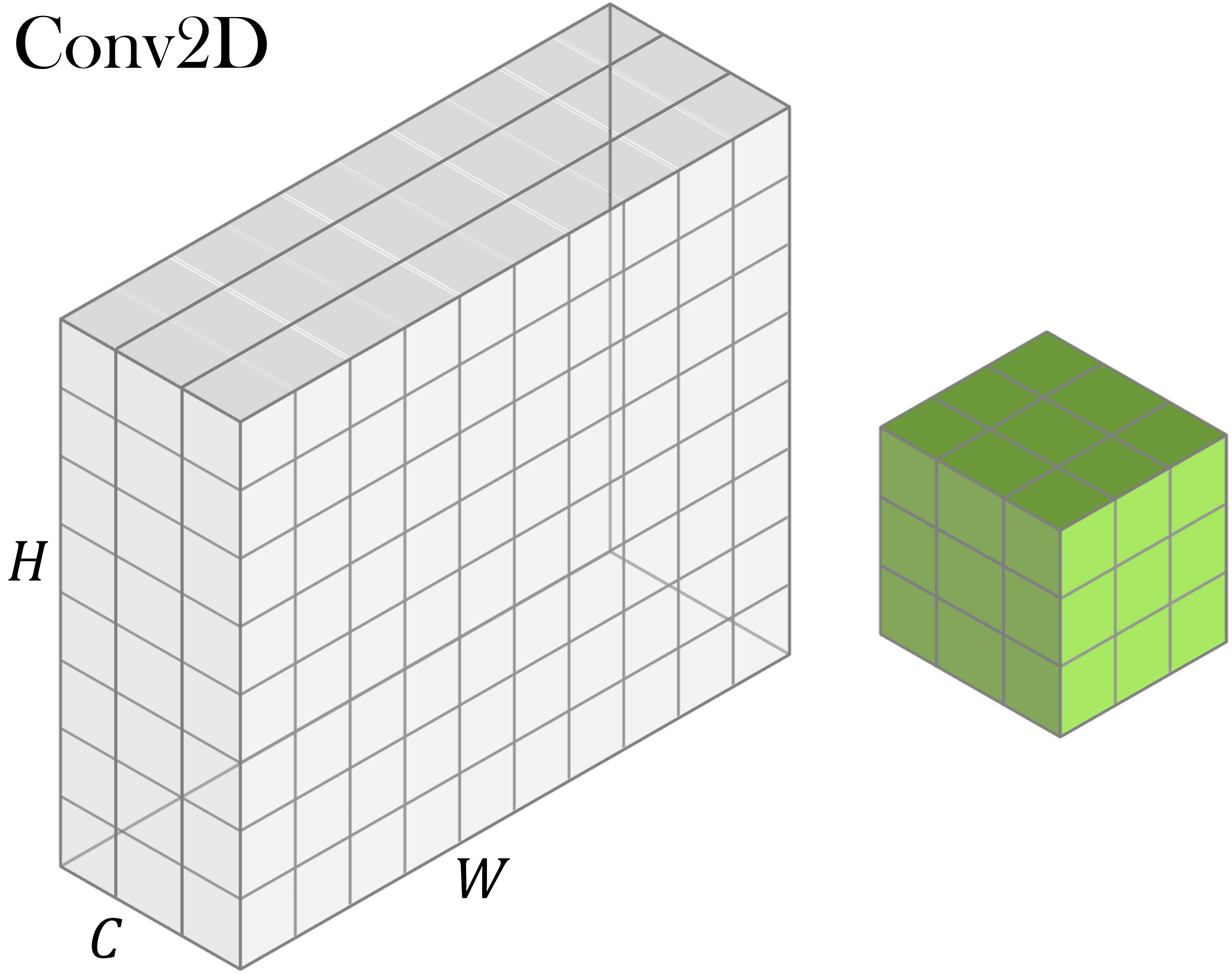


Conv2D



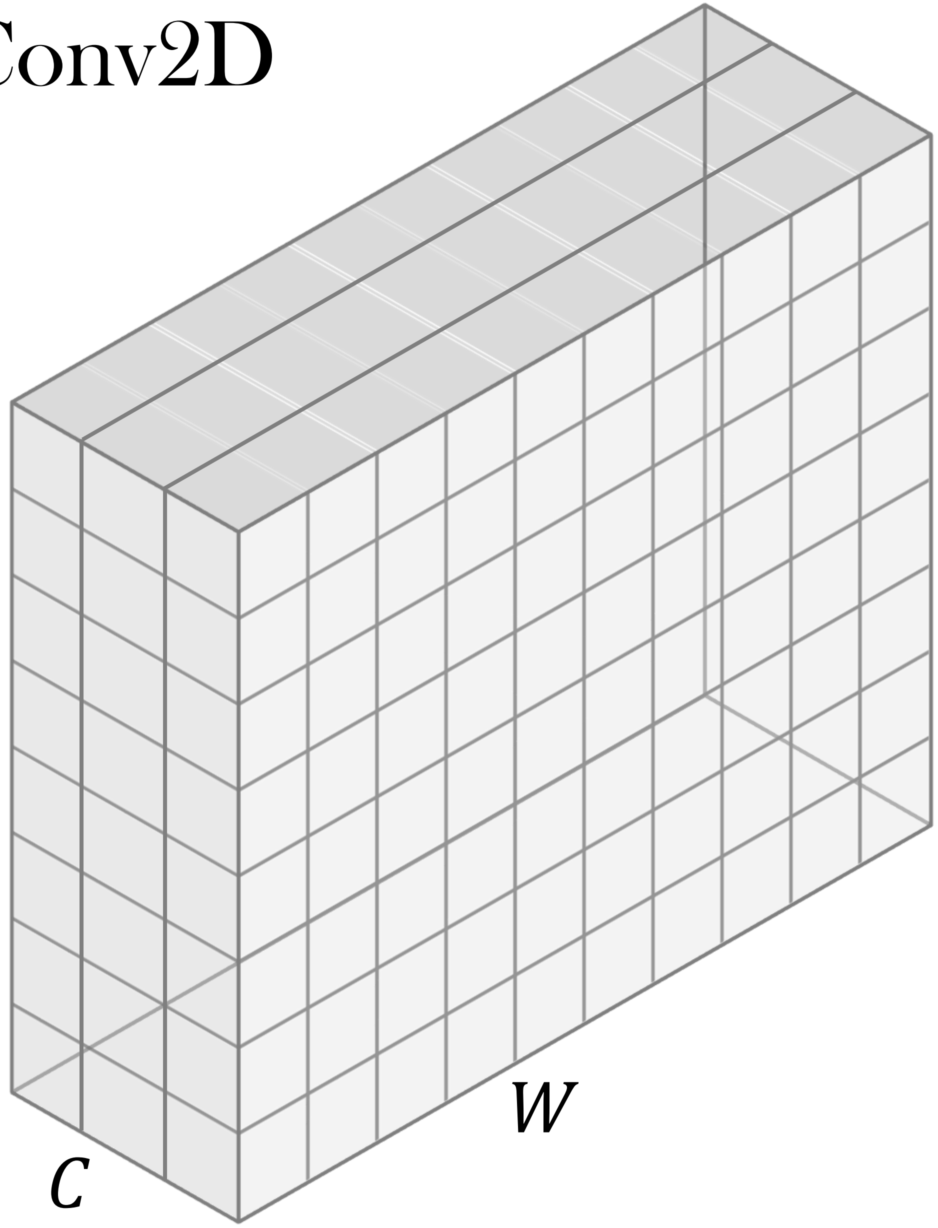
N, C, H, W

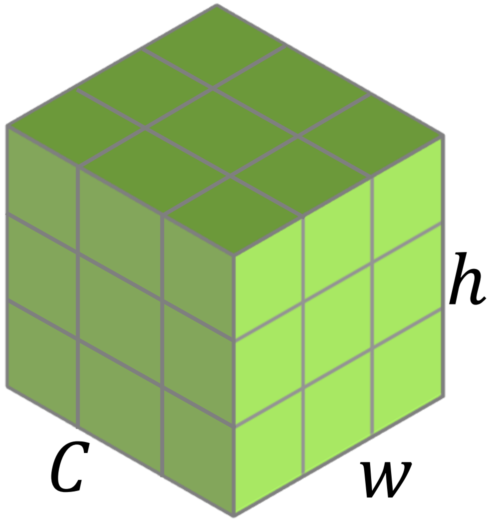
Conv2D



N, C, H, W

Conv2D

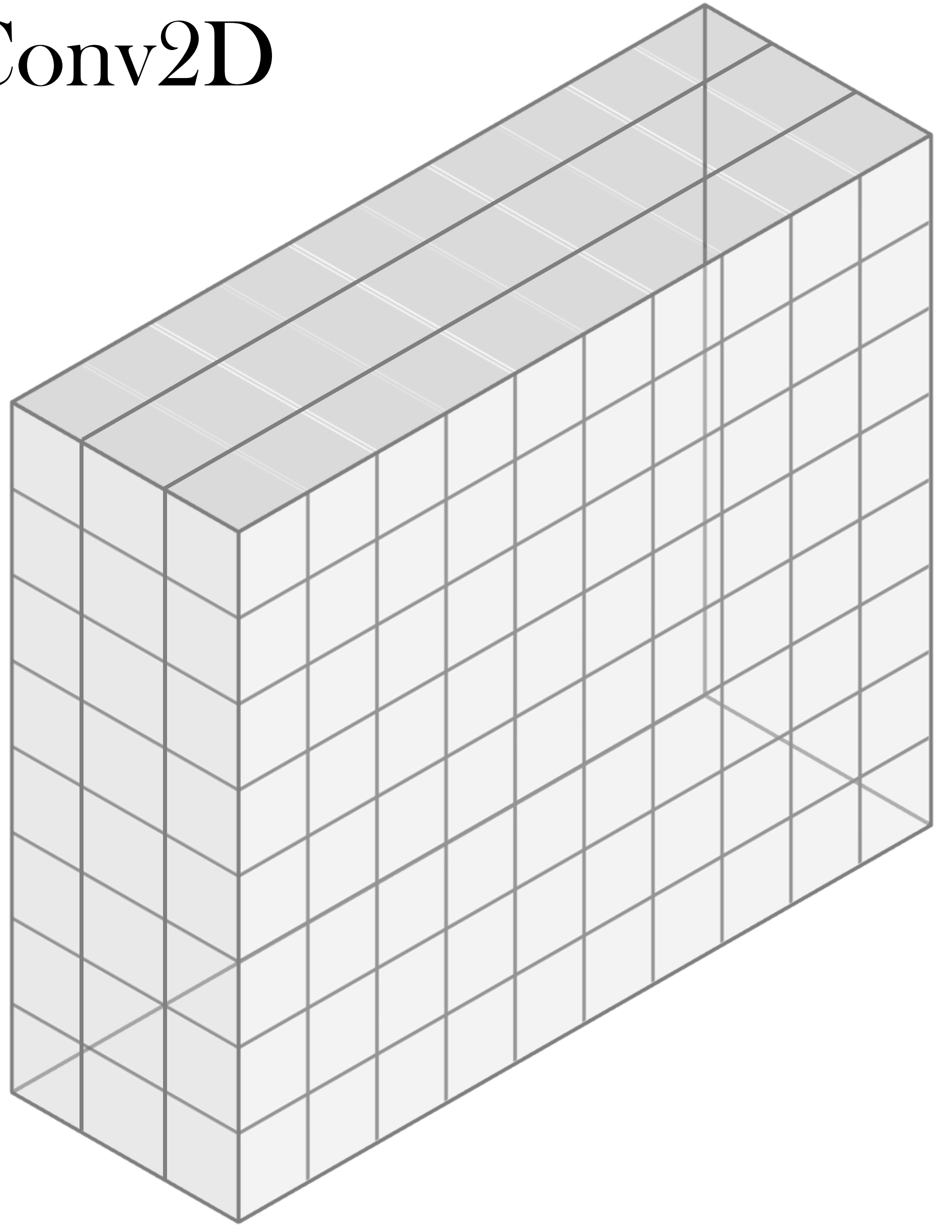




N, C, H, W

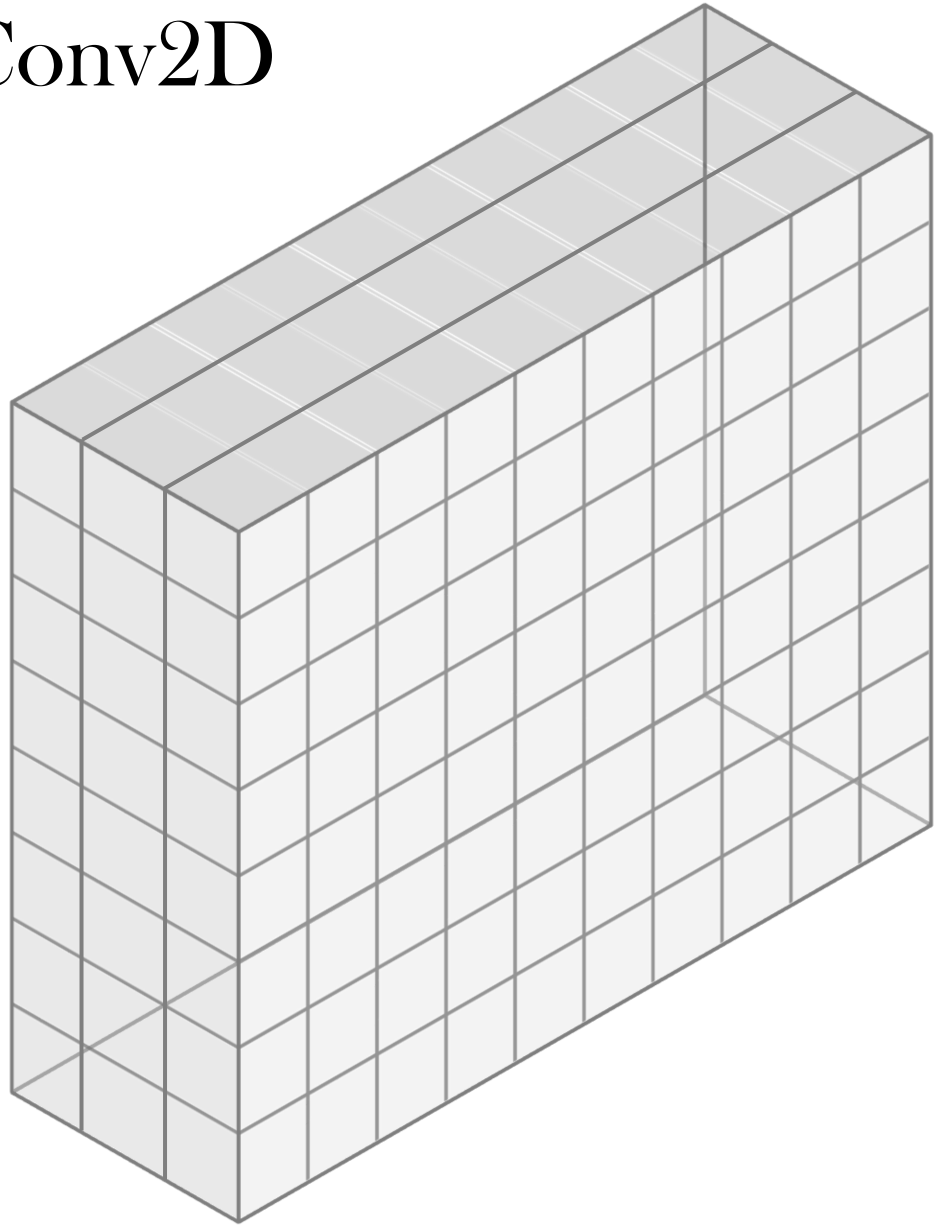
C, h, w

Conv2D



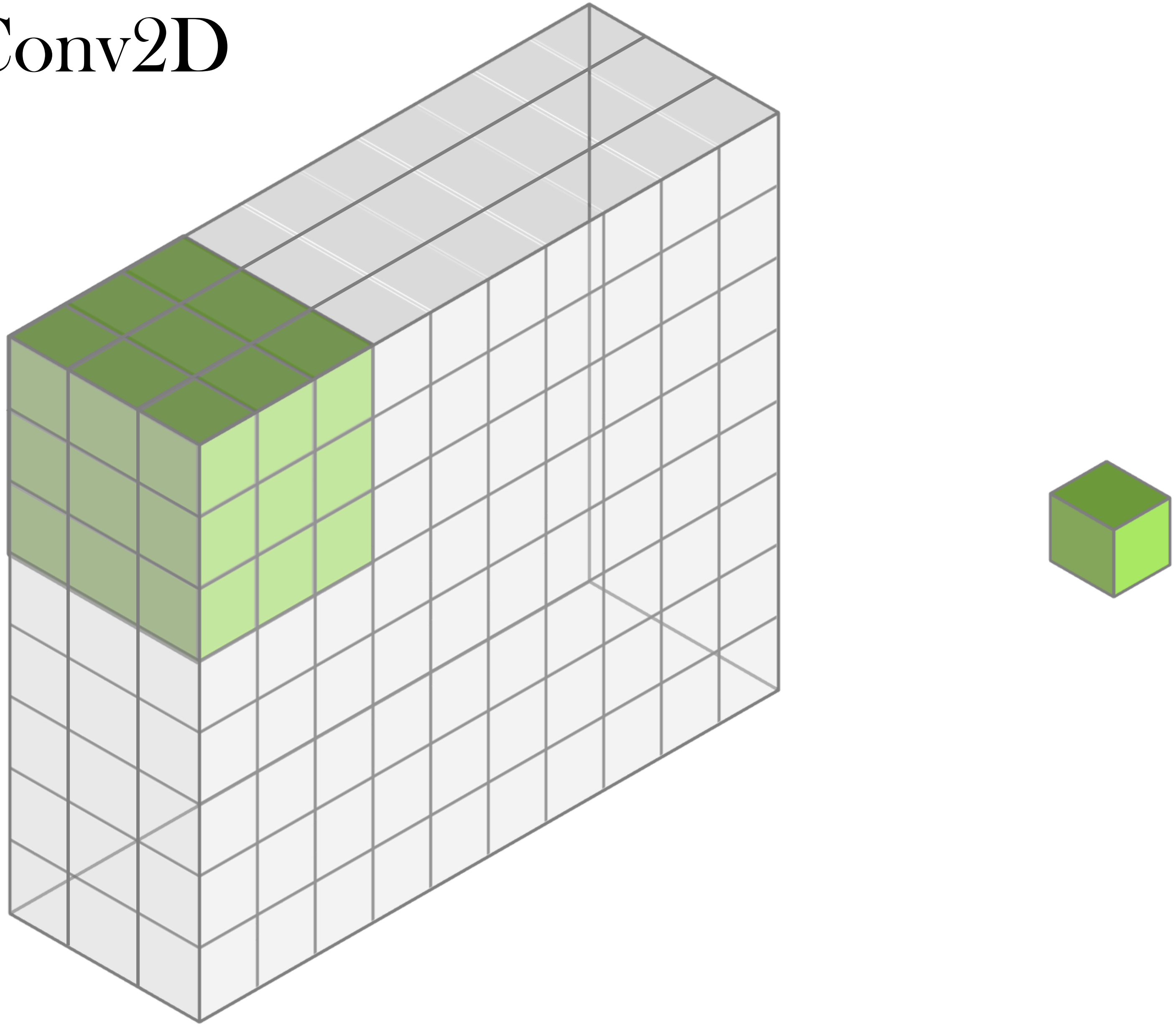
N, C, H, W

Conv2D



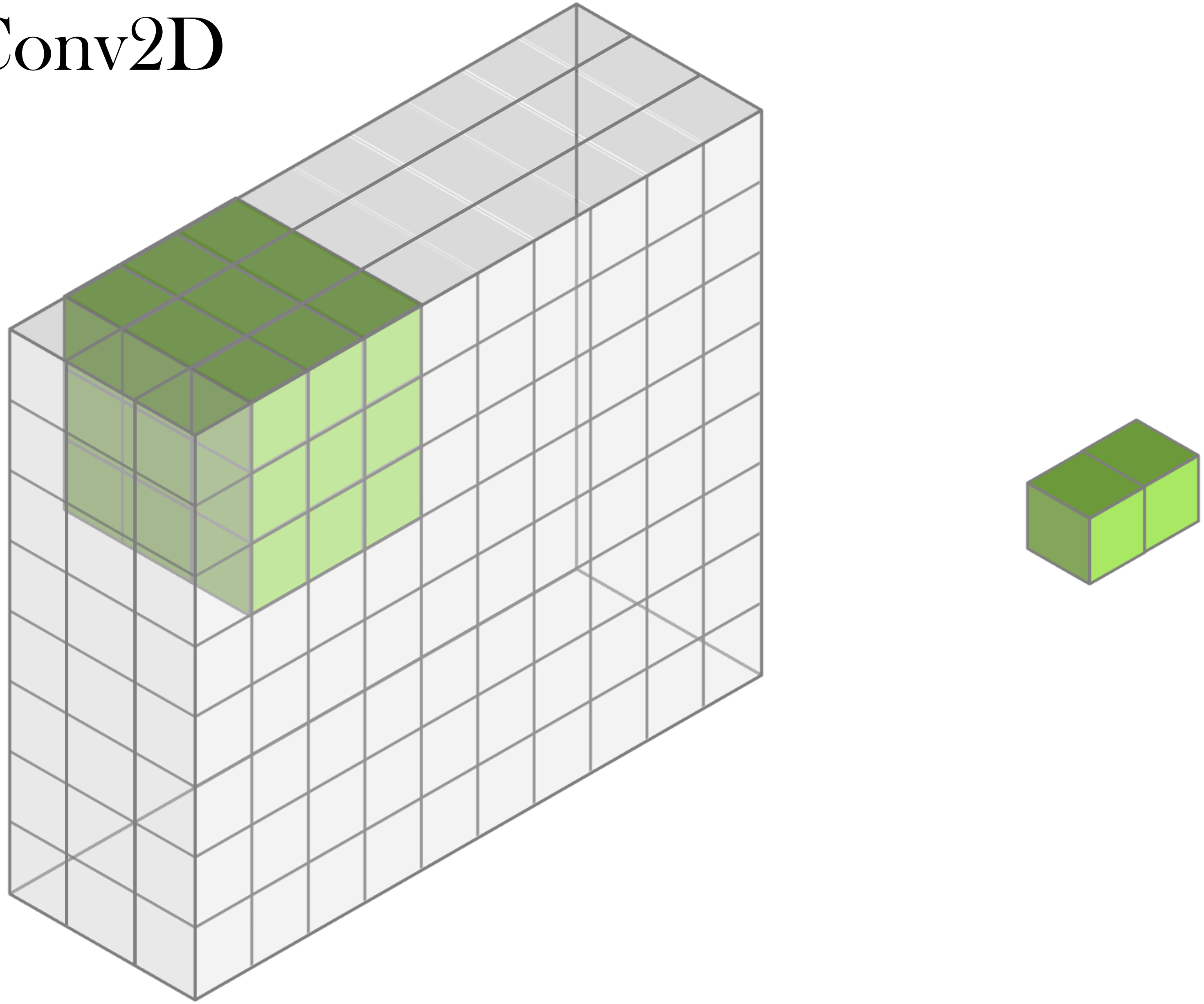
N, C, H, W

Conv2D



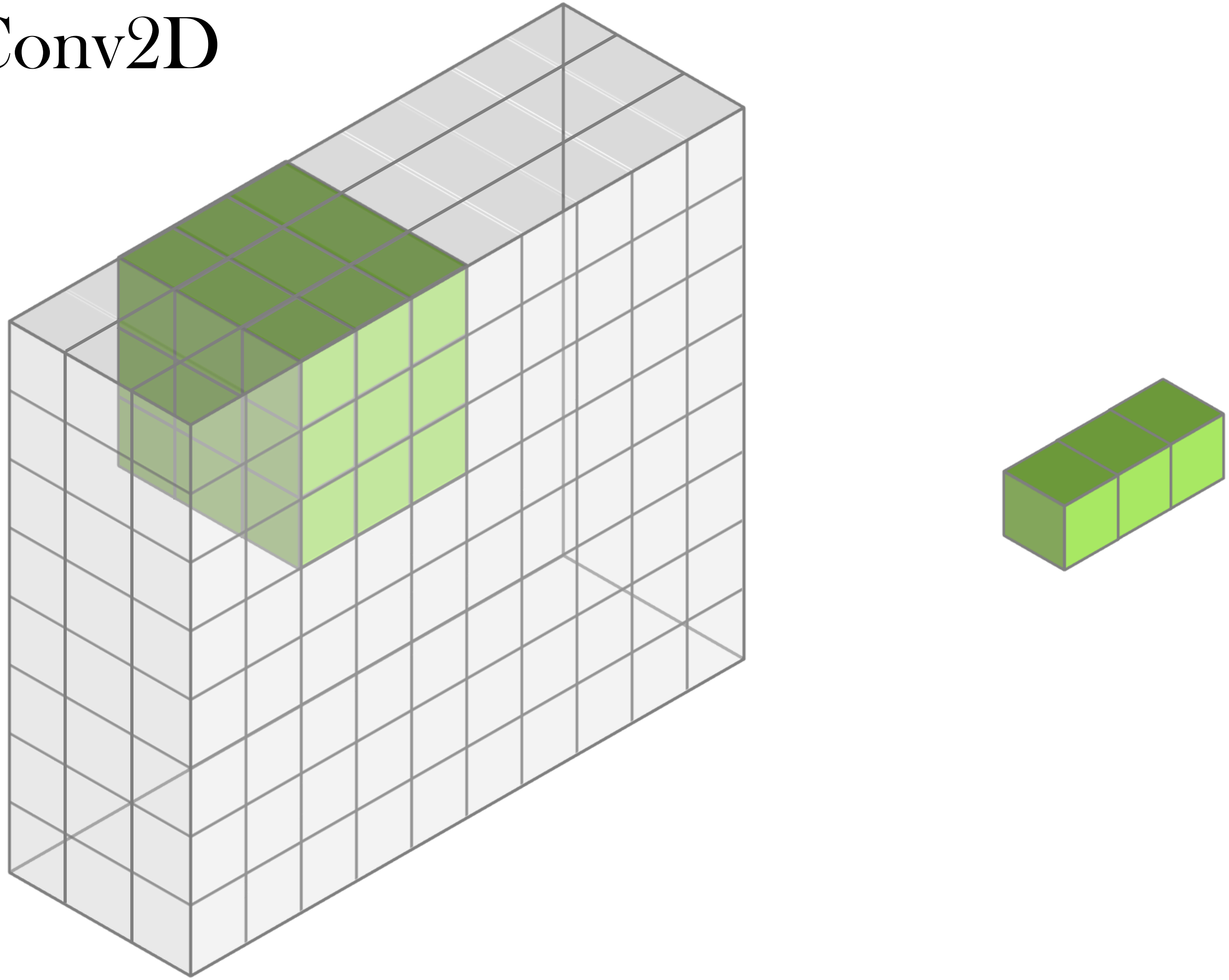
N, C, H, W

Conv2D



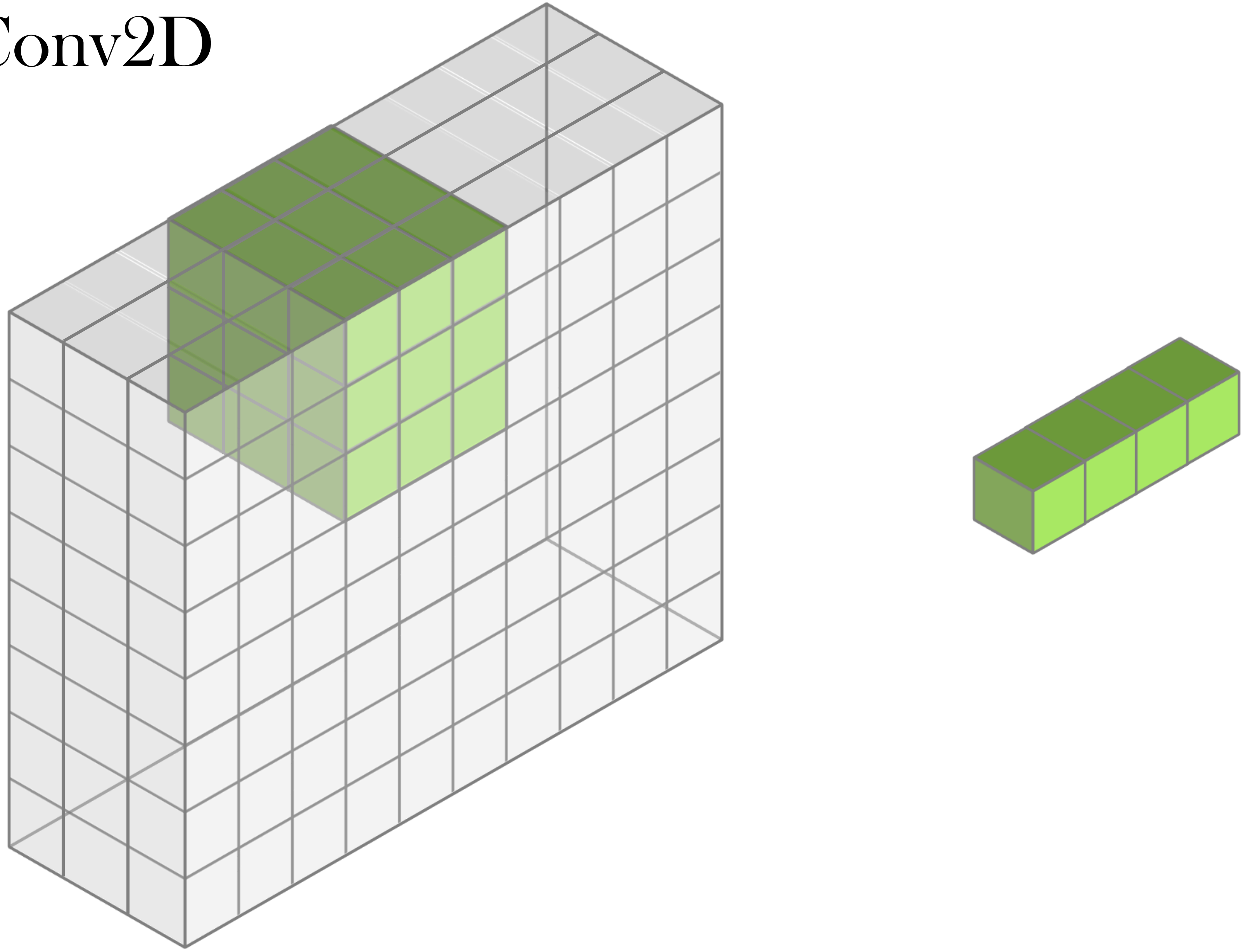
$$N, C, H, W$$

Conv2D



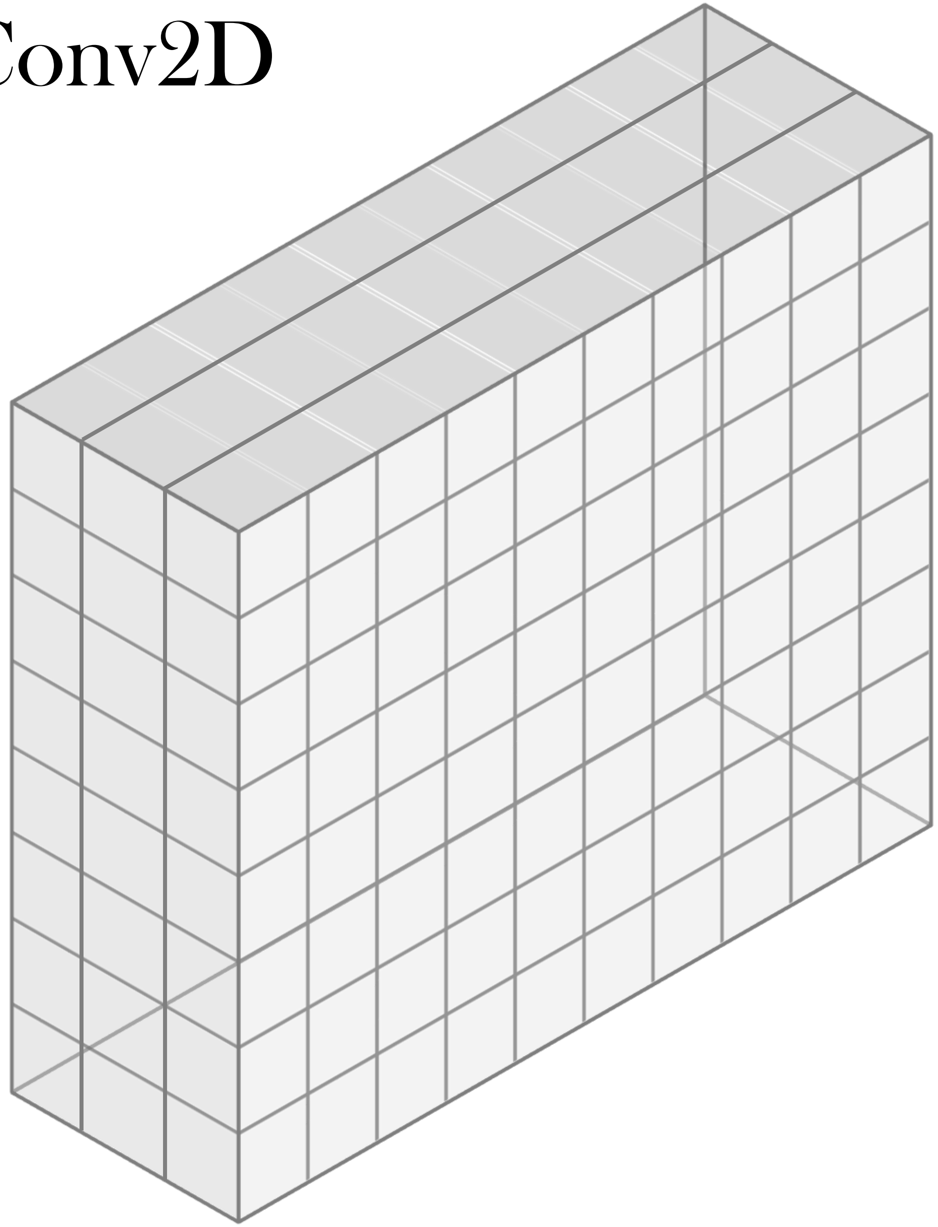
$$N, C, H, W$$

Conv2D

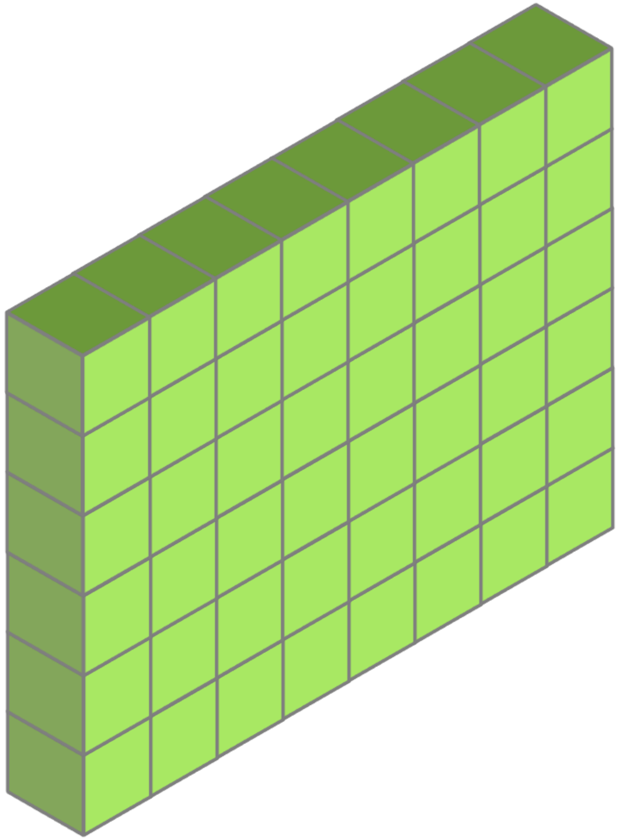


N, C, H, W

Conv2D

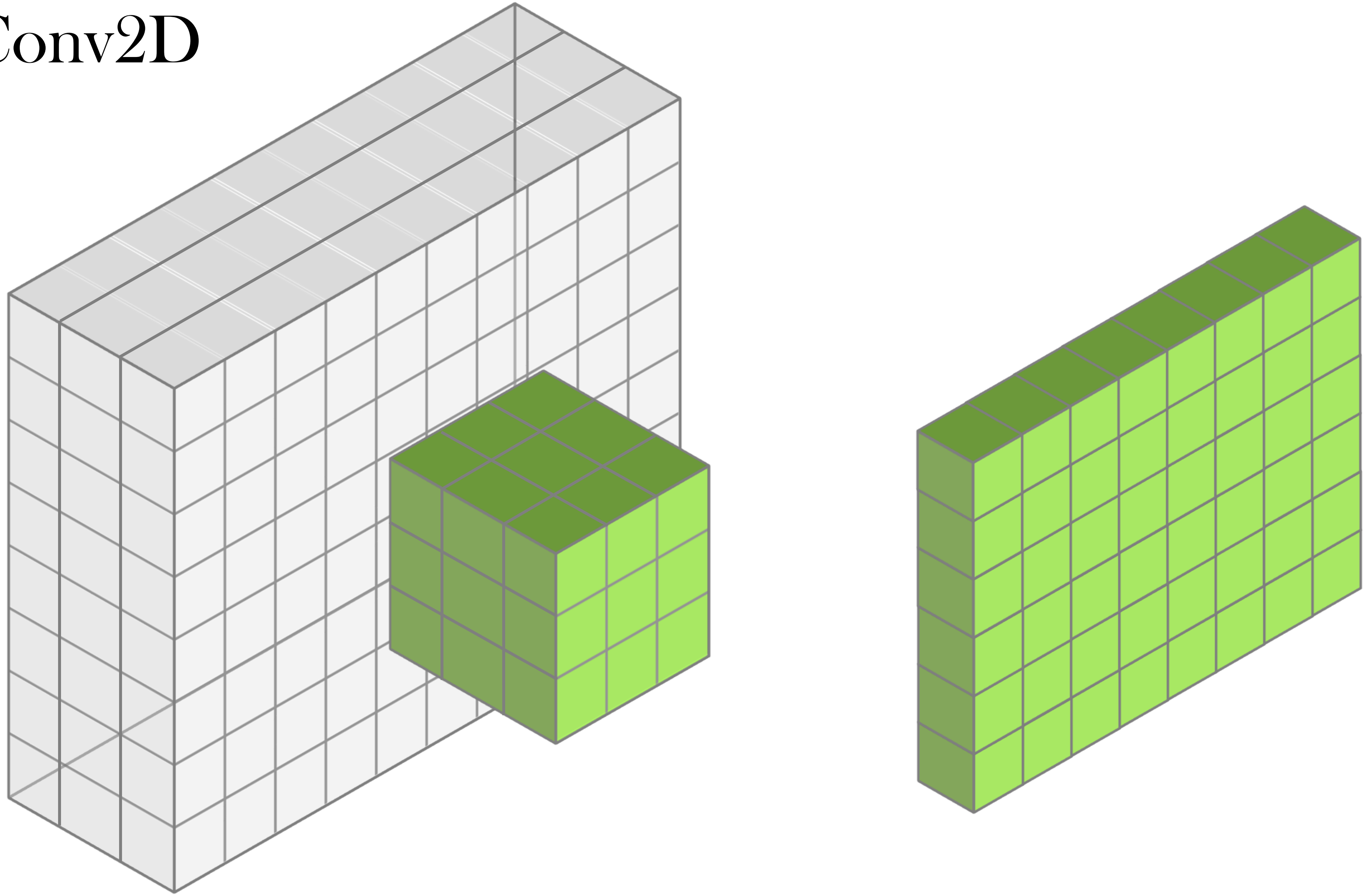


N, C, H, W

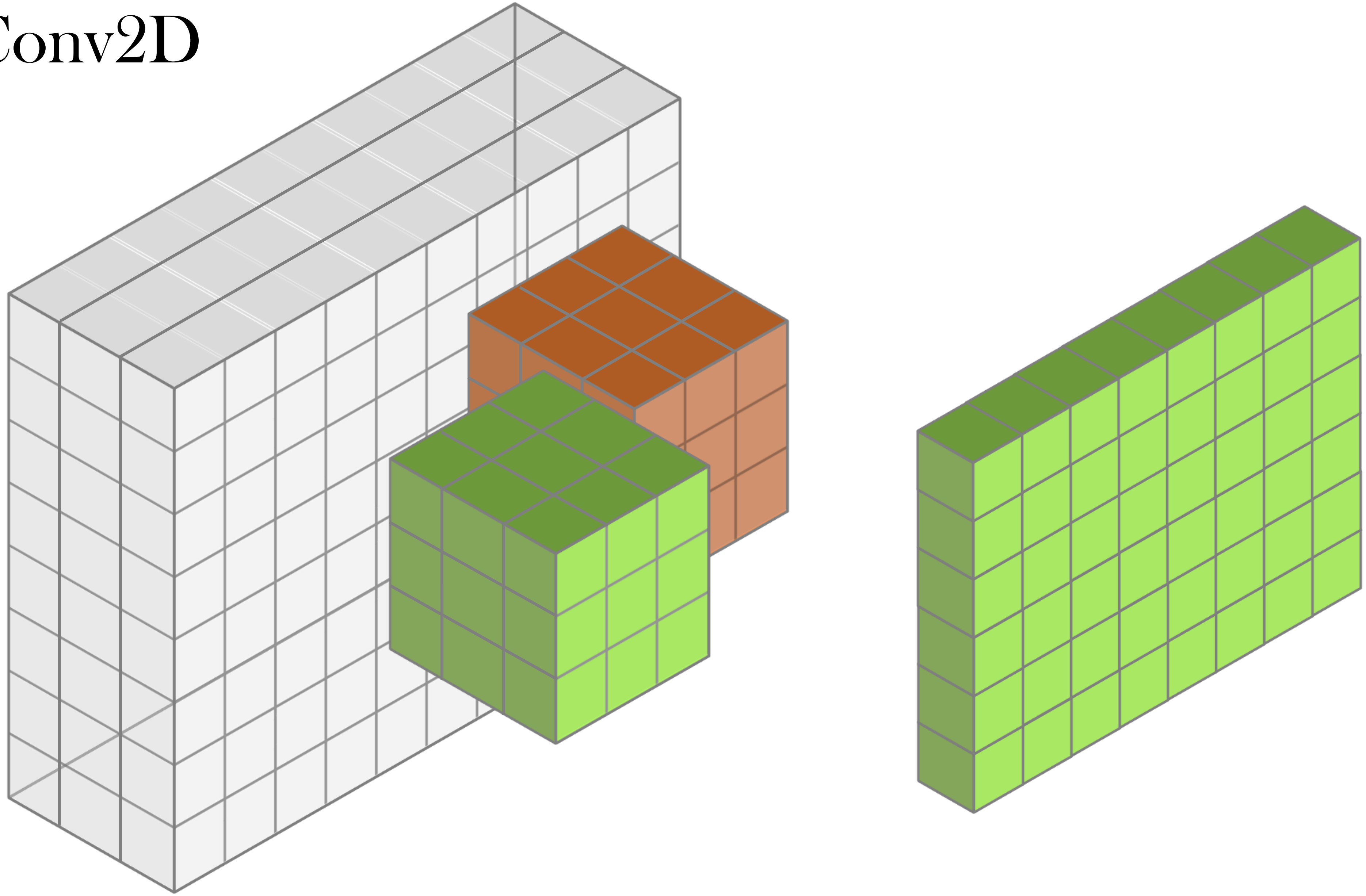


$[N, 1, \widetilde{H}, \widetilde{W}]$

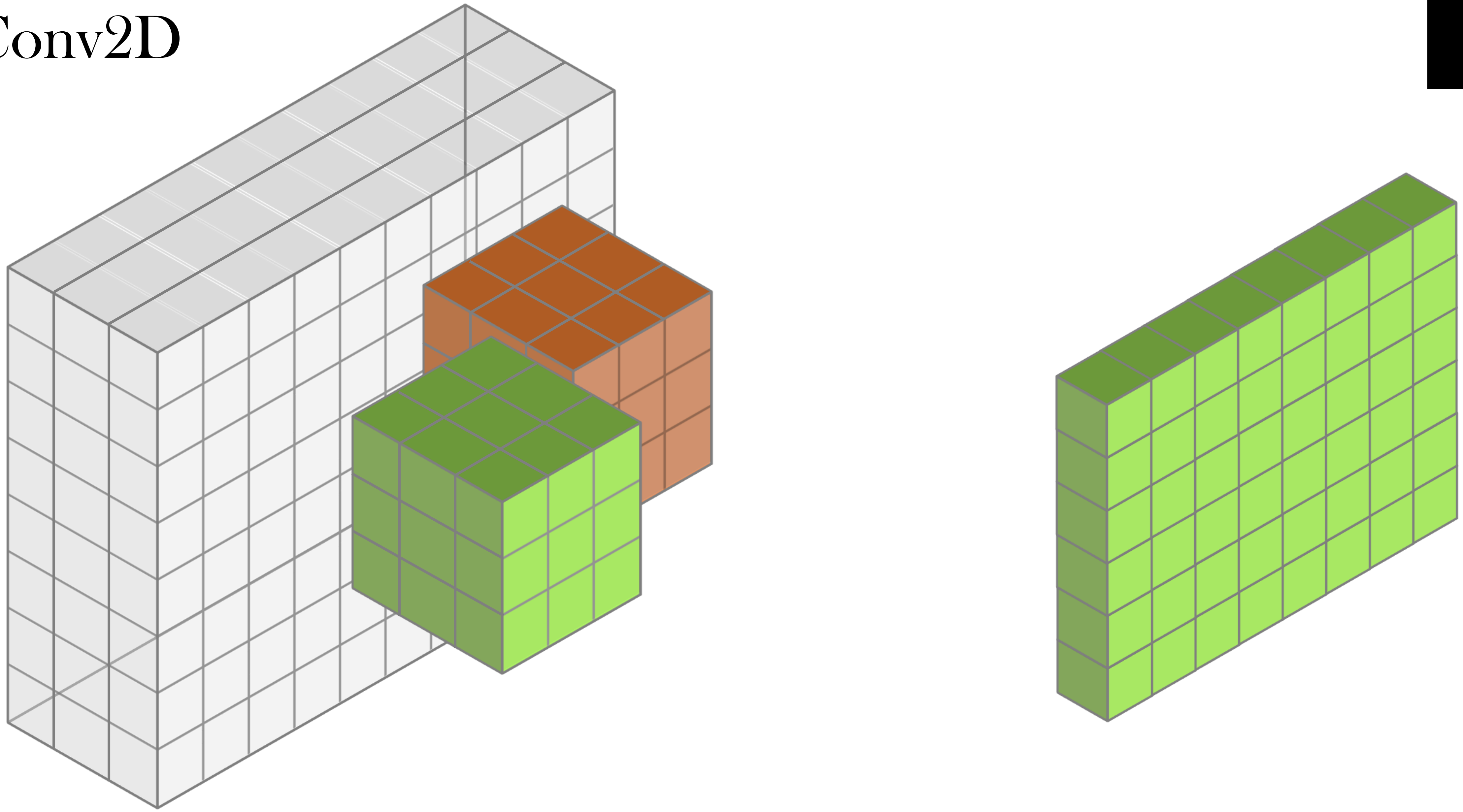
Conv2D



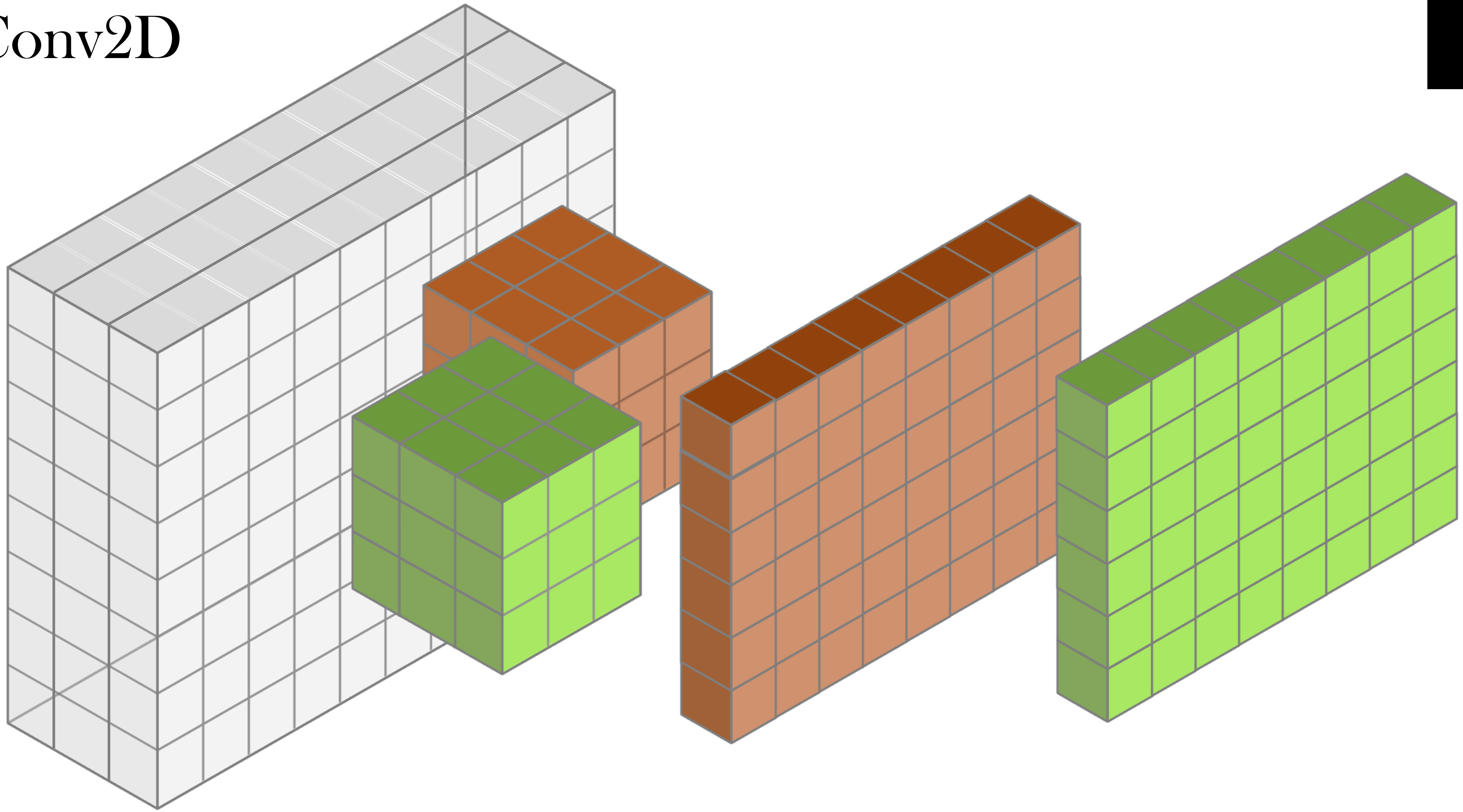
Conv2D



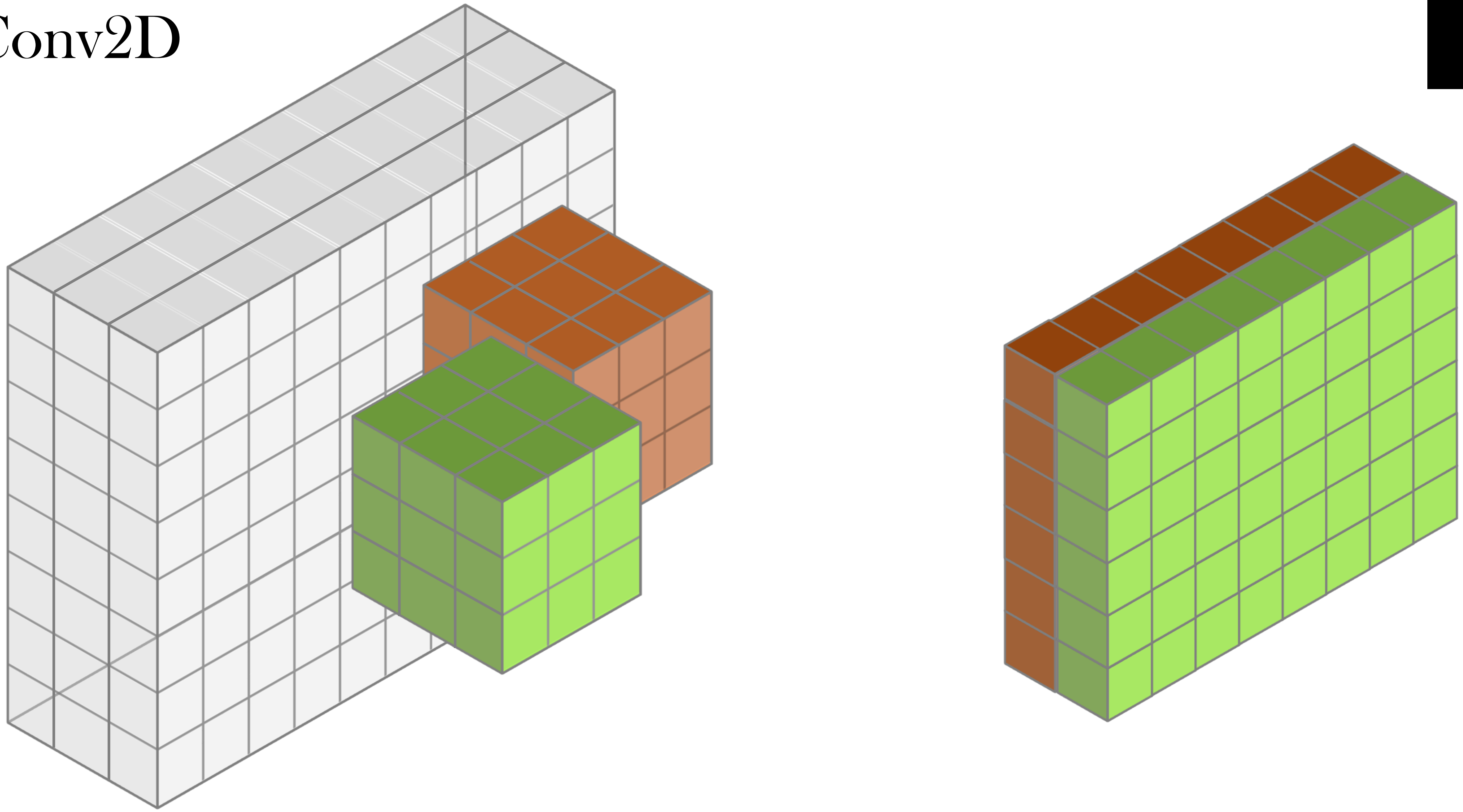
Conv2D



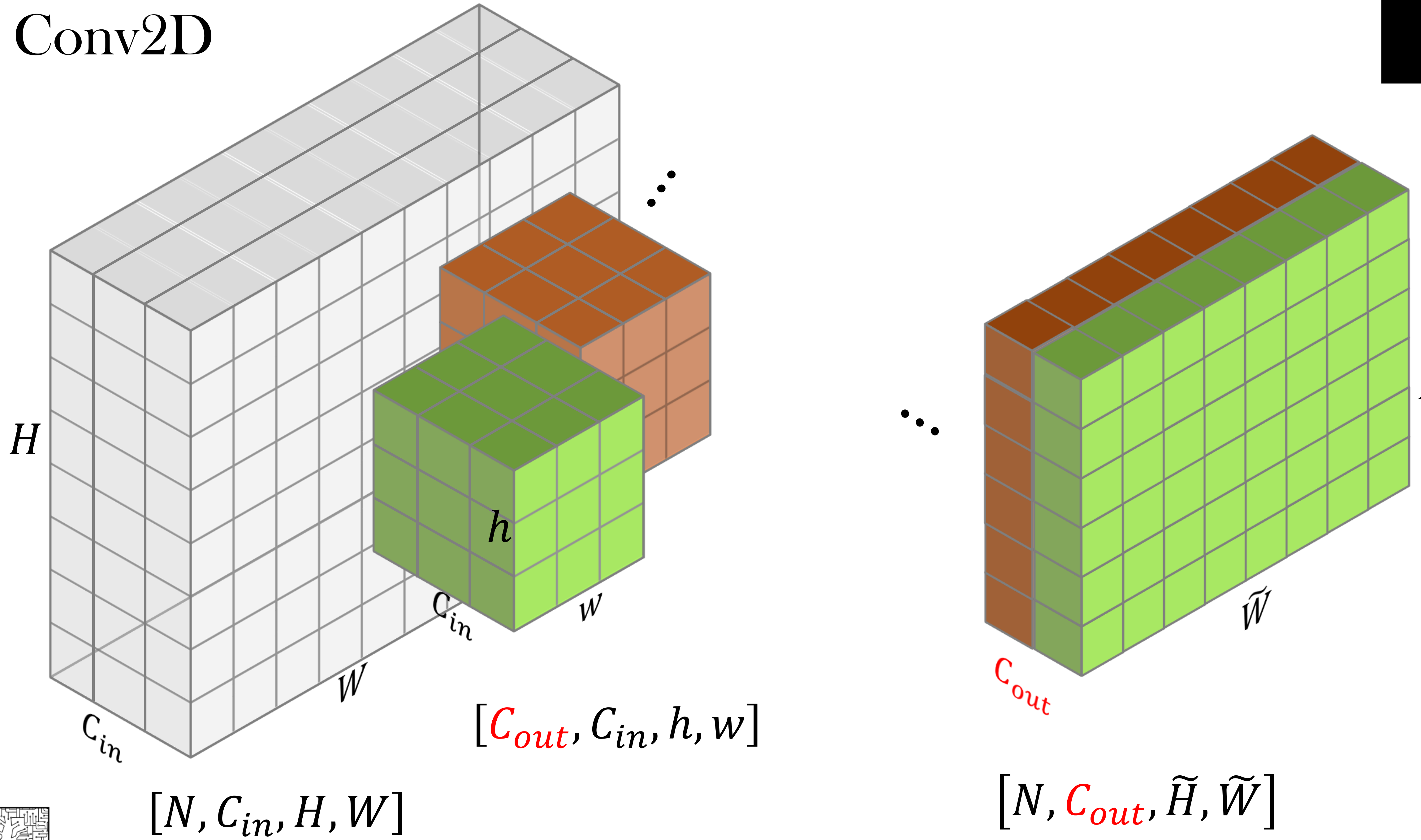
Conv2D



Conv2D



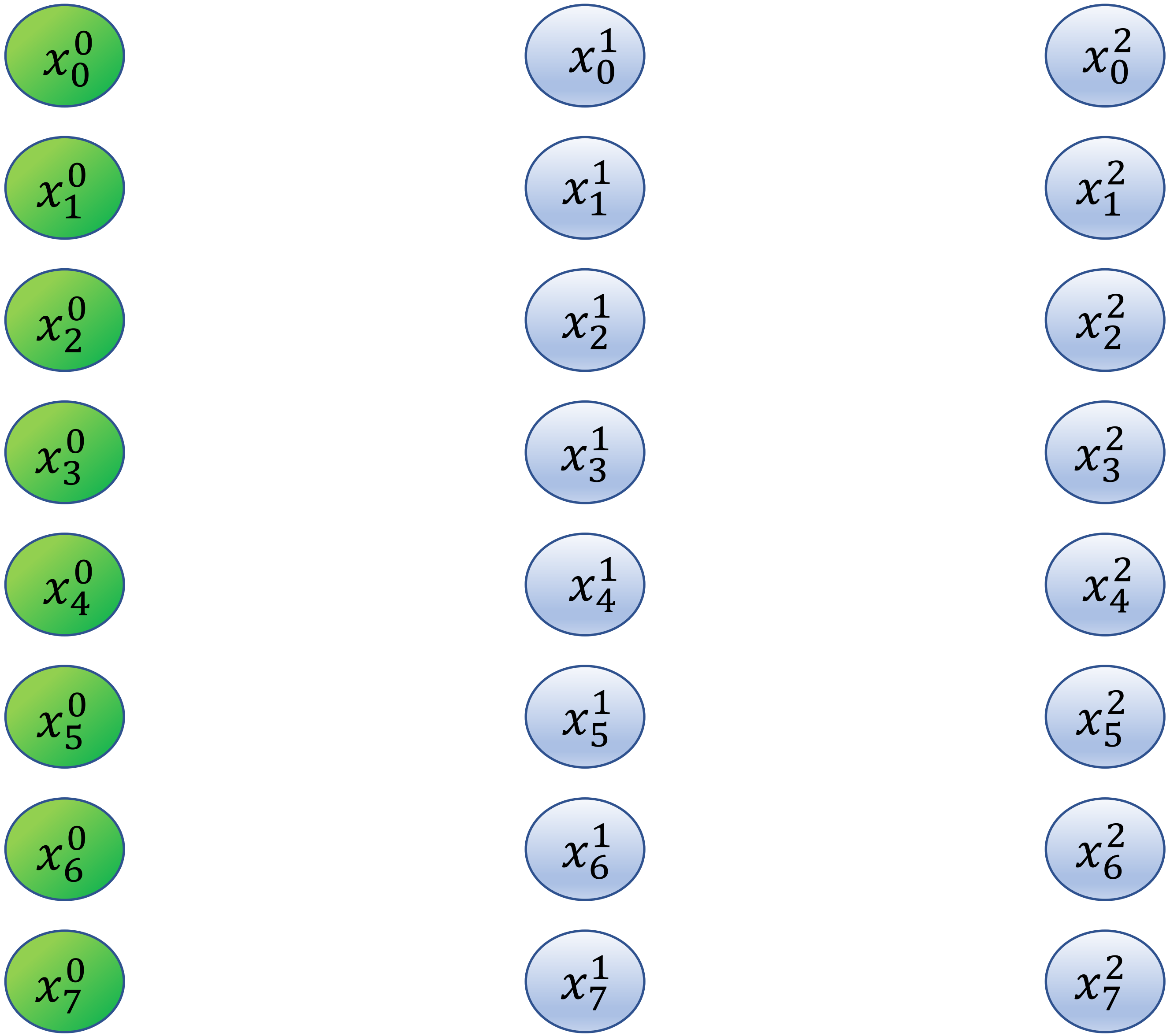
Conv2D



H
C_{in}
W
h
C_{in}
w
$\tilde{H}$
$\tilde{W}$
C_{out}
$[C_{out}, C_{in}, h, w]$
$[N, C_{in}, H, W]$
$[N, C_{out}, \tilde{H}, \tilde{W}]$

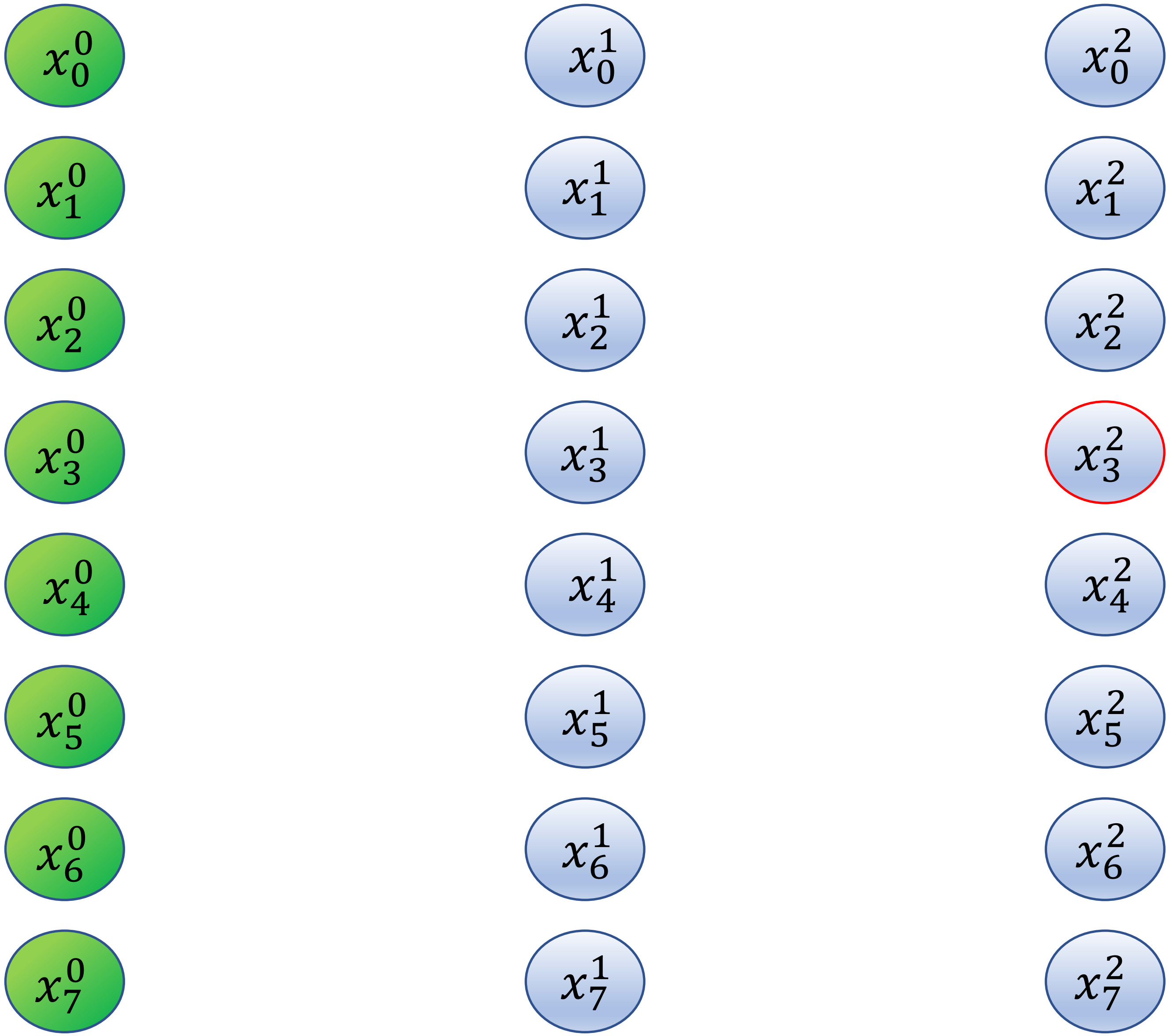
Receptive Field

$[Filter\ size: 3]$



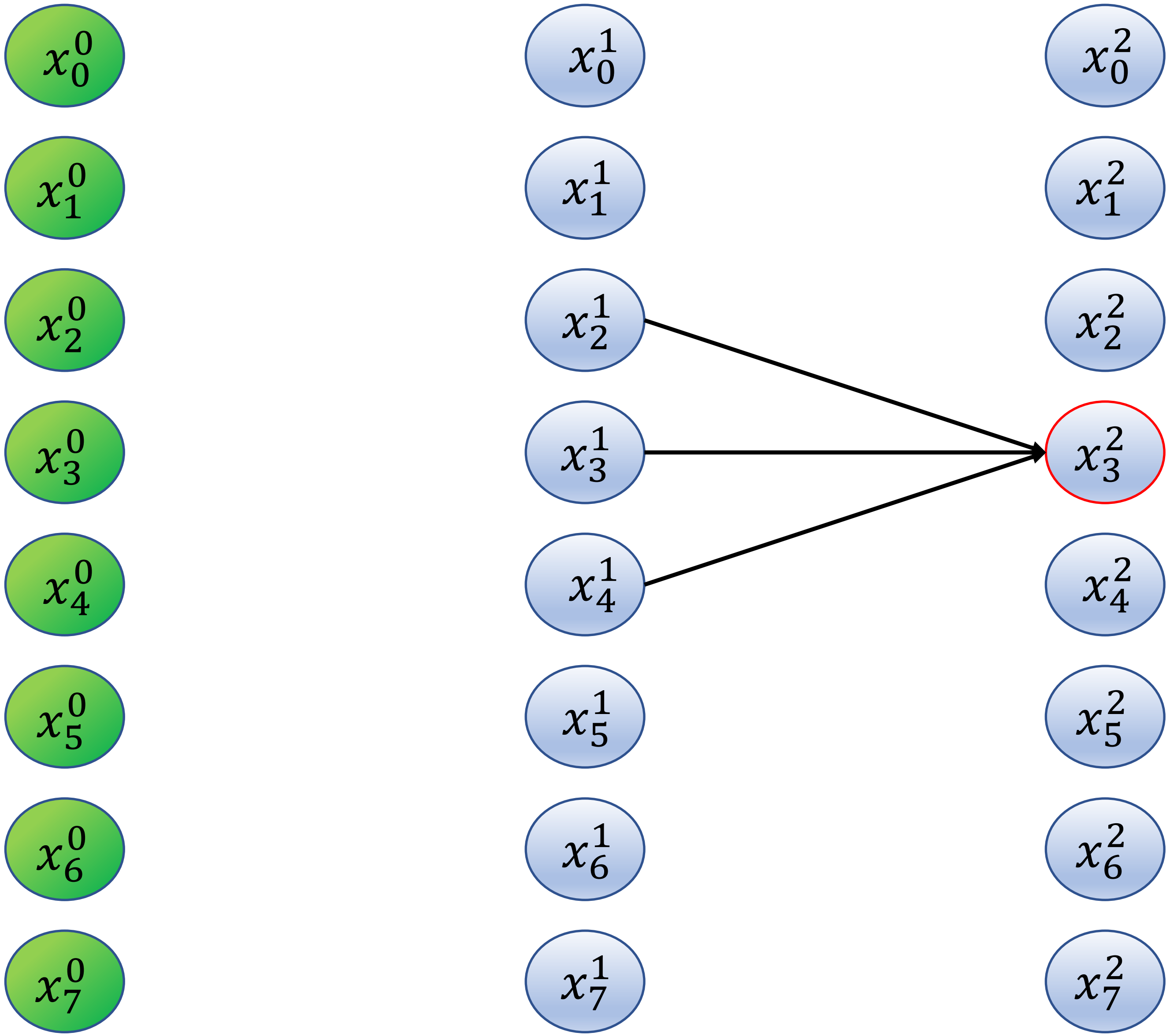
Receptive Field

$[Filter\ size{:}\ 3]$



Receptive Field

$[Filter\ size\!: 3]$



Receptive Field

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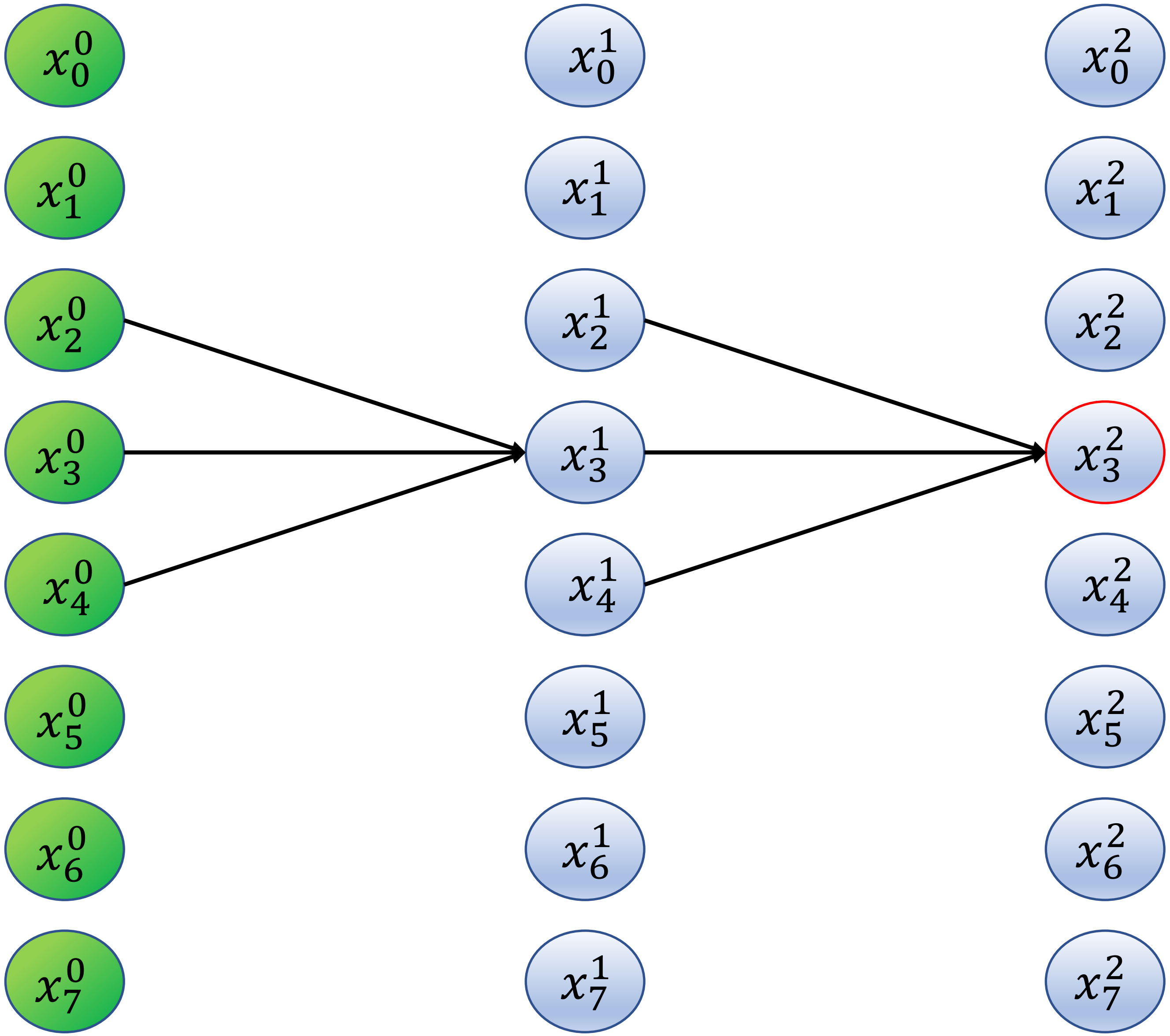

Receptive Field

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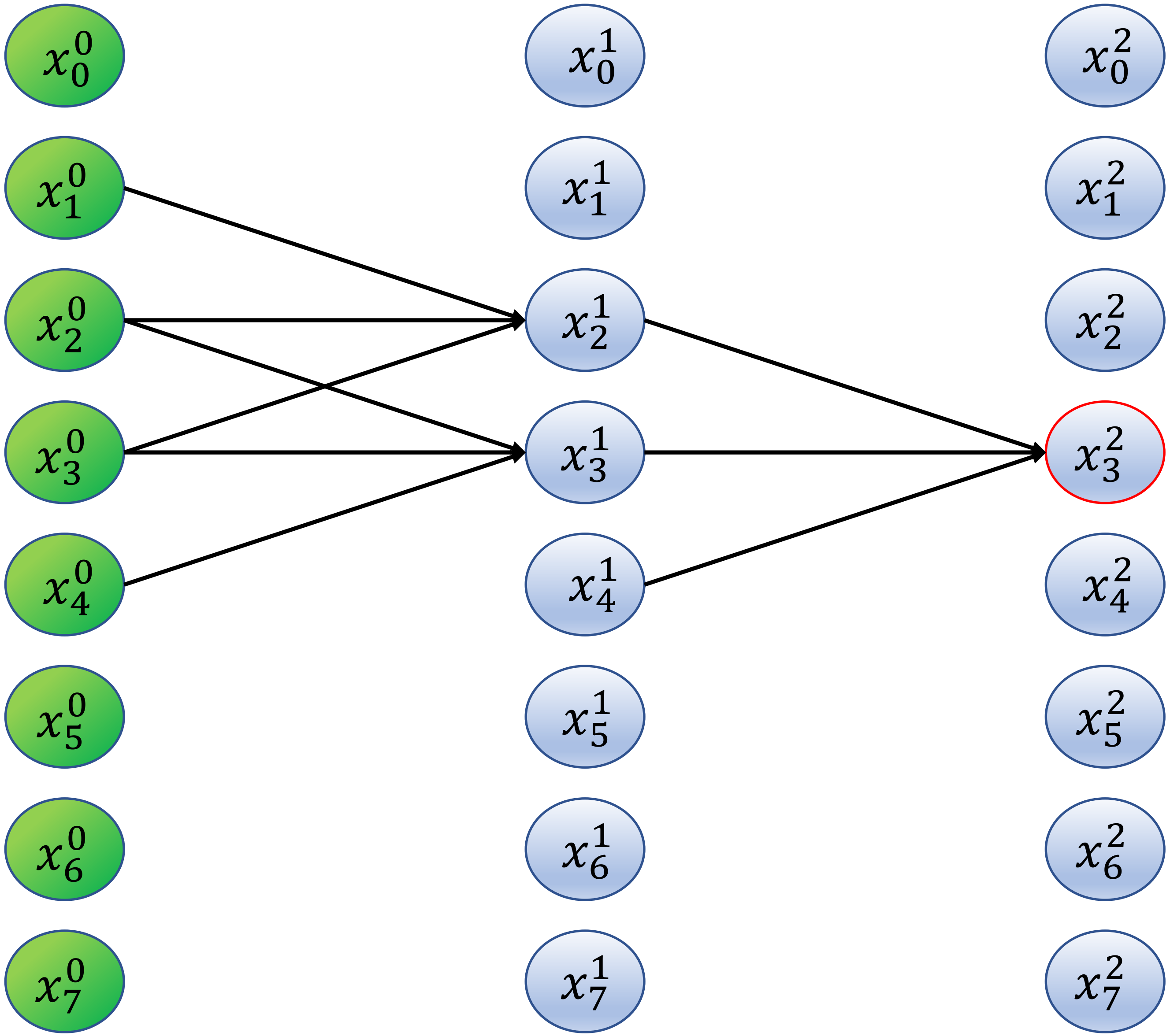

Receptive Field

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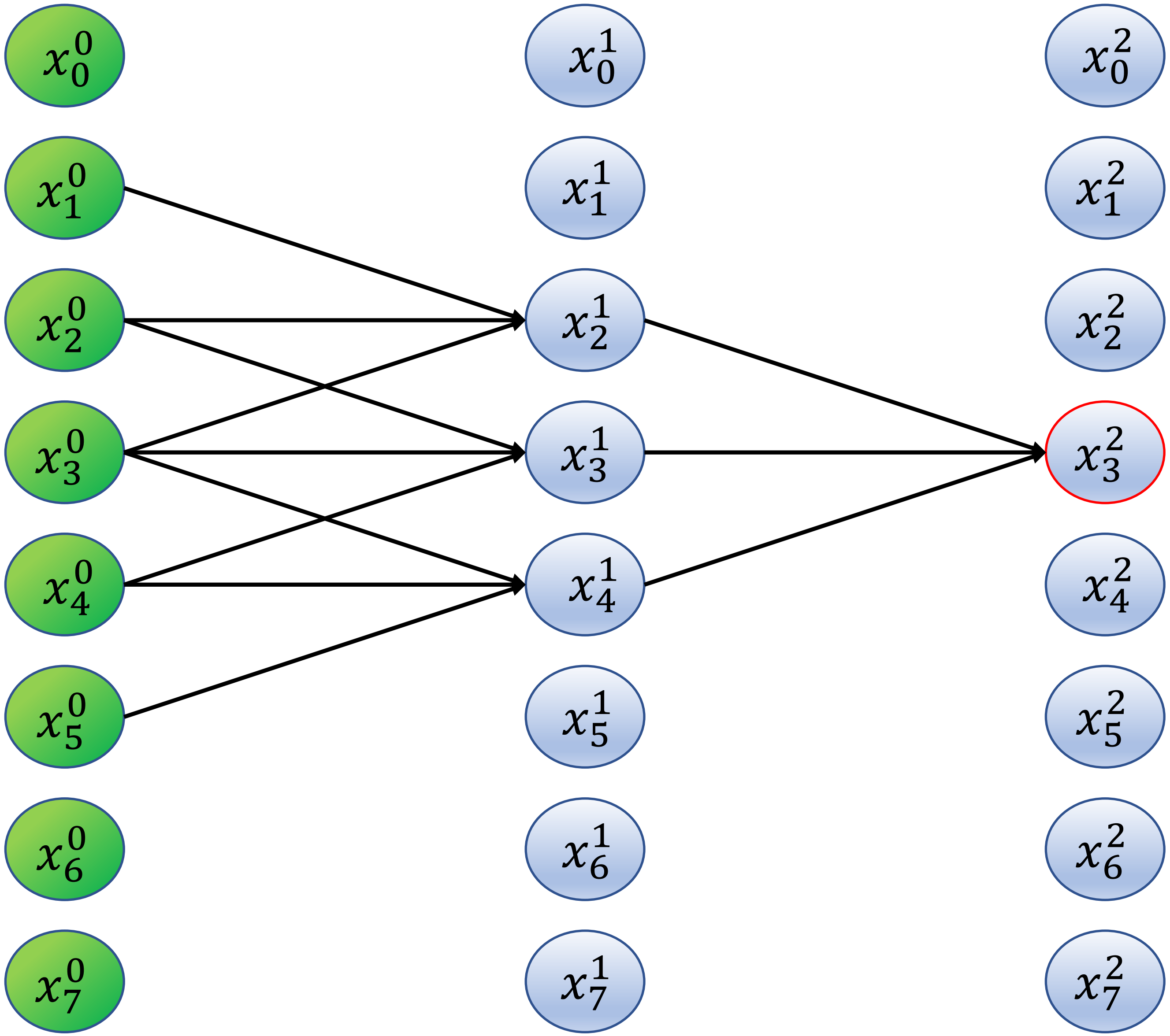
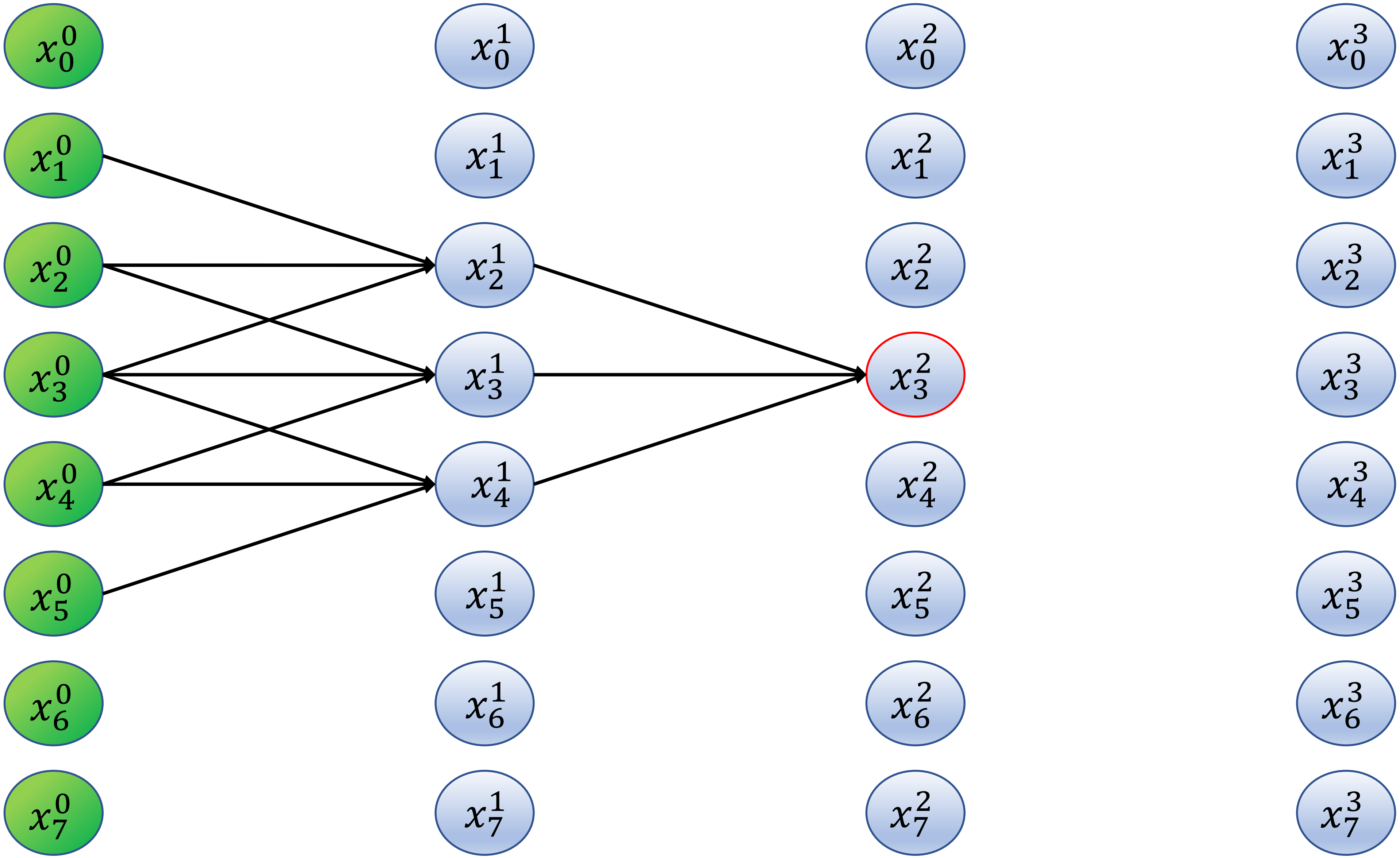


Receptive Field

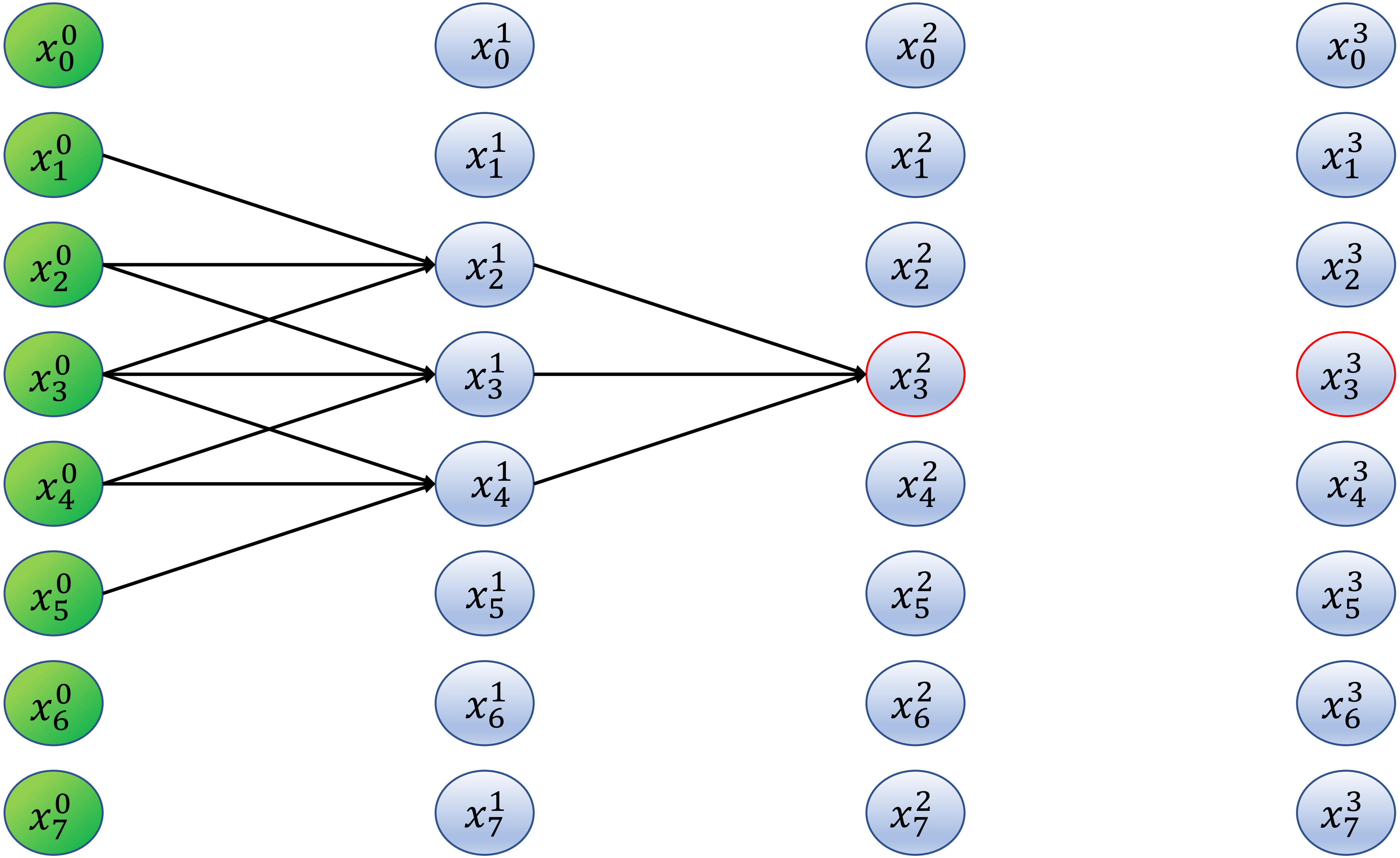
$[\textit{Filter size}: 3]$



Receptive Field

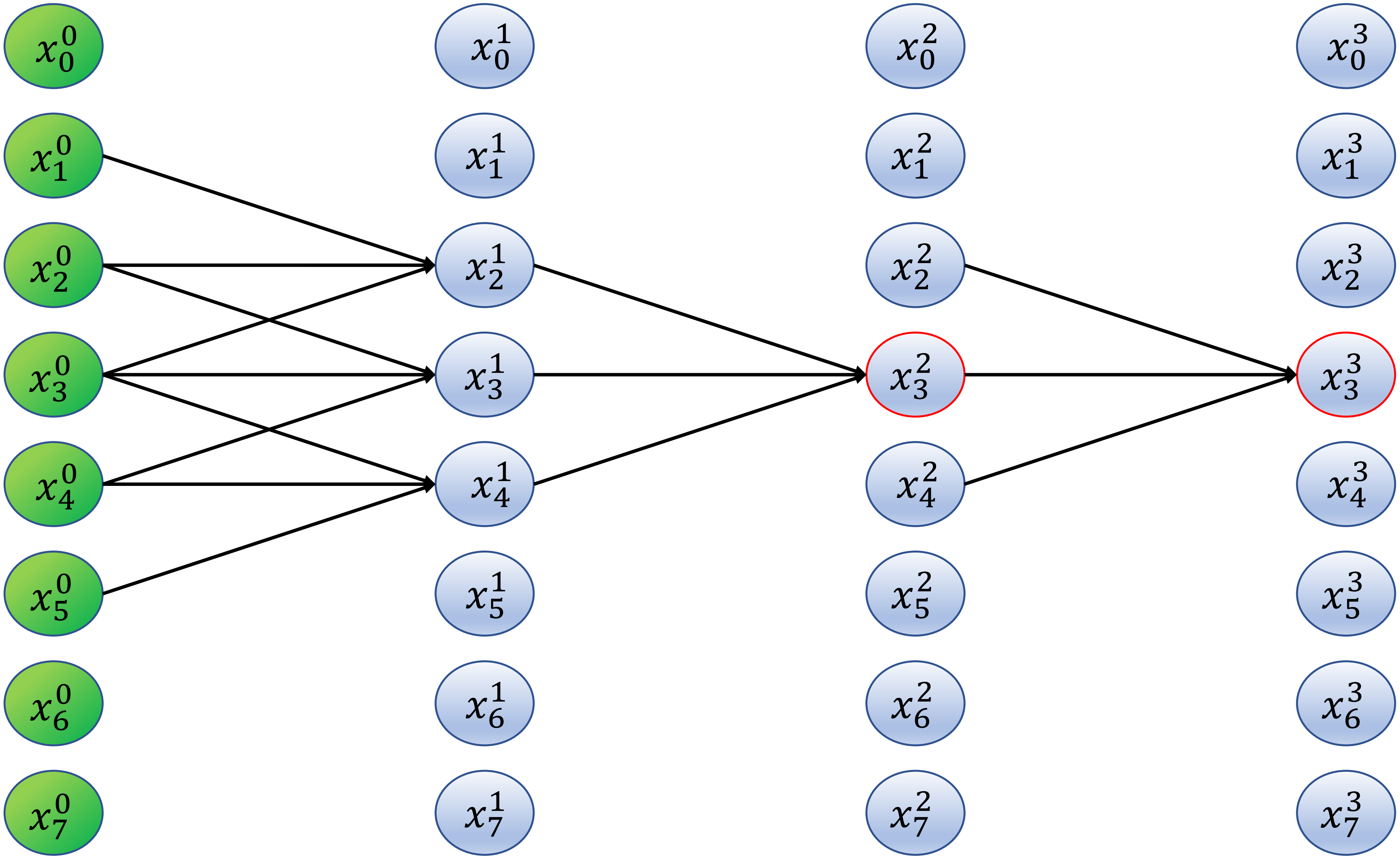
$[Filter\ size: 3]$

[redacted]



Receptive Field

$[Filter\ size: 3]$



Receptive Field

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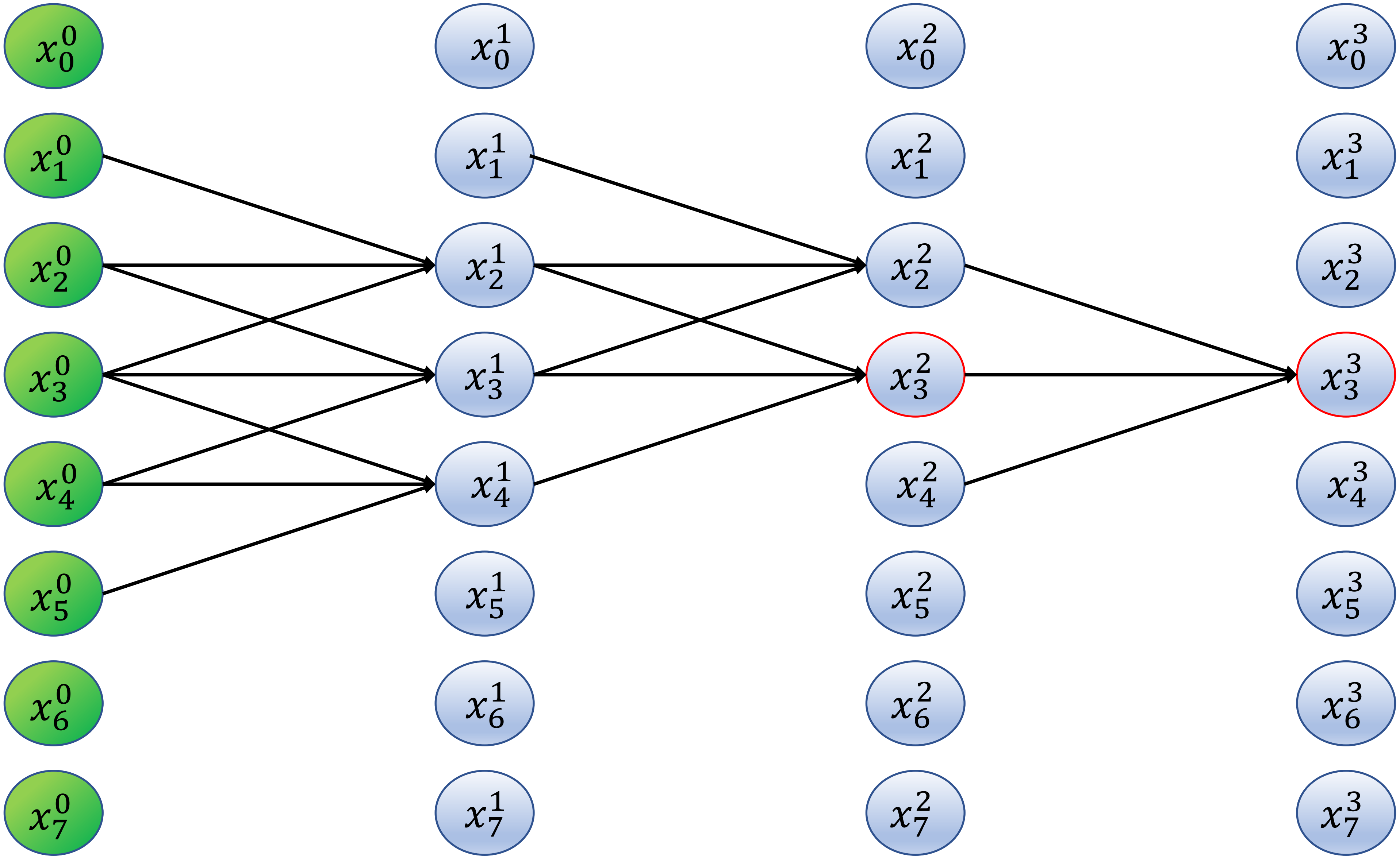

Receptive Field

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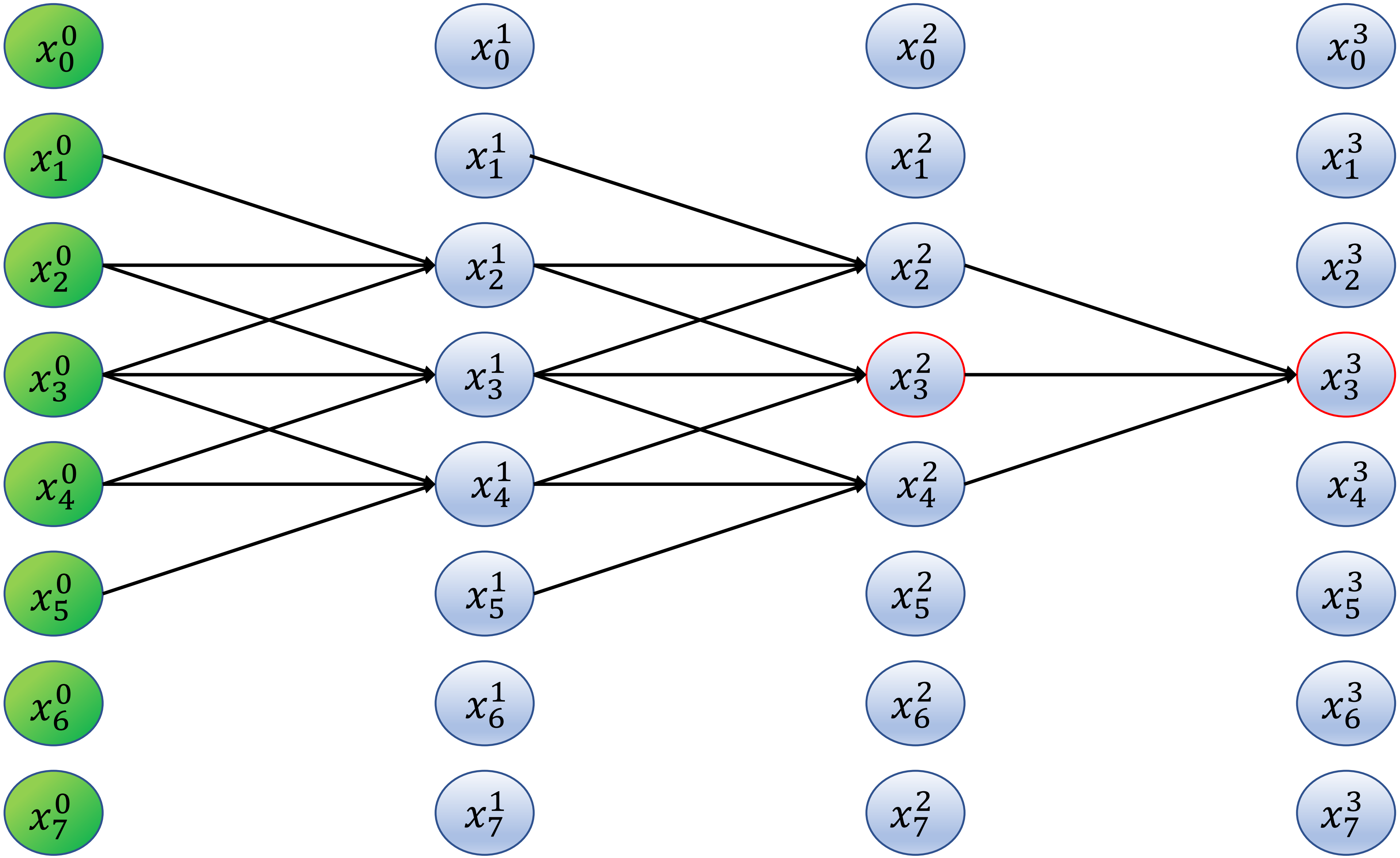
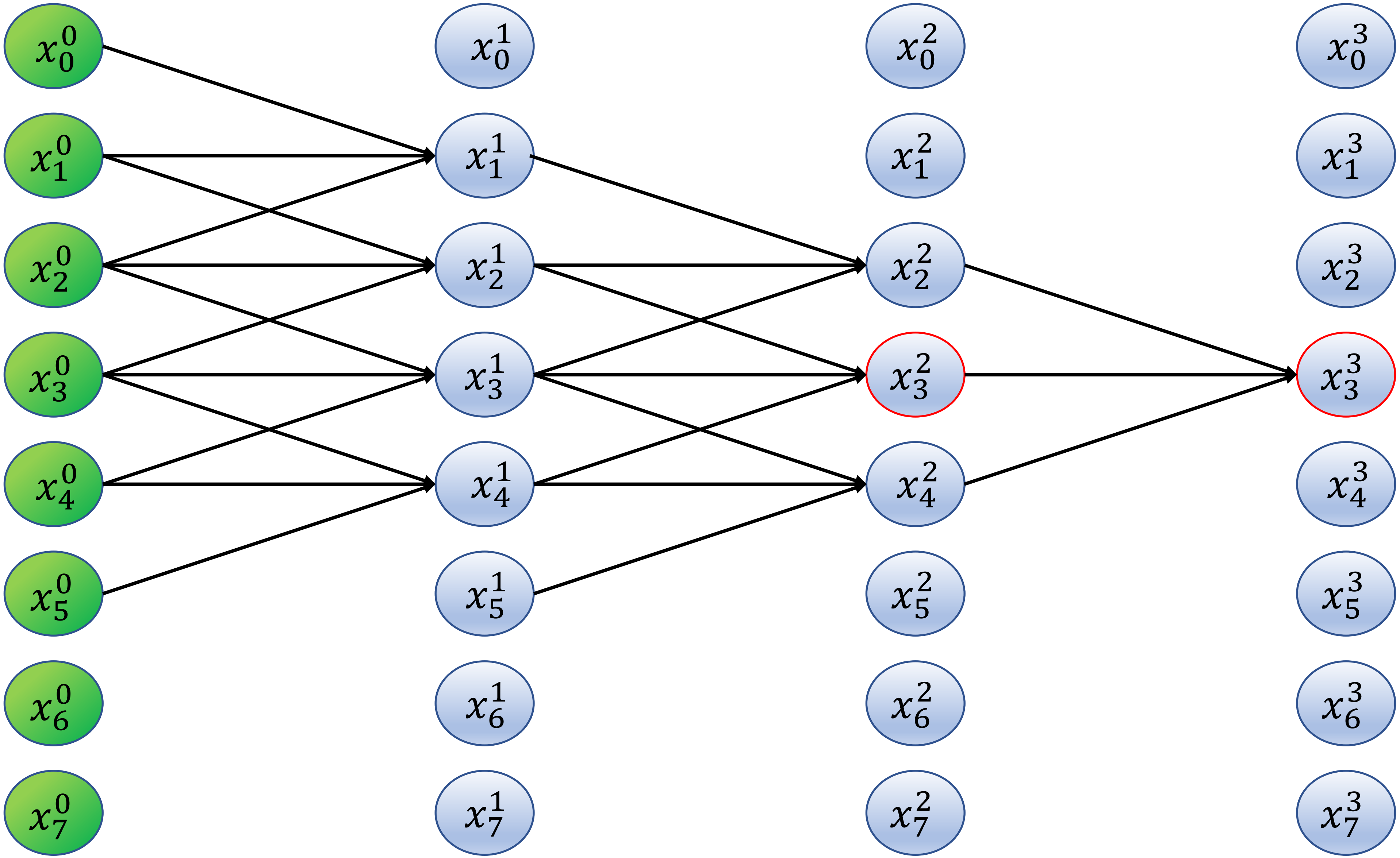


Receptive Field

$[Filter\ size\!: 3]$



Receptive Field

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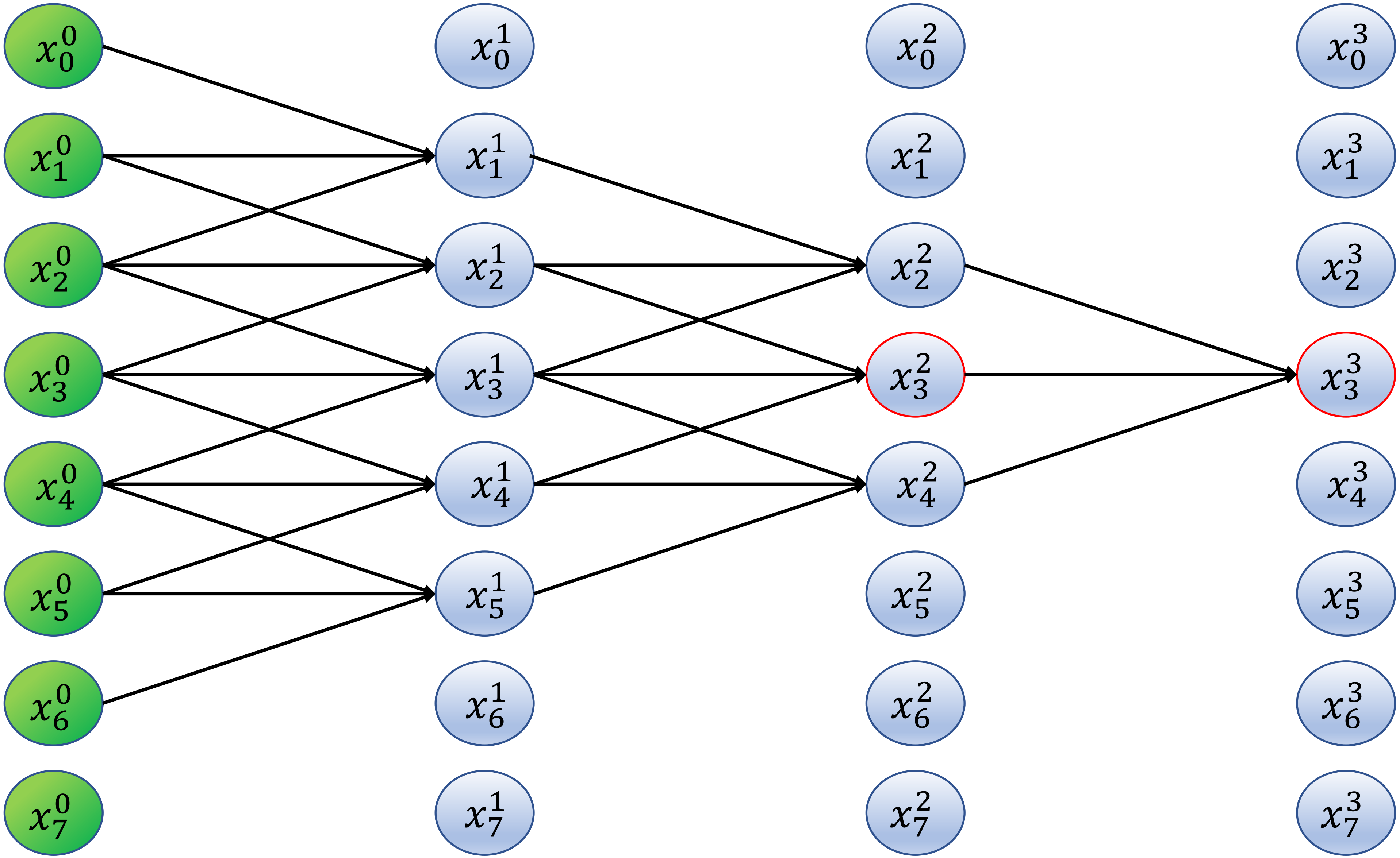

Receptive Field

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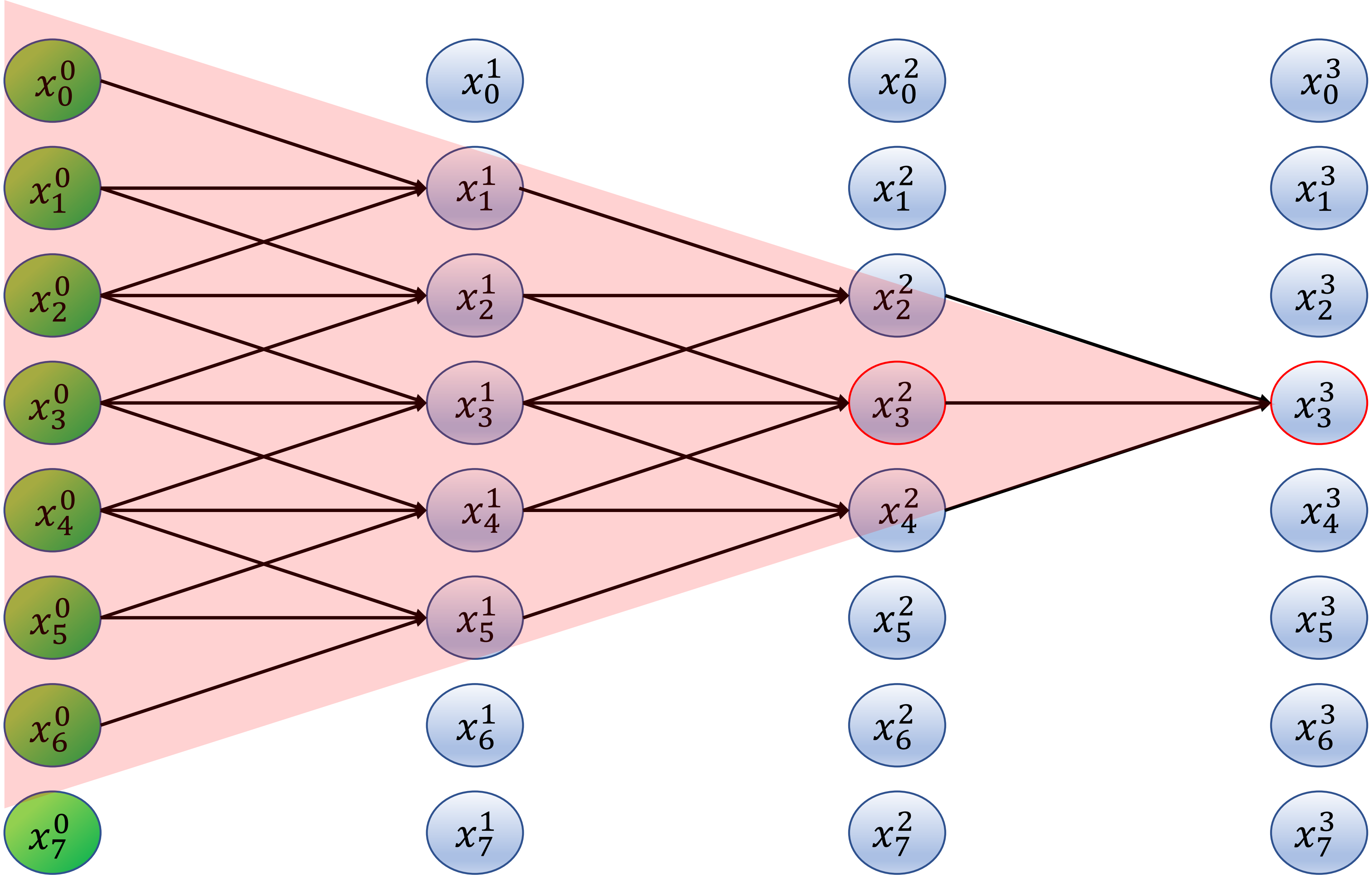
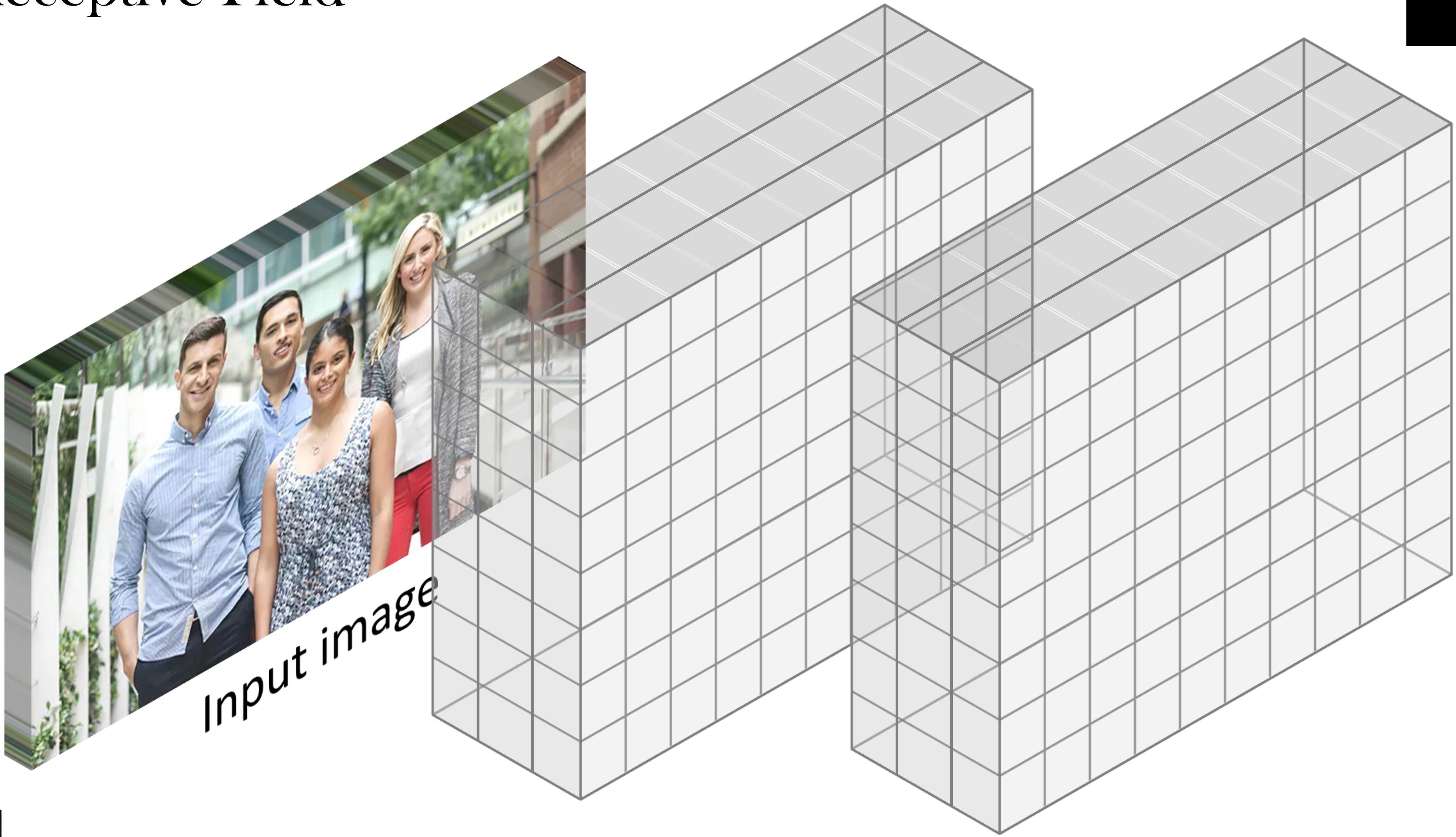
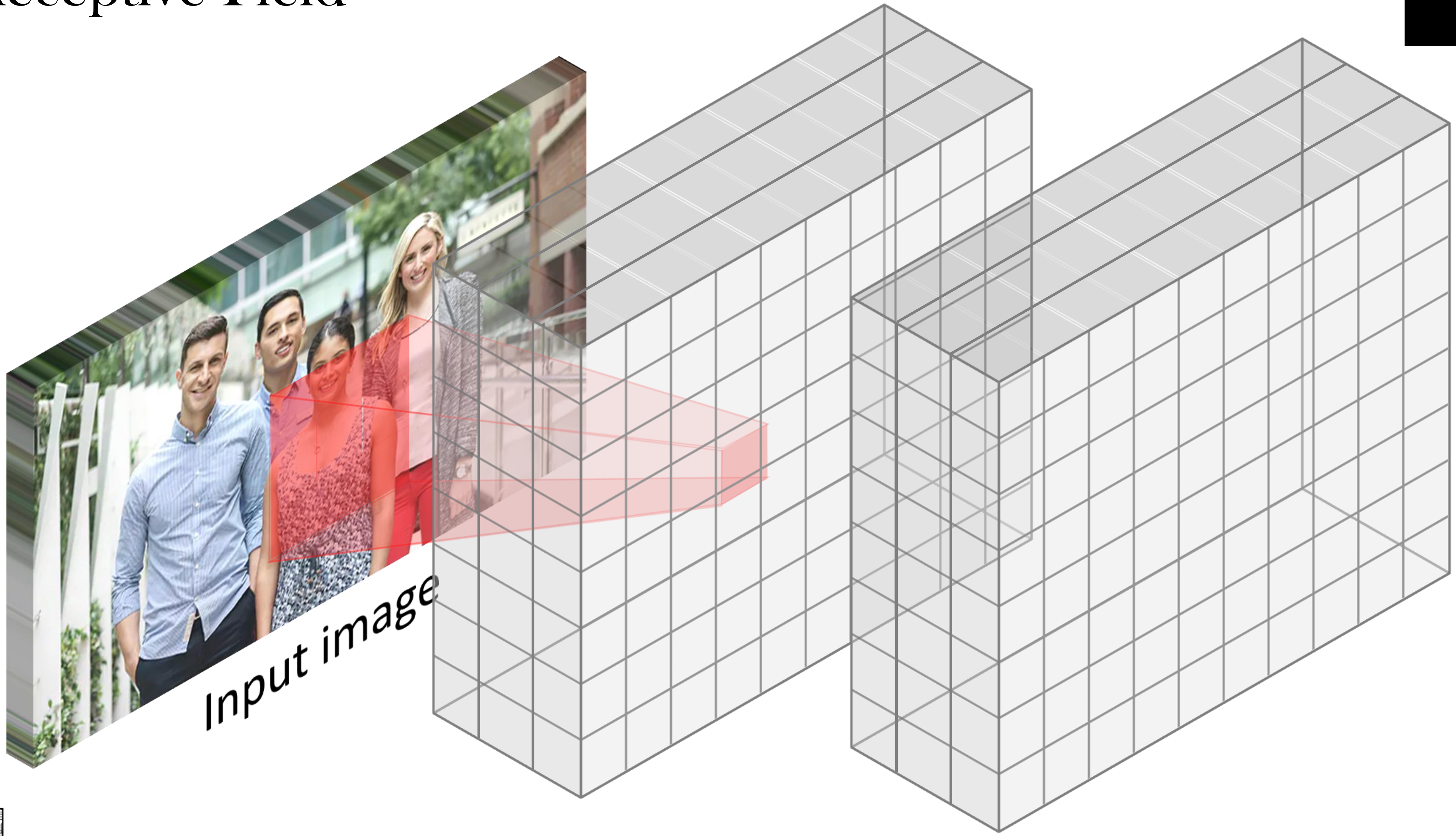


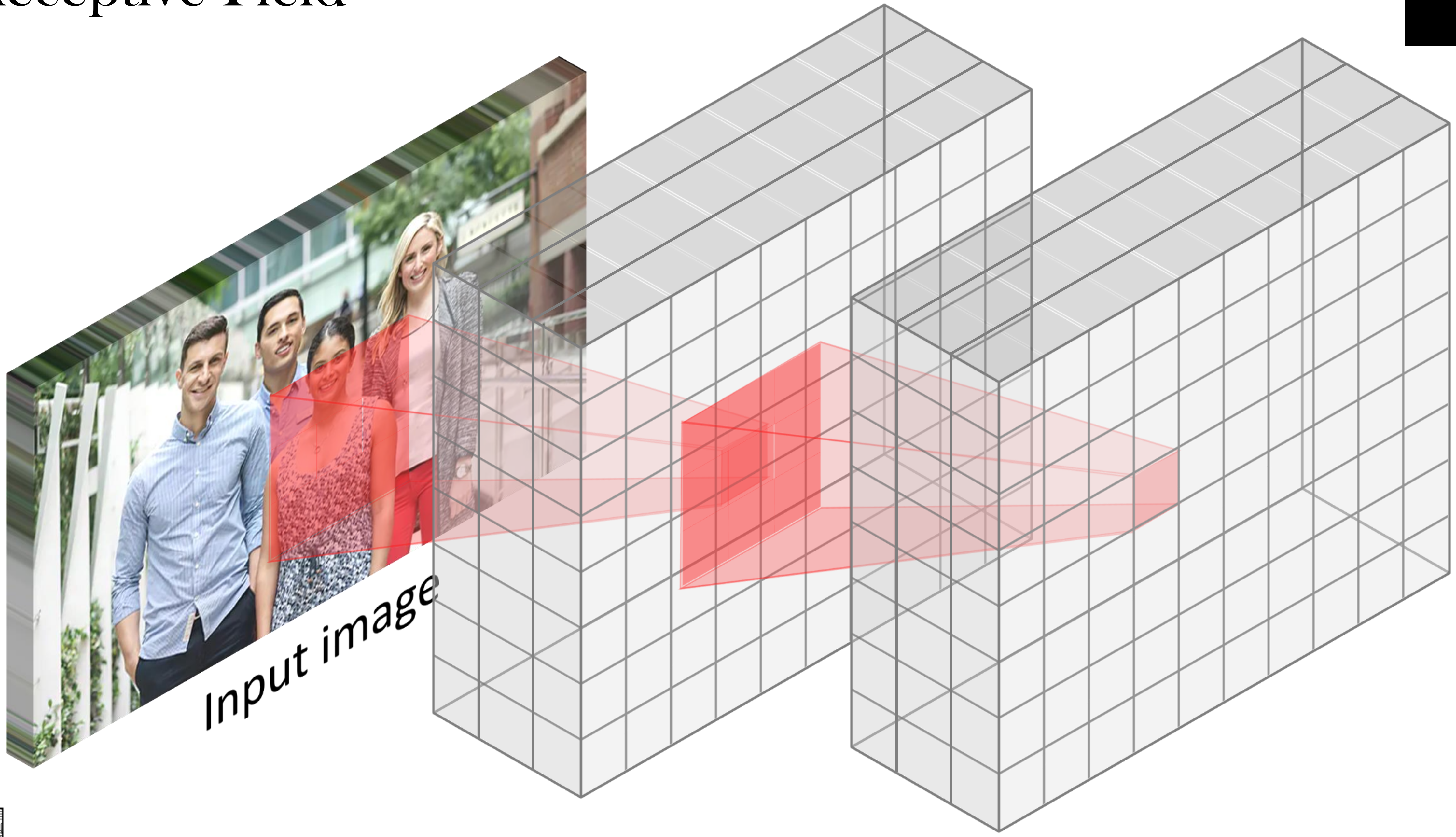
Receptive Field



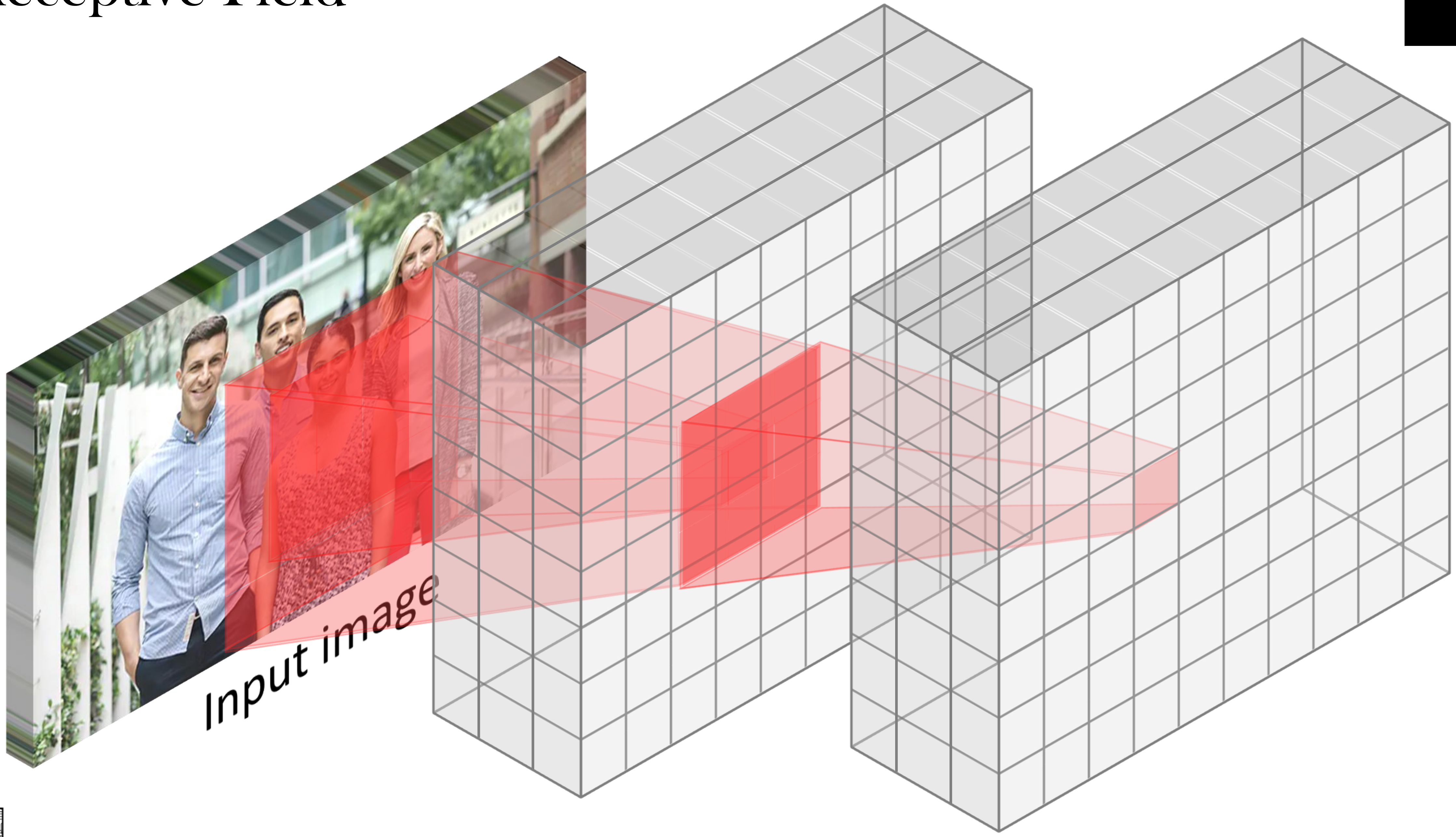
Receptive Field



Receptive Field



Receptive Field



Convs rock!

Convs rock!

1. Maintain 2D structure logic
2. Shift invariant (actually, equivariant)
3. Consider only local correlations
4. Hierarchically growing field of view
5. Hierarchically progressing complexity
6. Reasonable amount of params

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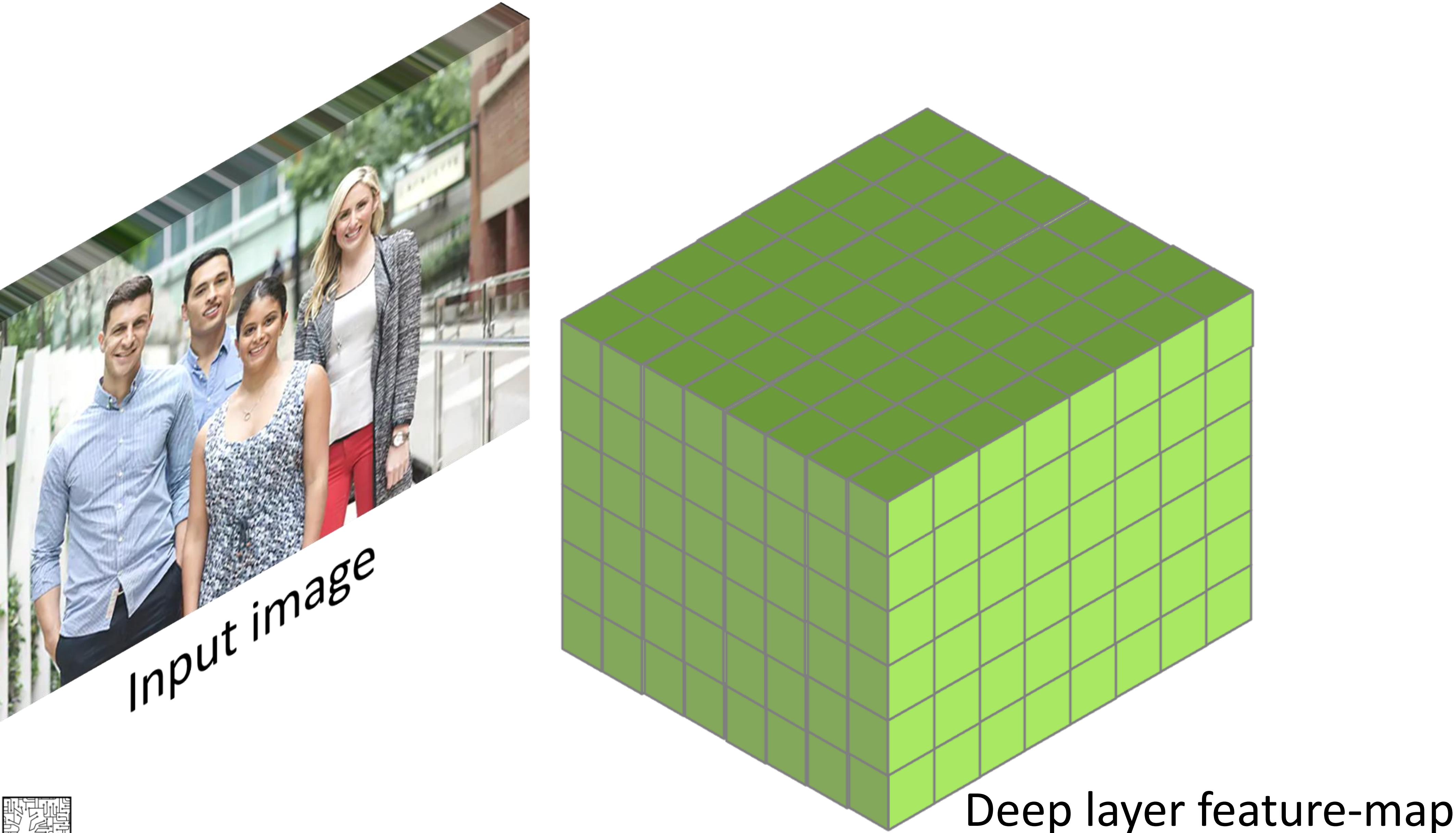
Two important intuitions about feature maps



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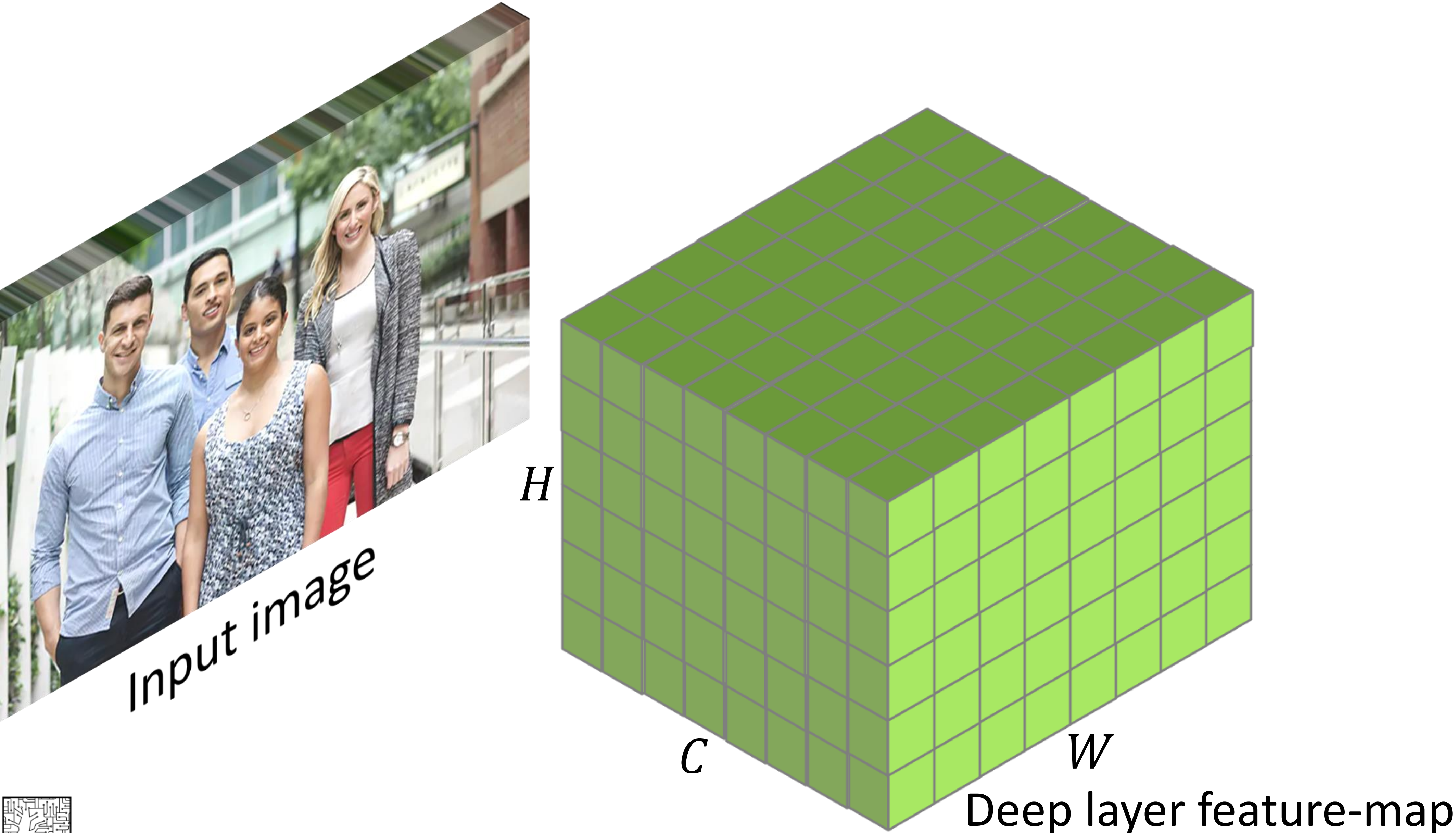

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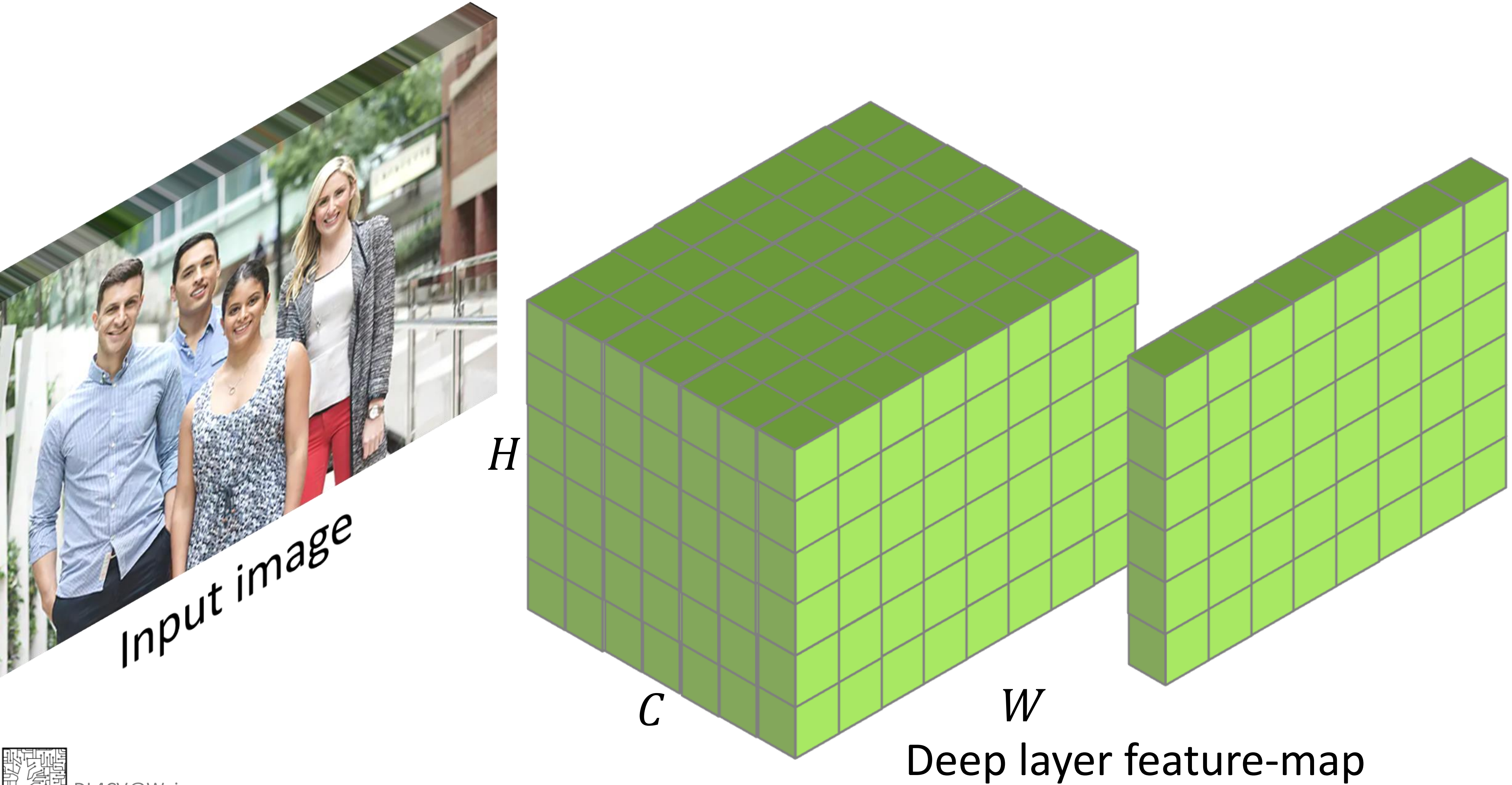

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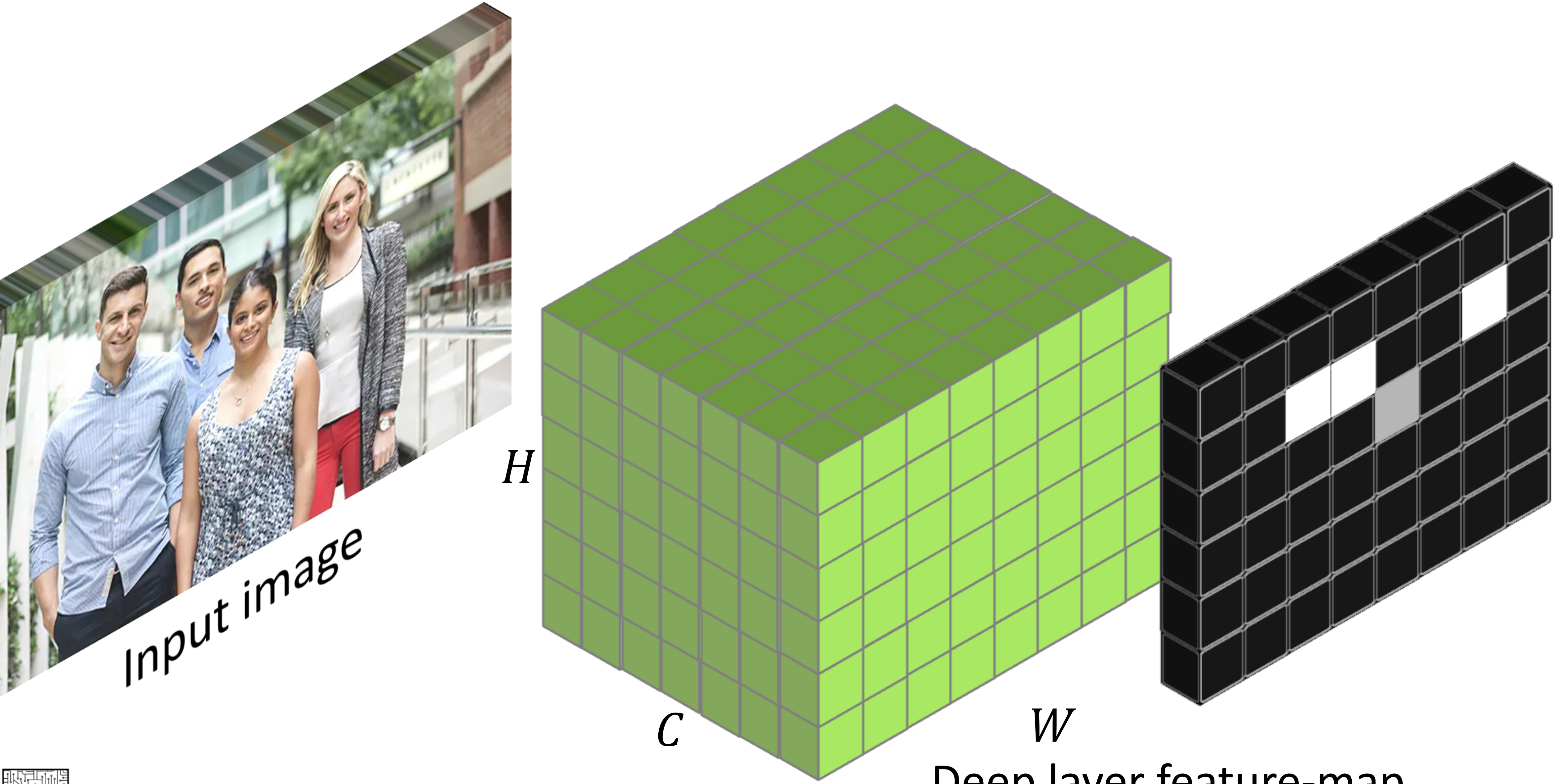
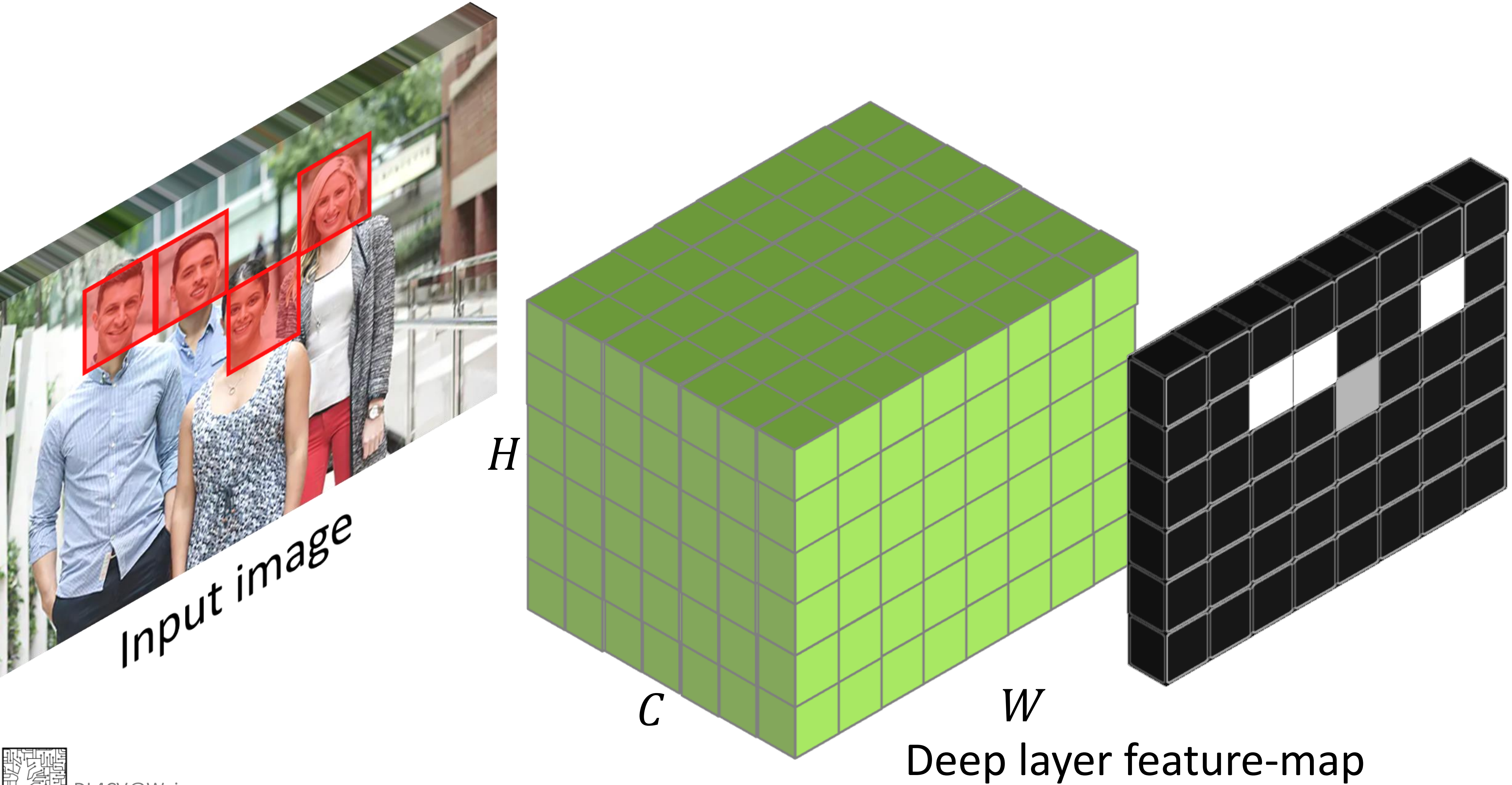


Deep layer feature-map

Two important intuitions about feature maps



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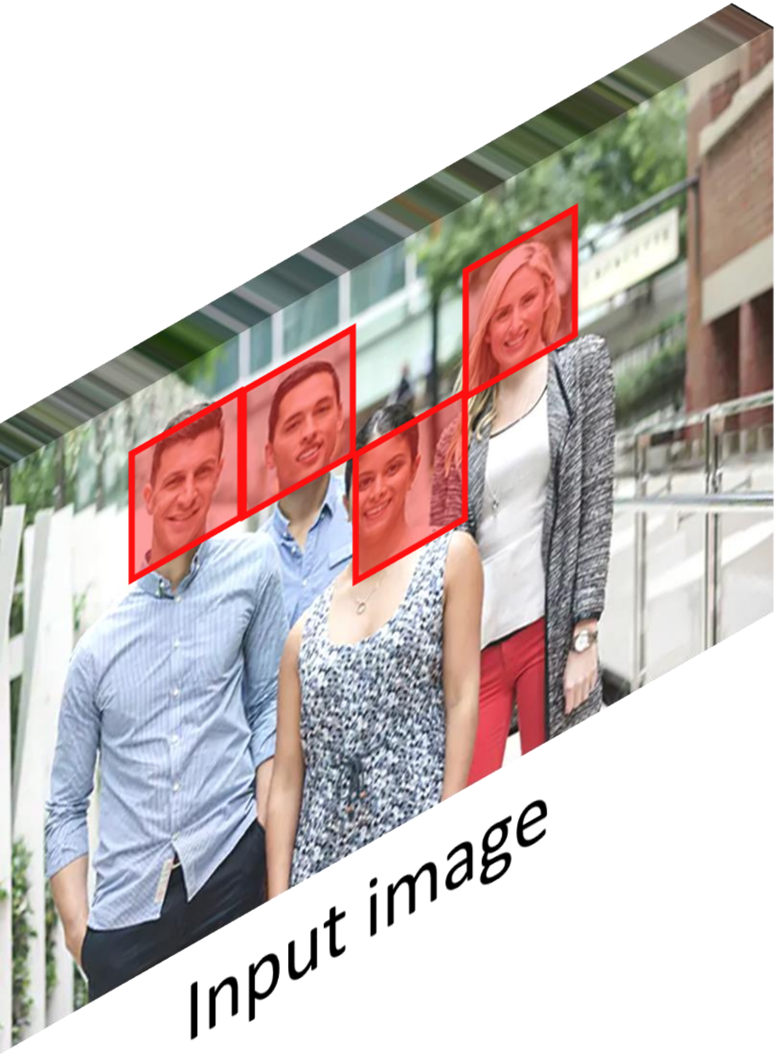

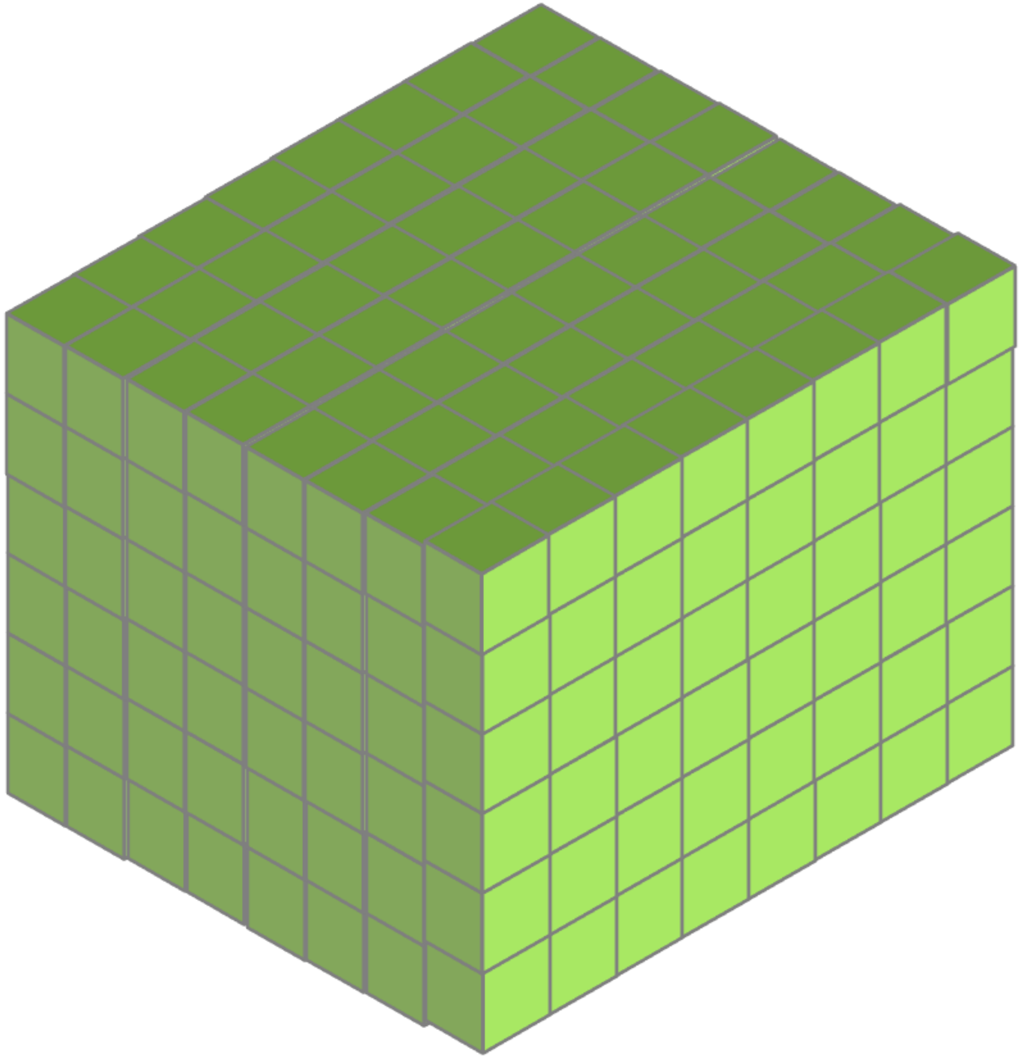

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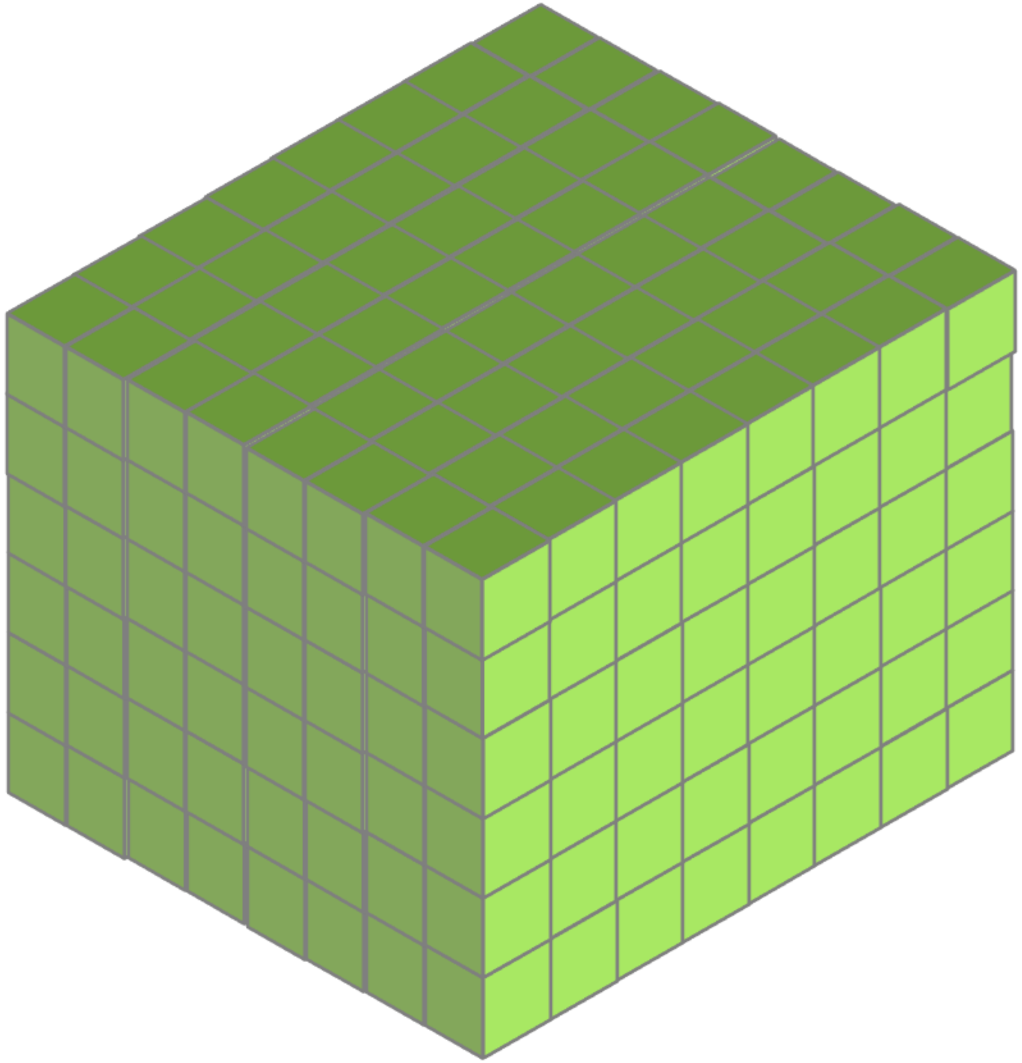

Deep layer feature-map

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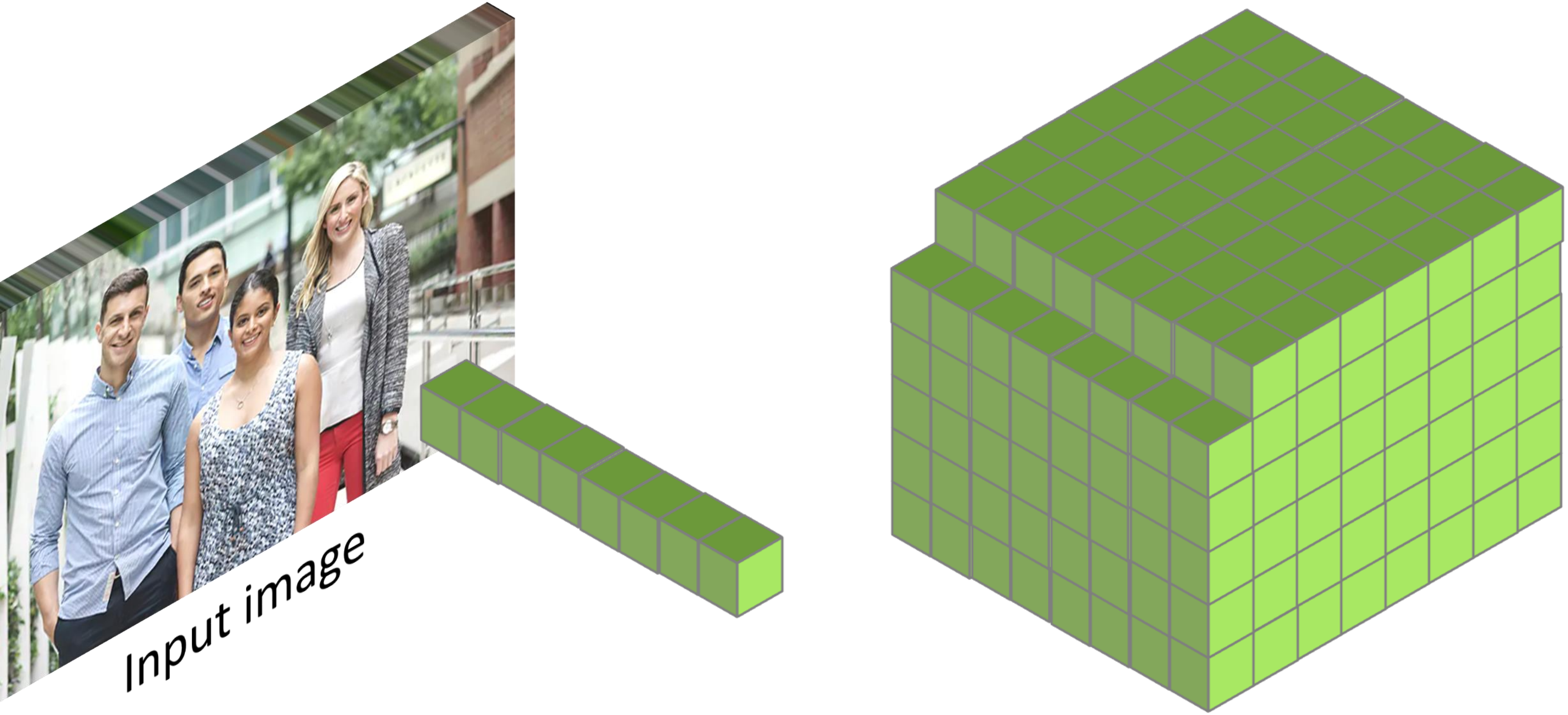

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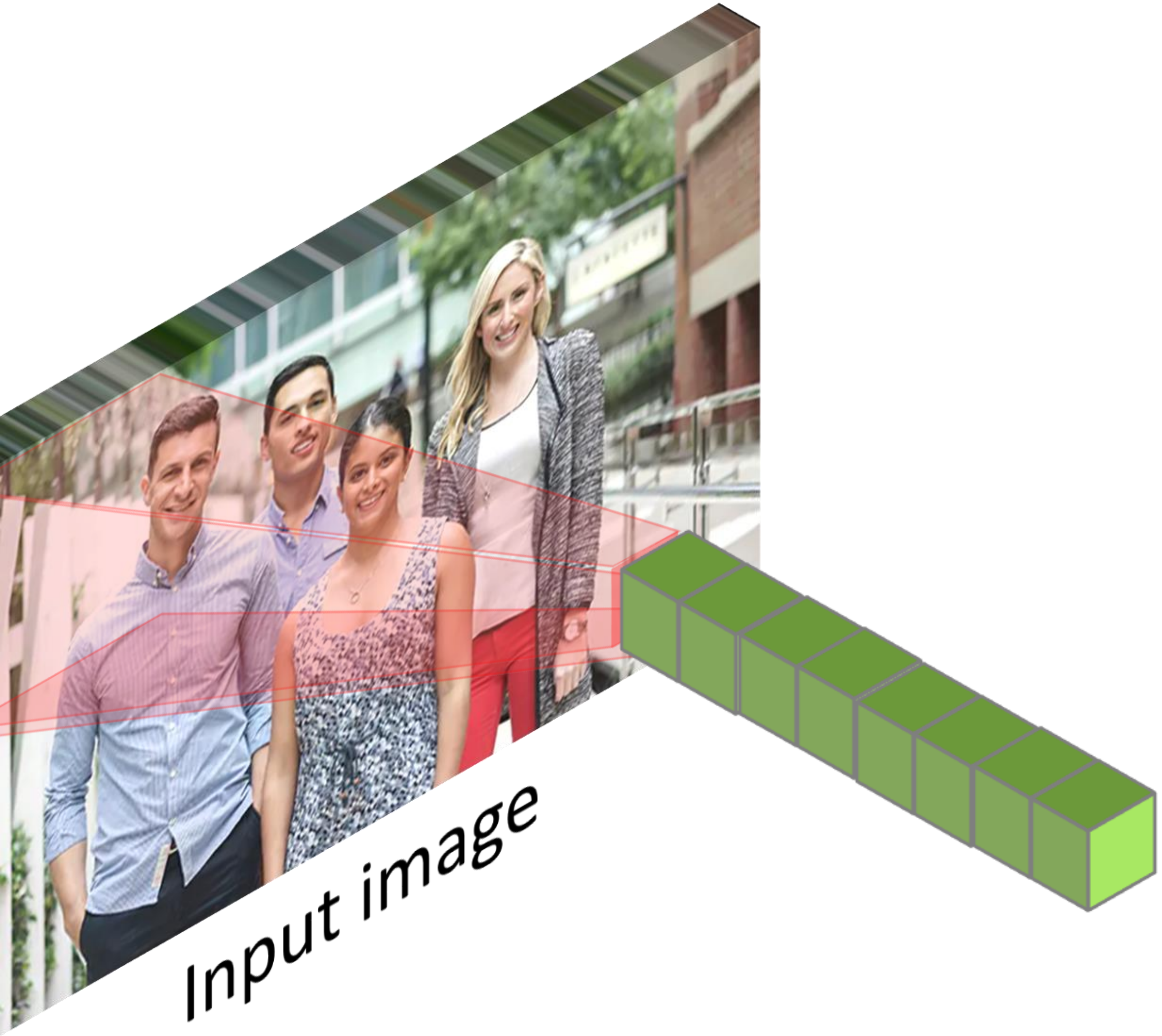

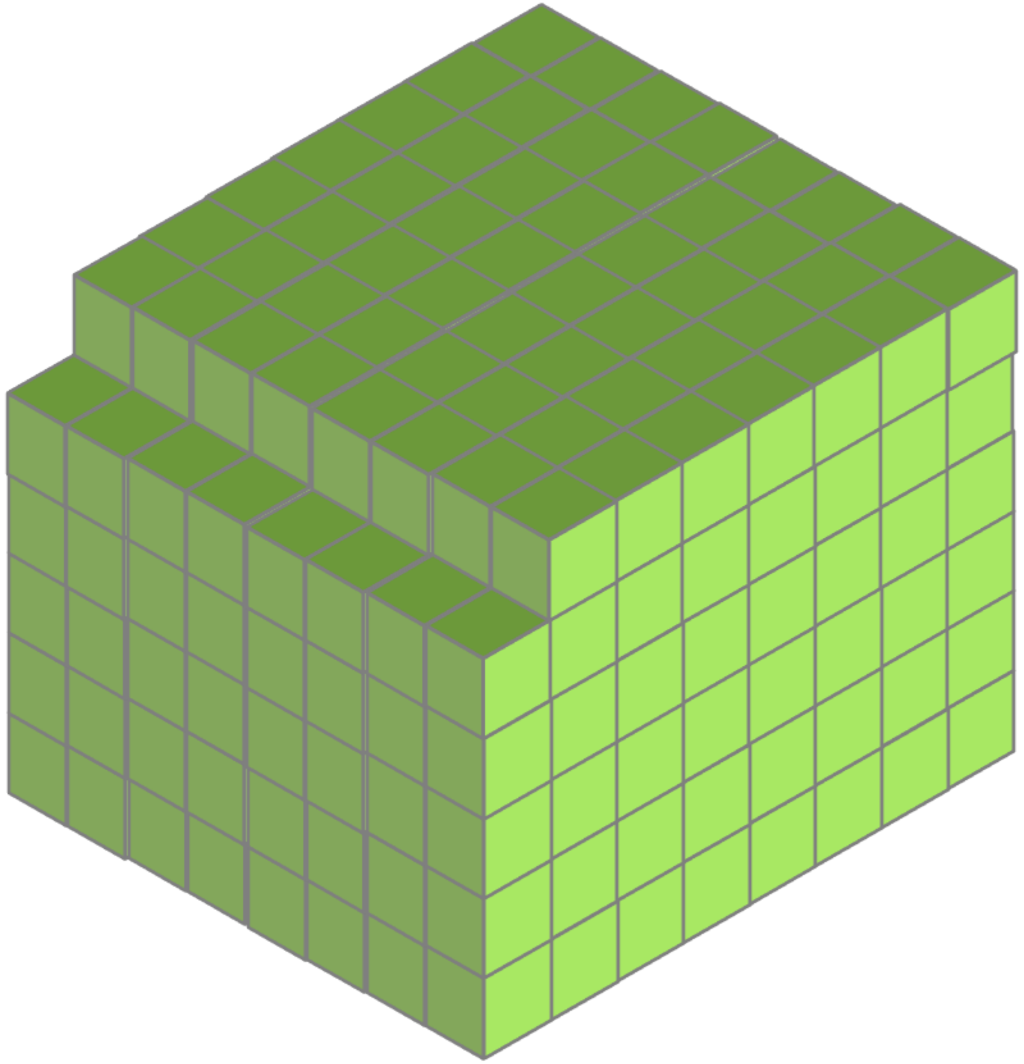

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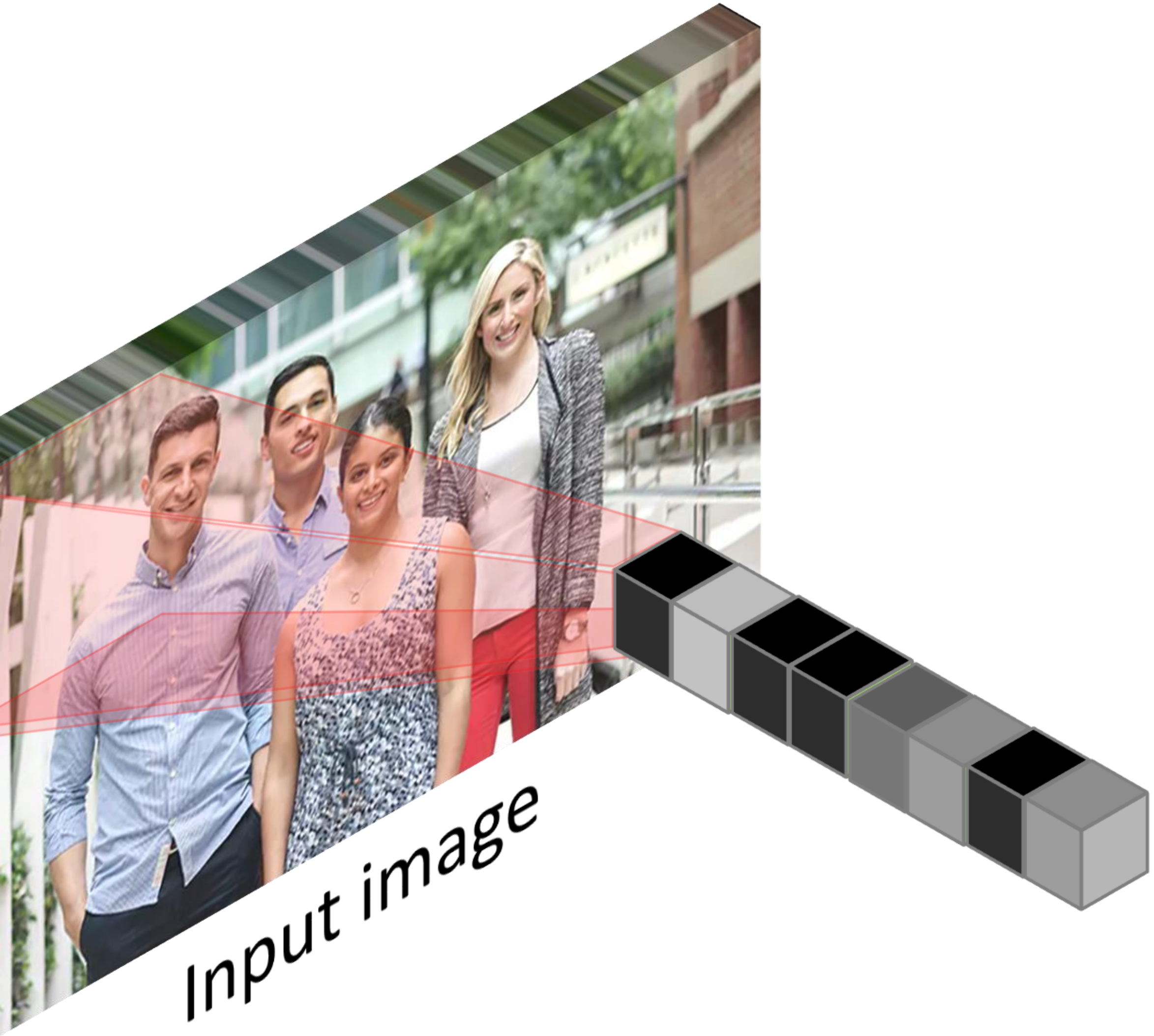
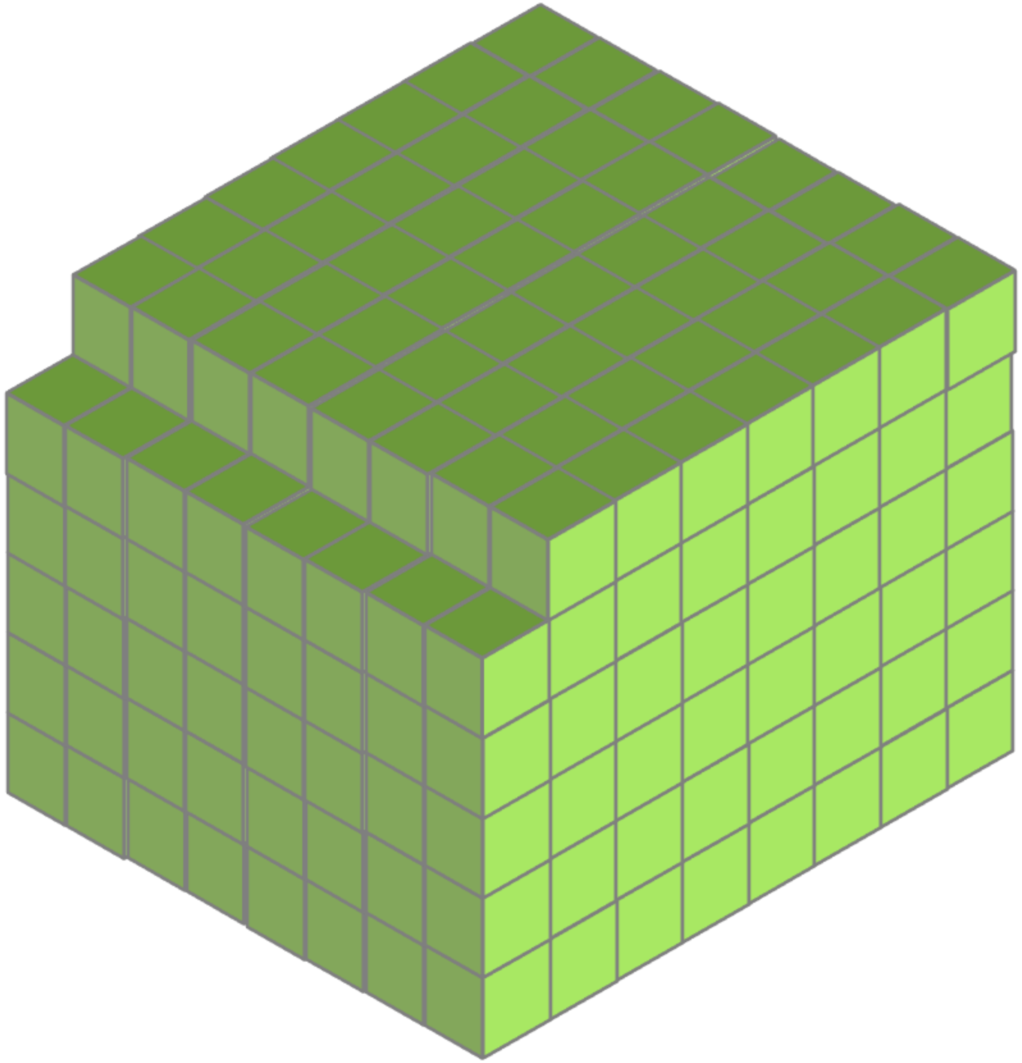
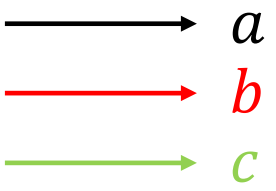
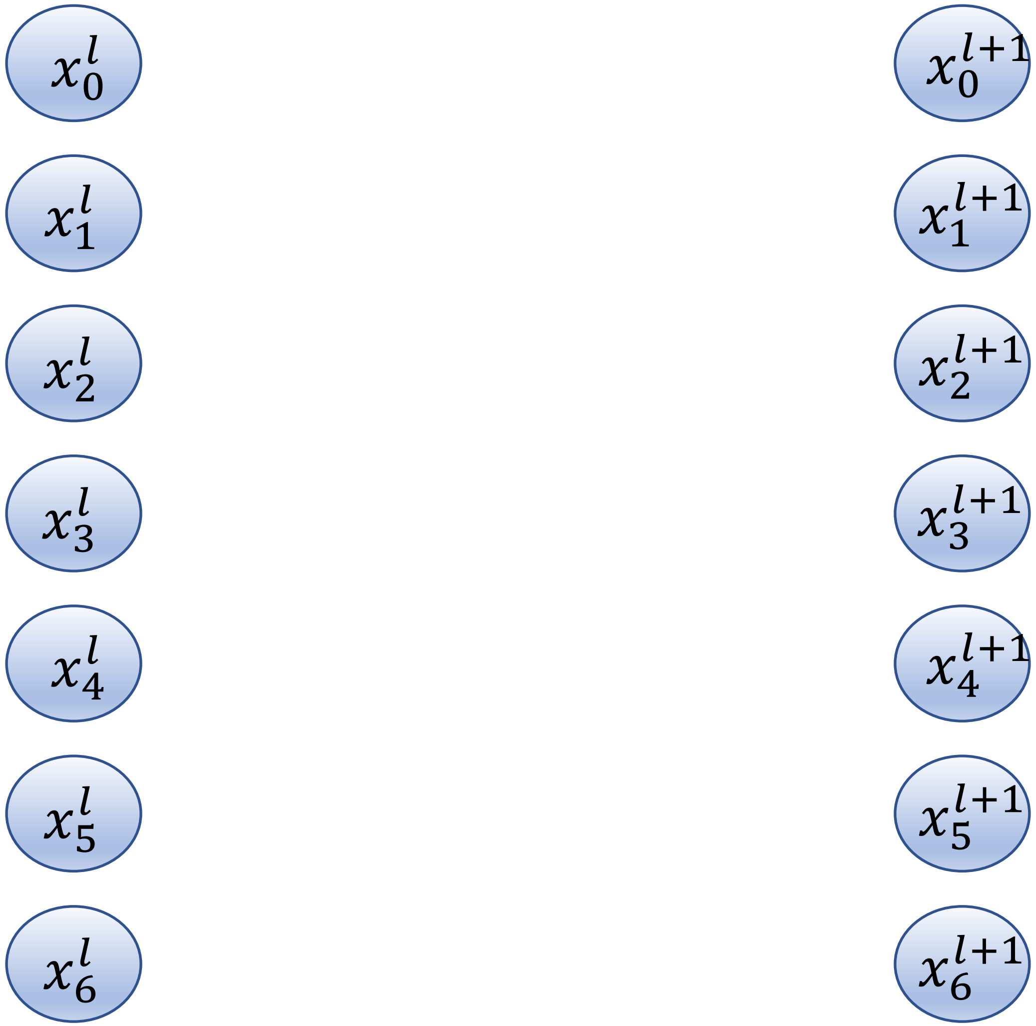




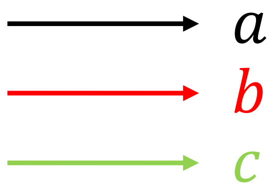
Deep layer feature-map

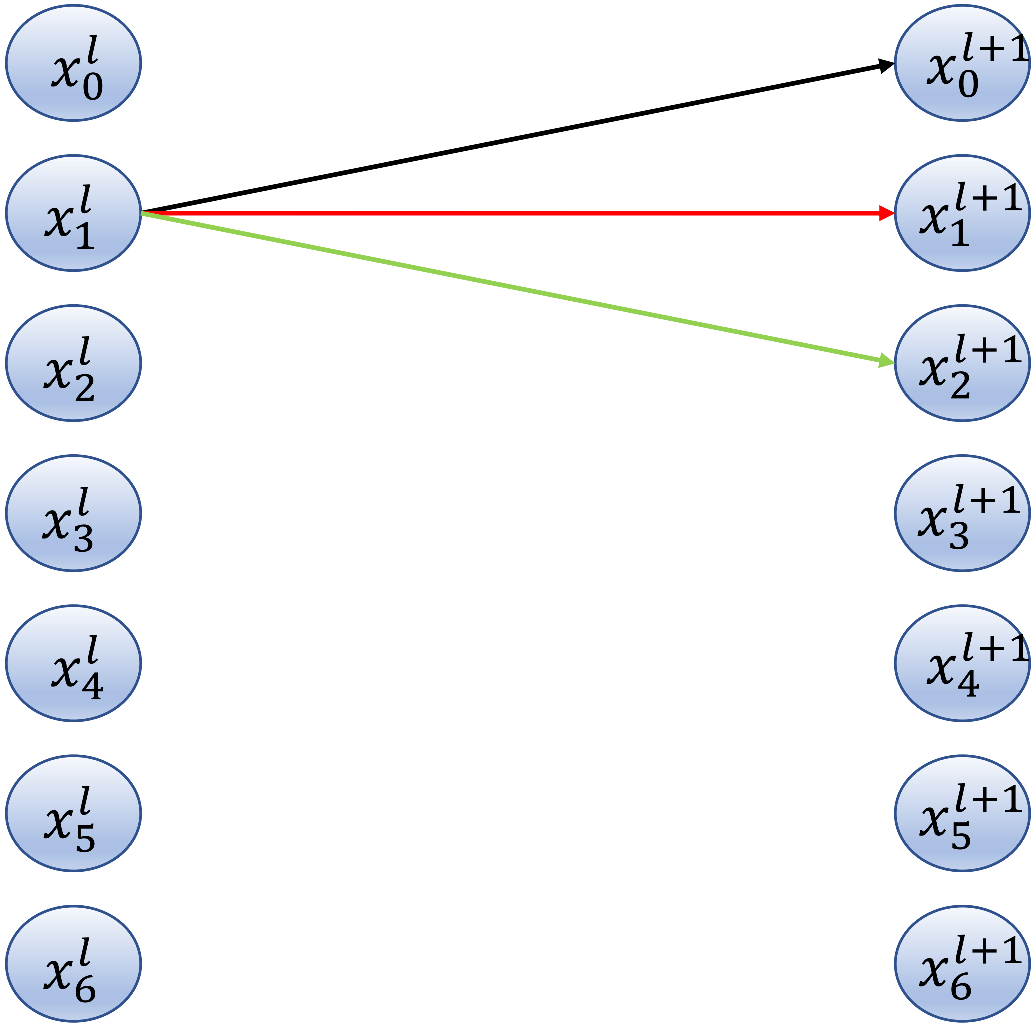
Transposed Convolution



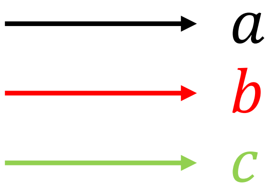


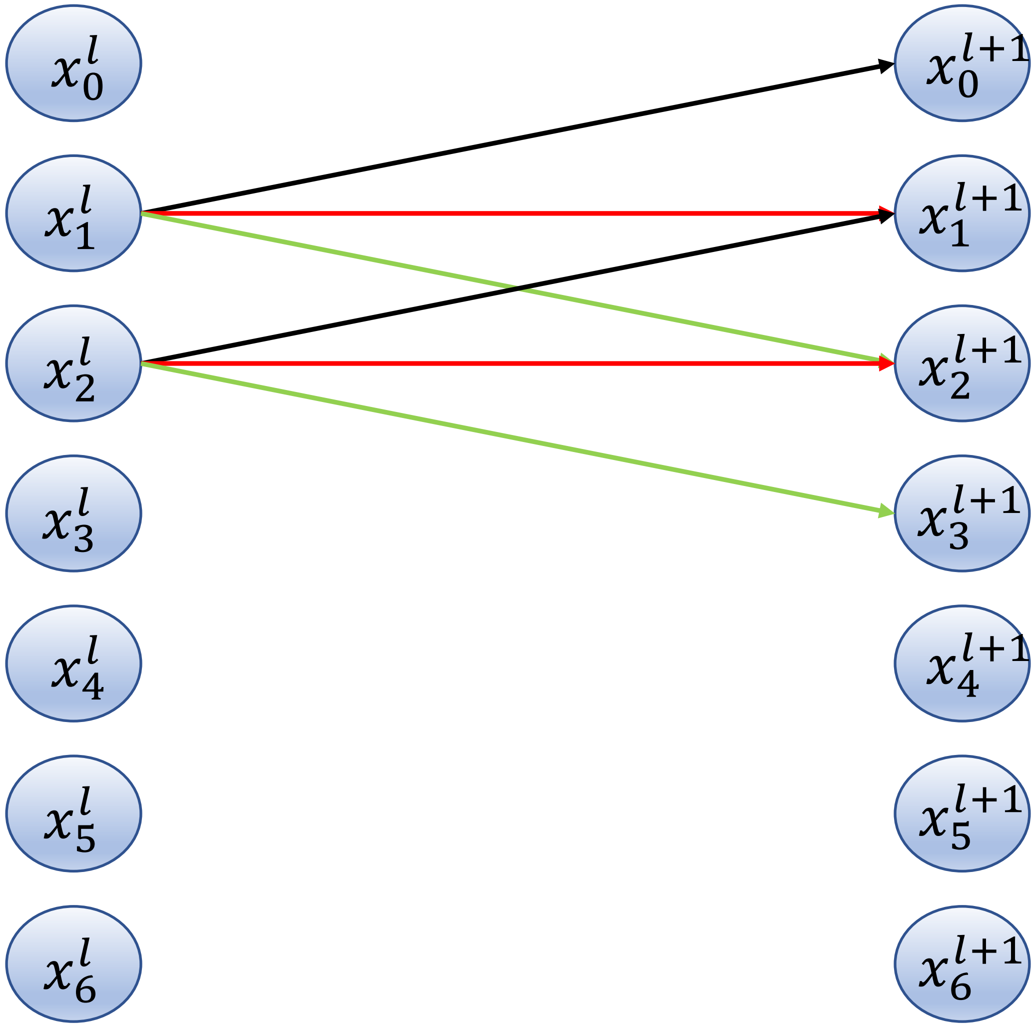
Transposed Convolution





Transposed Convolution





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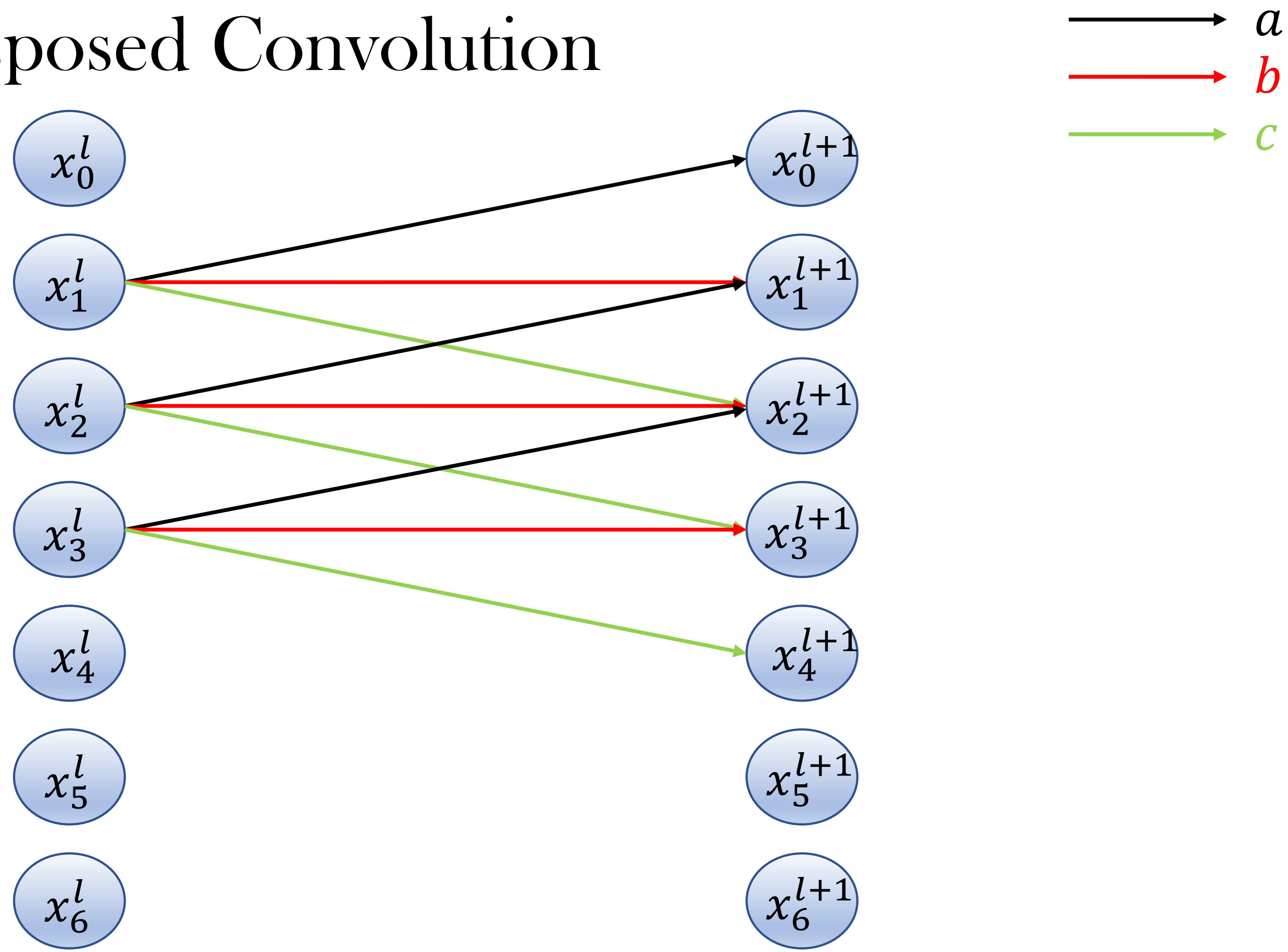

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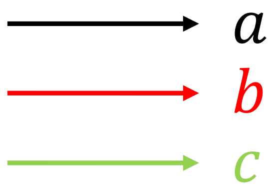

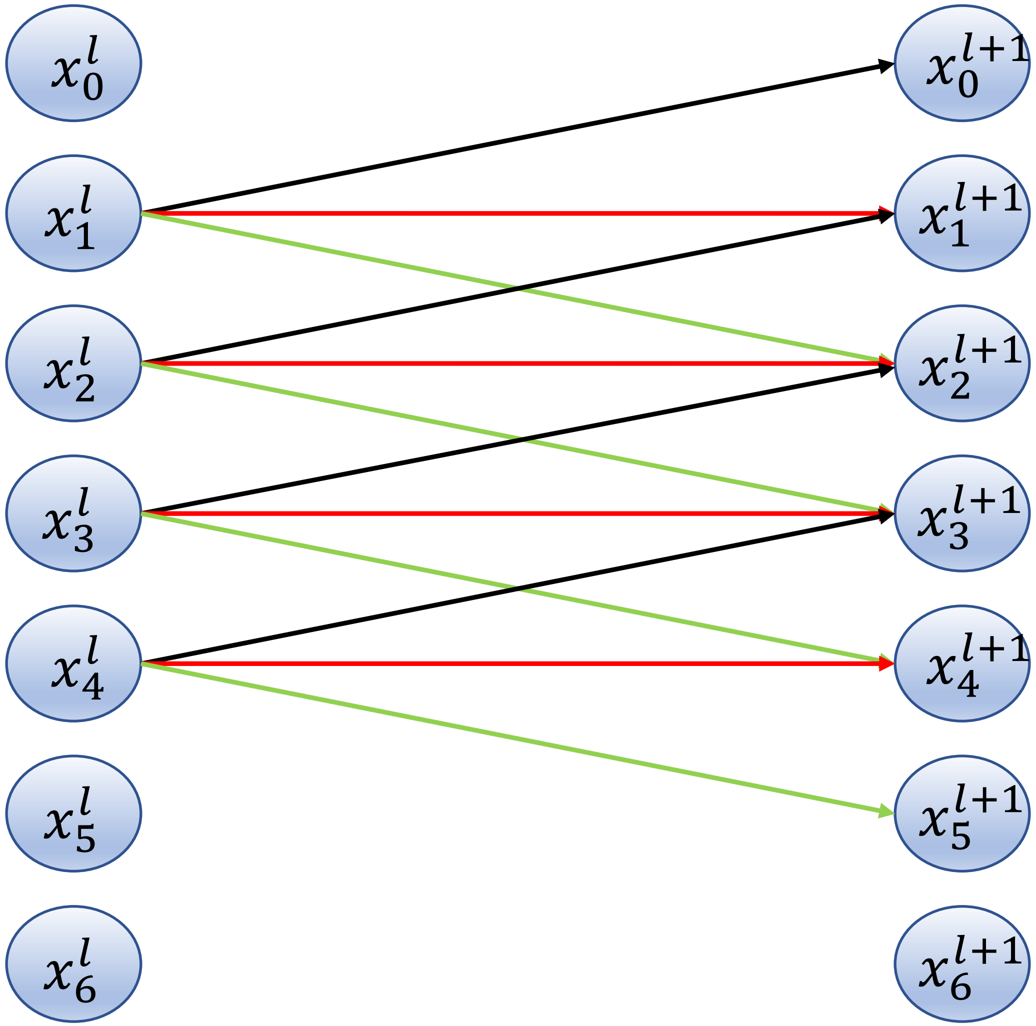

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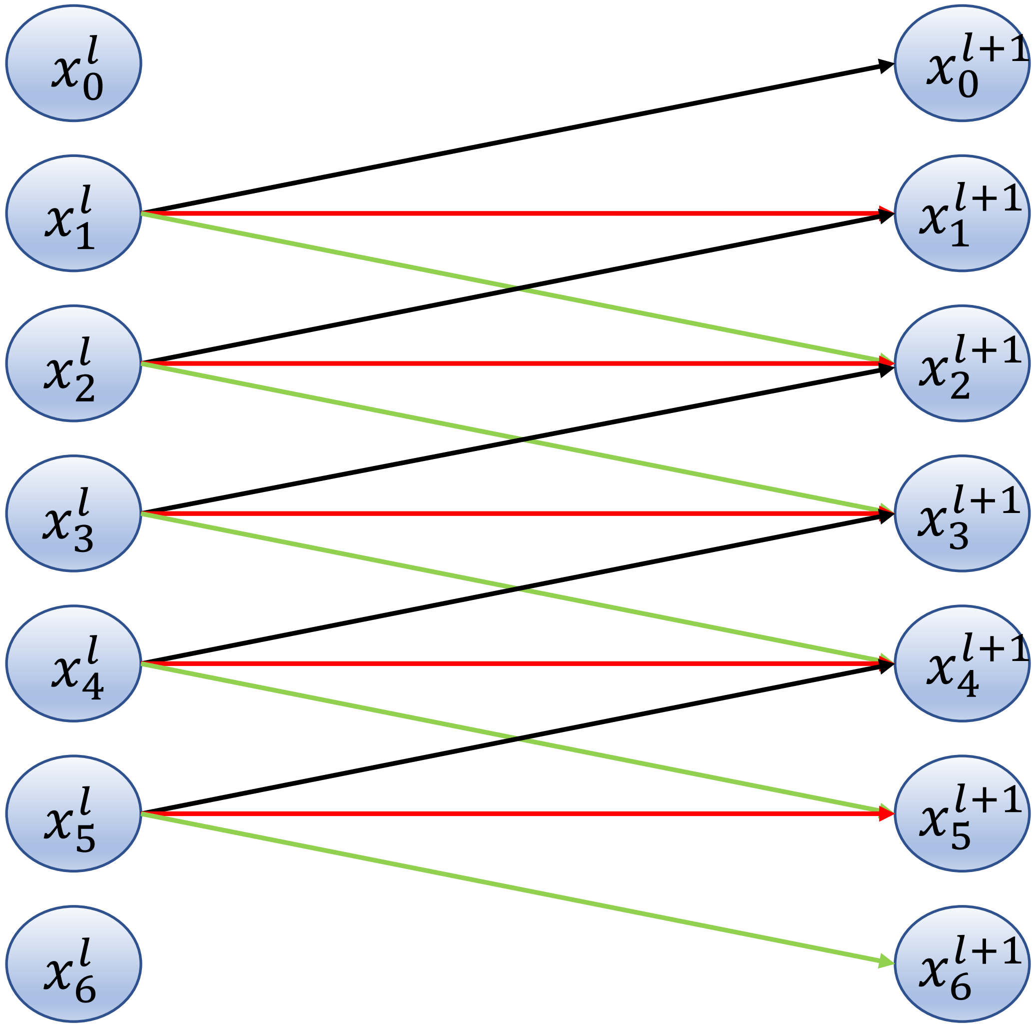

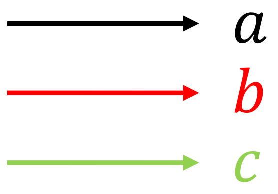

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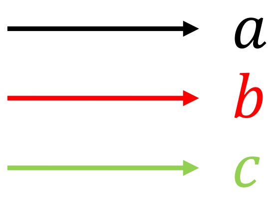

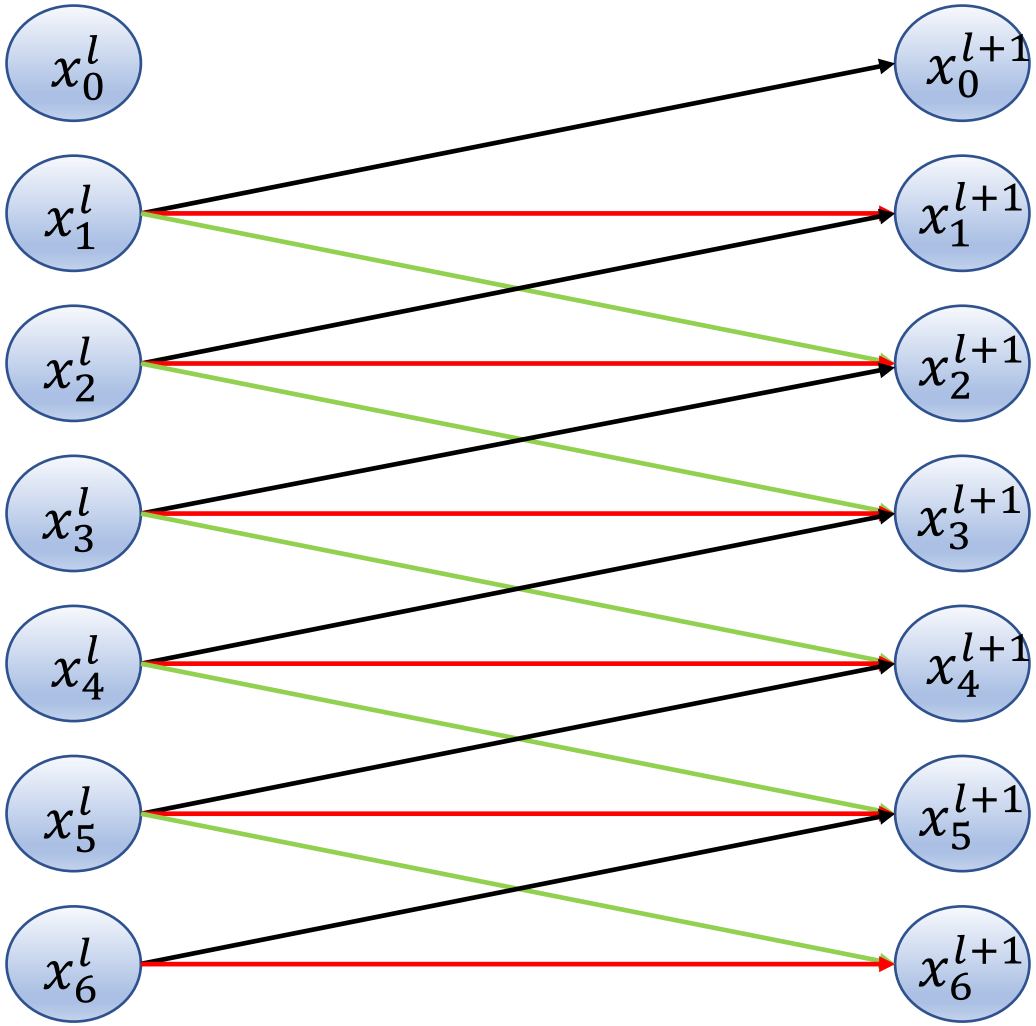

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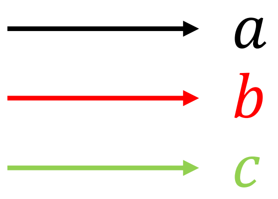

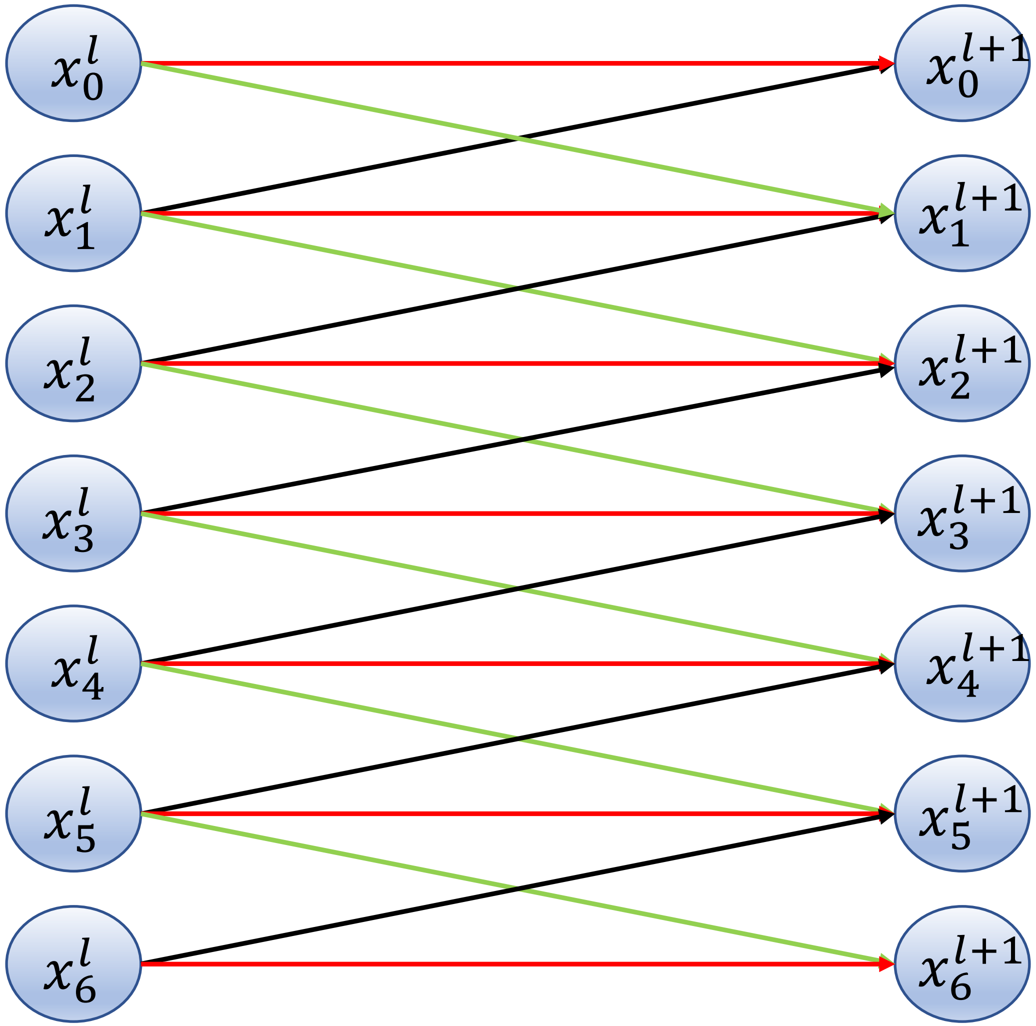

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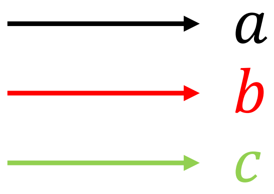
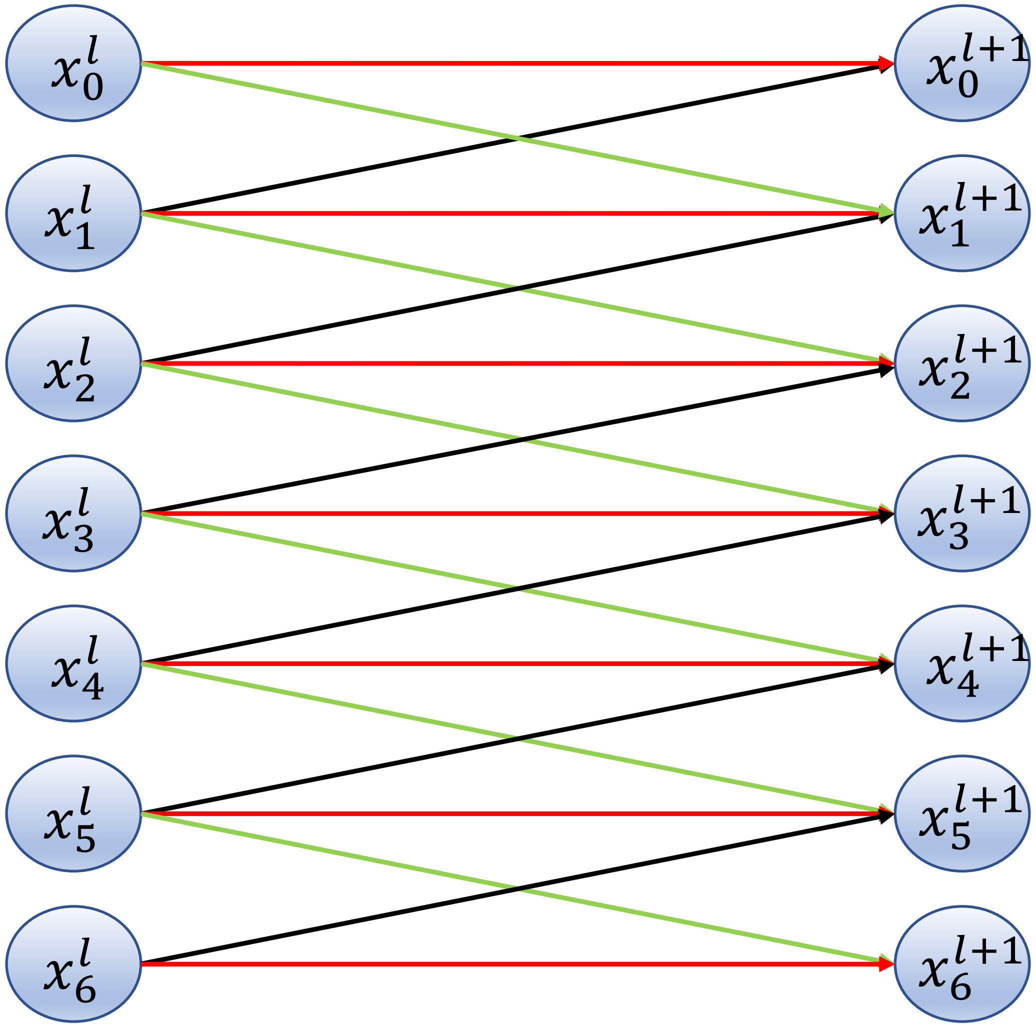
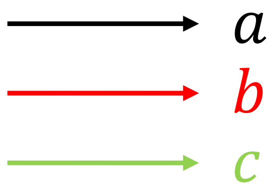
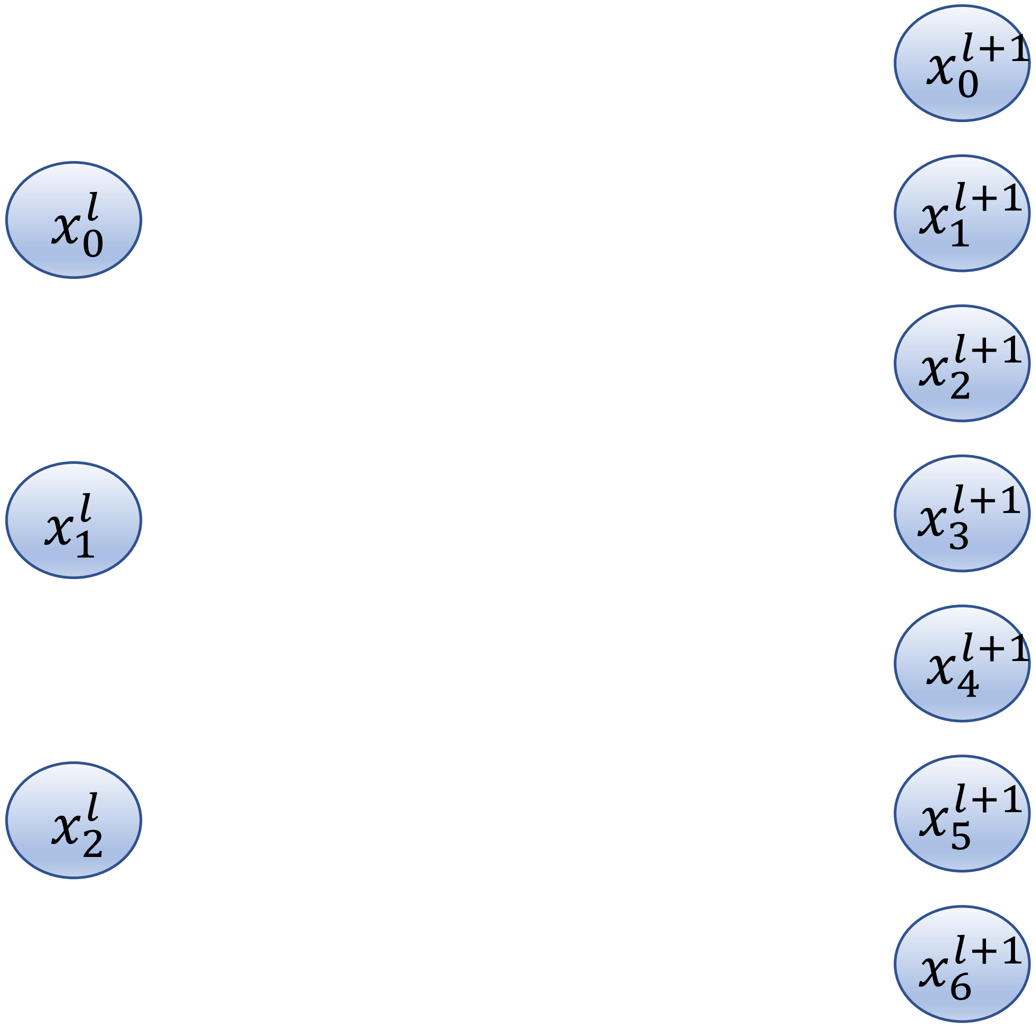




$$\begin{bmatrix} b & a & 0 & 0 & 0 & 0 & 0 \\ c & b & a & 0 & 0 & 0 & 0 \\ 0 & c & b & a & 0 & 0 & 0 \\ 0 & a & c & b & a & 0 & 0 \\ 0 & 0 & a & c & b & a & 0 \\ 0 & 0 & 0 & 0 & c & b & a \\ 0 & 0 & 0 & 0 & 0 & c & b \end{bmatrix}$$

Transposed Convolution with stride





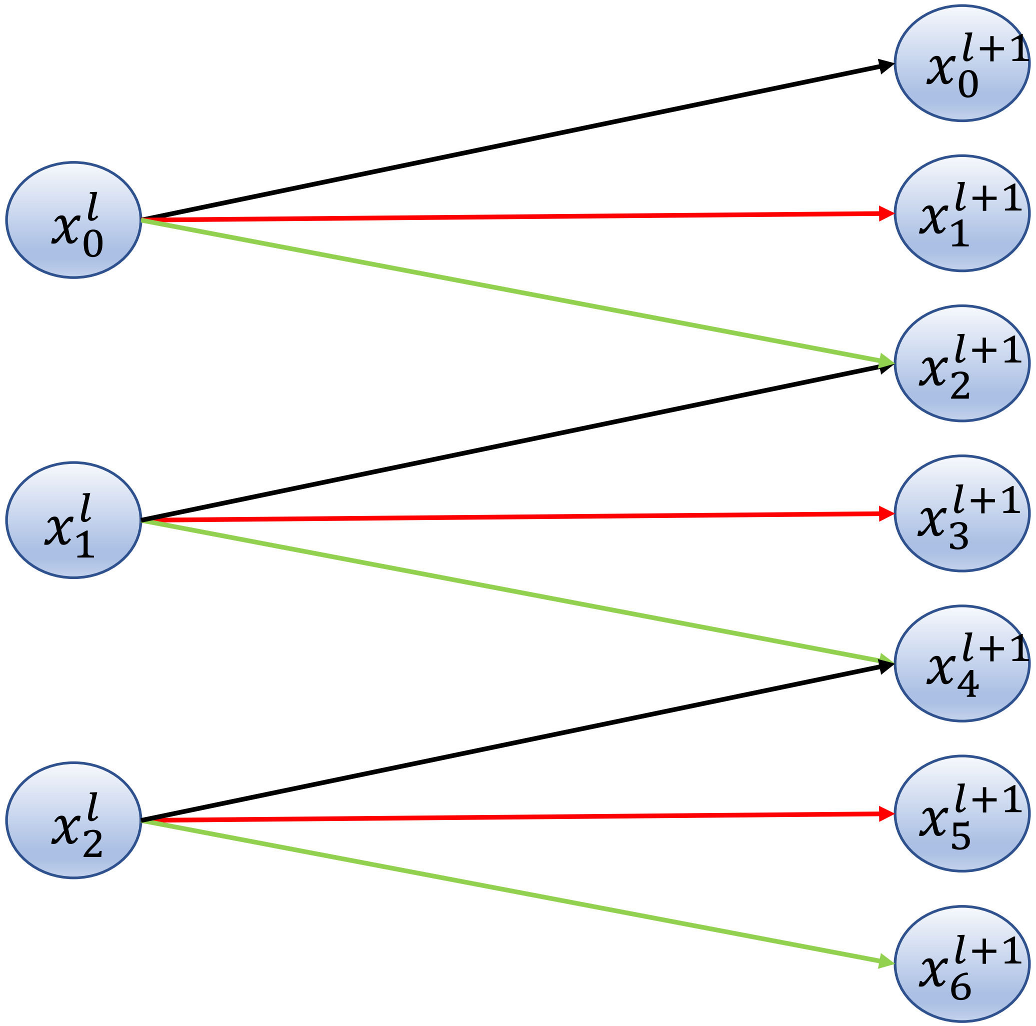
$$\begin{bmatrix} b & a & 0 & 0 & 0 & 0 & 0 \\ c & b & a & 0 & 0 & 0 & 0 \\ 0 & c & b & a & 0 & 0 & 0 \\ 0 & a & c & b & a & 0 & 0 \\ 0 & 0 & a & c & b & a & 0 \\ 0 & 0 & 0 & 0 & c & b & a \\ 0 & 0 & 0 & 0 & 0 & c & b \end{bmatrix}$$

Transposed Convolution with stride

$\longrightarrow a$

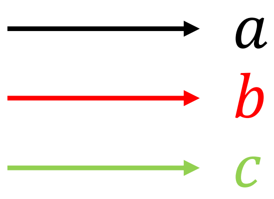
$\longrightarrow b$

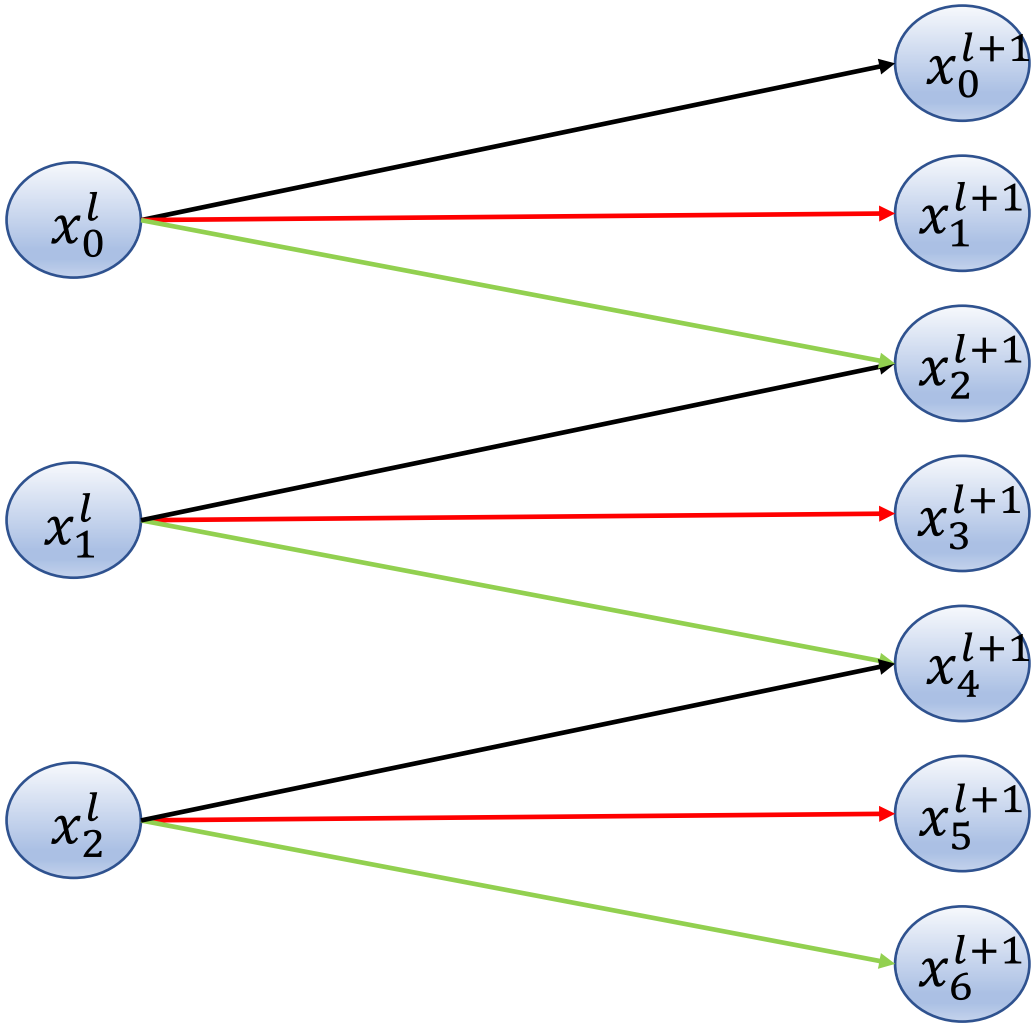
$\longrightarrow c$



$$\begin{bmatrix} b & a & 0 & 0 & 0 & 0 & 0 \\ c & b & a & 0 & 0 & 0 & 0 \\ 0 & c & b & a & 0 & 0 & 0 \\ 0 & a & c & b & a & 0 & 0 \\ 0 & 0 & a & c & b & a & 0 \\ 0 & 0 & 0 & 0 & c & b & a \\ 0 & 0 & 0 & 0 & 0 & c & b \end{bmatrix}$$

Transposed Convolution with stride





$$
\begin{bmatrix}
b & a & 0 & 0 & 0 & 0 & 0 \\
c & b & a & 0 & 0 & 0 & 0 \\
0 & c & b & a & 0 & 0 & 0 \\
0 & a & c & b & a & 0 & 0 \\
0 & 0 & a & c & b & a & 0 \\
0 & 0 & 0 & 0 & c & b & a \\
0 & 0 & 0 & 0 & 0 & c & b
\end{bmatrix}
$$

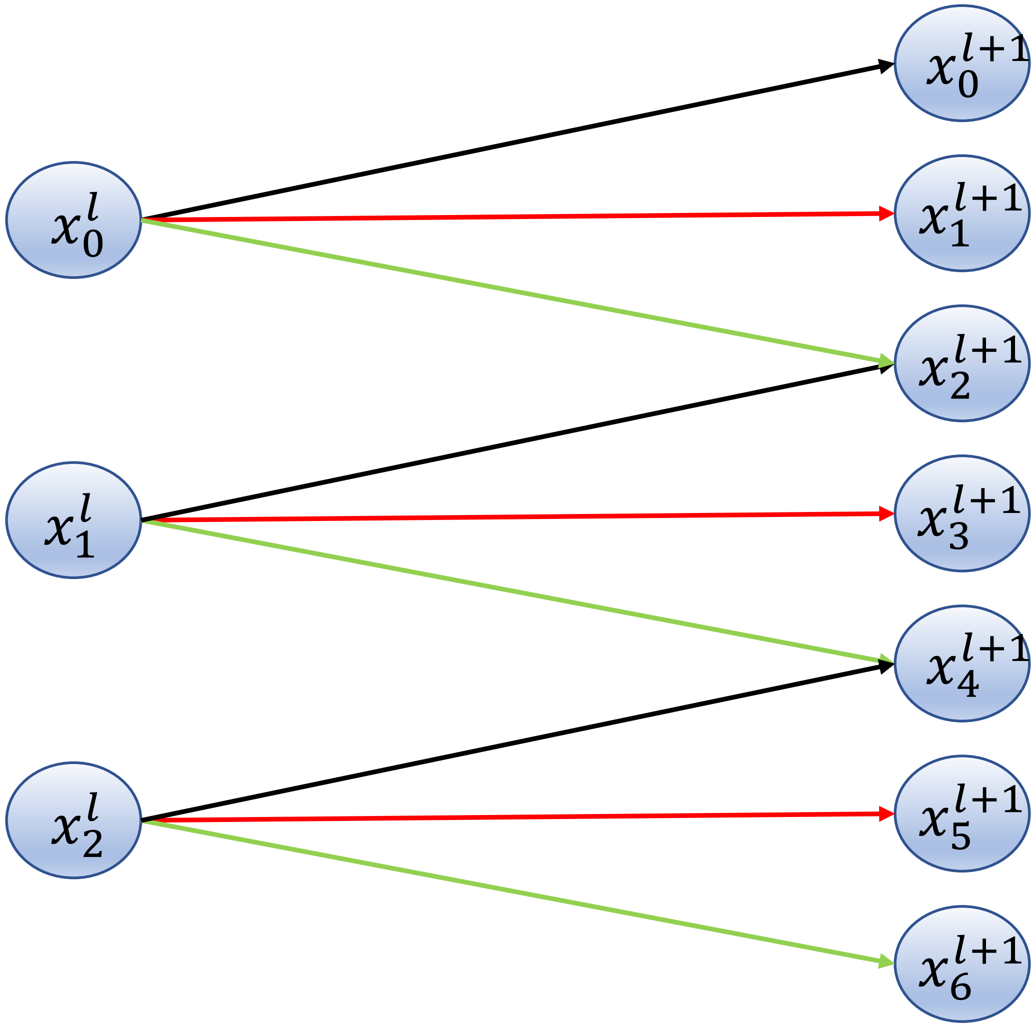
Transposed Convolution with stride

[redacted]

$\rightarrow a$

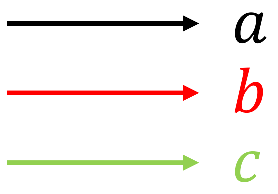
$\rightarrow b$

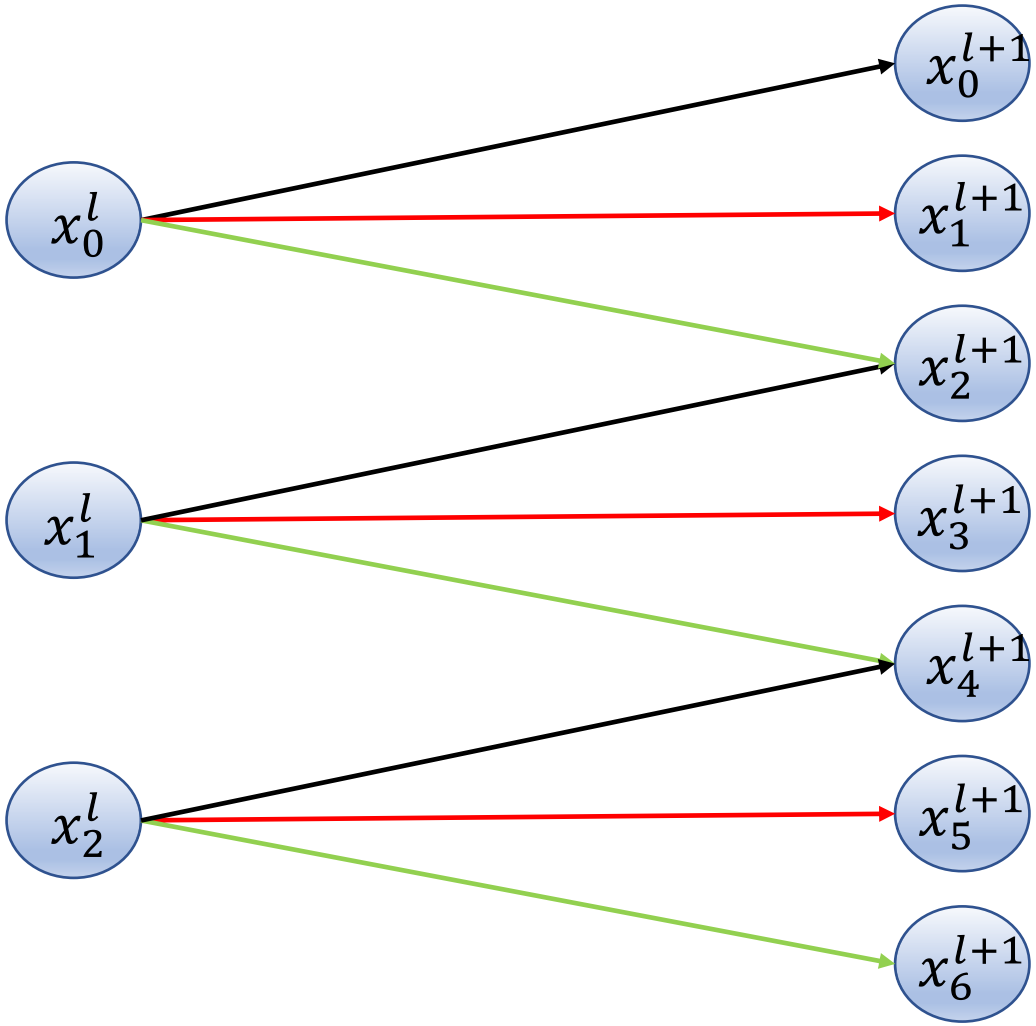
$\rightarrow c$



$$\begin{bmatrix} \boldsymbol{a} & 0 & 0 \\ \boldsymbol{b} & 0 & 0 \\ \boldsymbol{c} & \boldsymbol{a} & 0 \\ a & \boldsymbol{b} & 0 \\ 0 & \boldsymbol{c} & \boldsymbol{a} \\ 0 & 0 & \boldsymbol{b} \\ 0 & 0 & \boldsymbol{c} \end{bmatrix}$$

Transposed Convolution with stride





$$\begin{bmatrix} \boldsymbol{a} & 0 & 0 \\ \boldsymbol{b} & 0 & 0 \\ \boldsymbol{c} & \boldsymbol{a} & 0 \\ a & \boldsymbol{b} & 0 \\ 0 & \boldsymbol{c} & \boldsymbol{a} \\ 0 & 0 & \boldsymbol{b} \\ 0 & 0 & \boldsymbol{c} \end{bmatrix}$$

Recall- stride 2 conv:

$$\begin{bmatrix} \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} & 0 & 0 & 0 & 0 \\ 0 & 0 & \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} & 0 & 0 \\ 0 & 0 & 0 & 0 & \boldsymbol{a} & \boldsymbol{b} & \boldsymbol{c} \end{bmatrix}$$

Transposed Convolution with stride

$\longrightarrow a$

$\longrightarrow b$

$\longrightarrow c$

$$\begin{bmatrix} a & 0 & 0 \\ b & 0 & 0 \\ c & a & 0 \\ a & b & 0 \\ 0 & c & a \\ 0 & 0 & b \\ 0 & 0 & c \end{bmatrix}$$

Recall- stride 2 conv:

$$\begin{bmatrix} a & b & c & 0 & 0 & 0 & 0 \\ 0 & 0 & a & b & c & 0 & 0 \\ 0 & 0 & 0 & 0 & a & b & c \end{bmatrix}$$

A note about the implementation of conv

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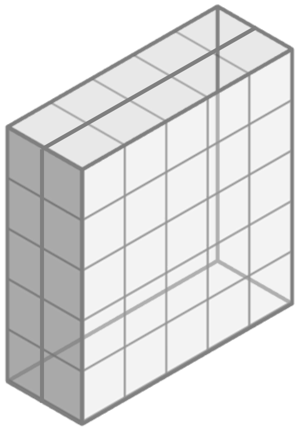
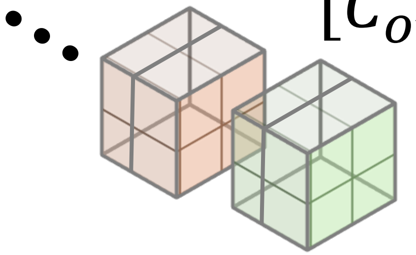
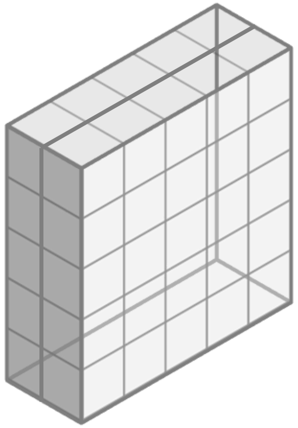


$[N, C_{in}, H, W]$

A note about the implementation of conv



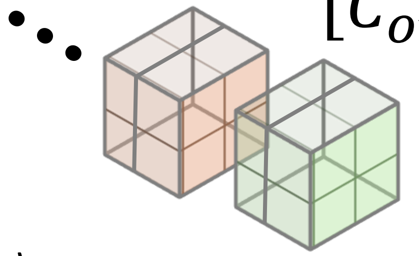
$[C_{out}, C_{in}, h, w]$



$[N, C_{in}, H, W]$

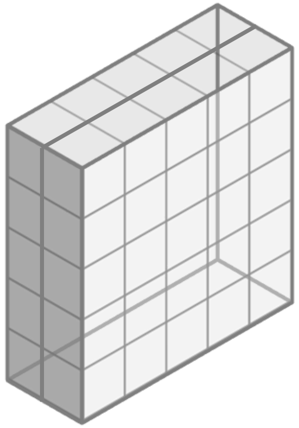
A note about the implementation of conv

$[C_{out}, C_{in}, h, w]$



$Unfold$

(*kernel_size, stride)*



$[N, C_{in}, H, W]$

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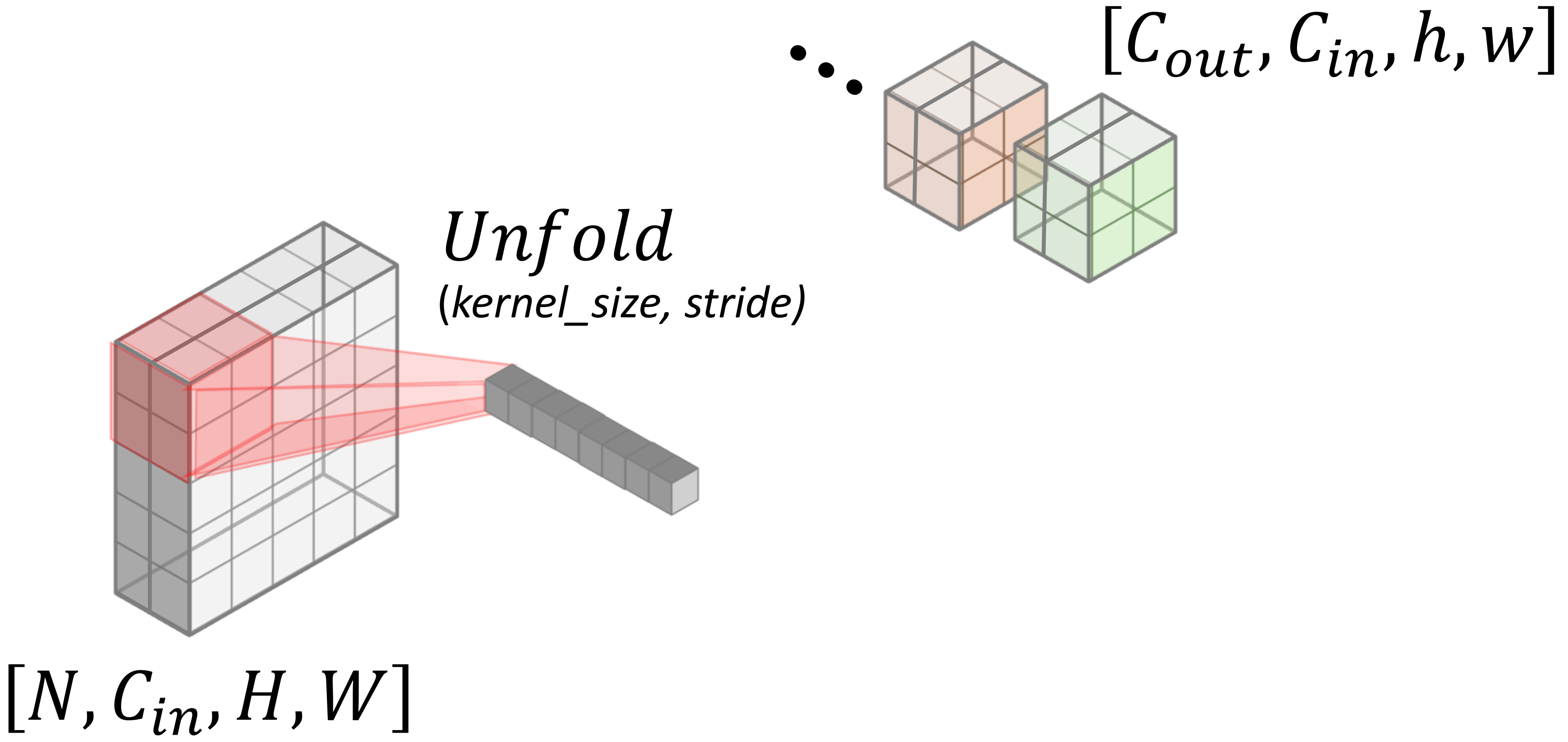

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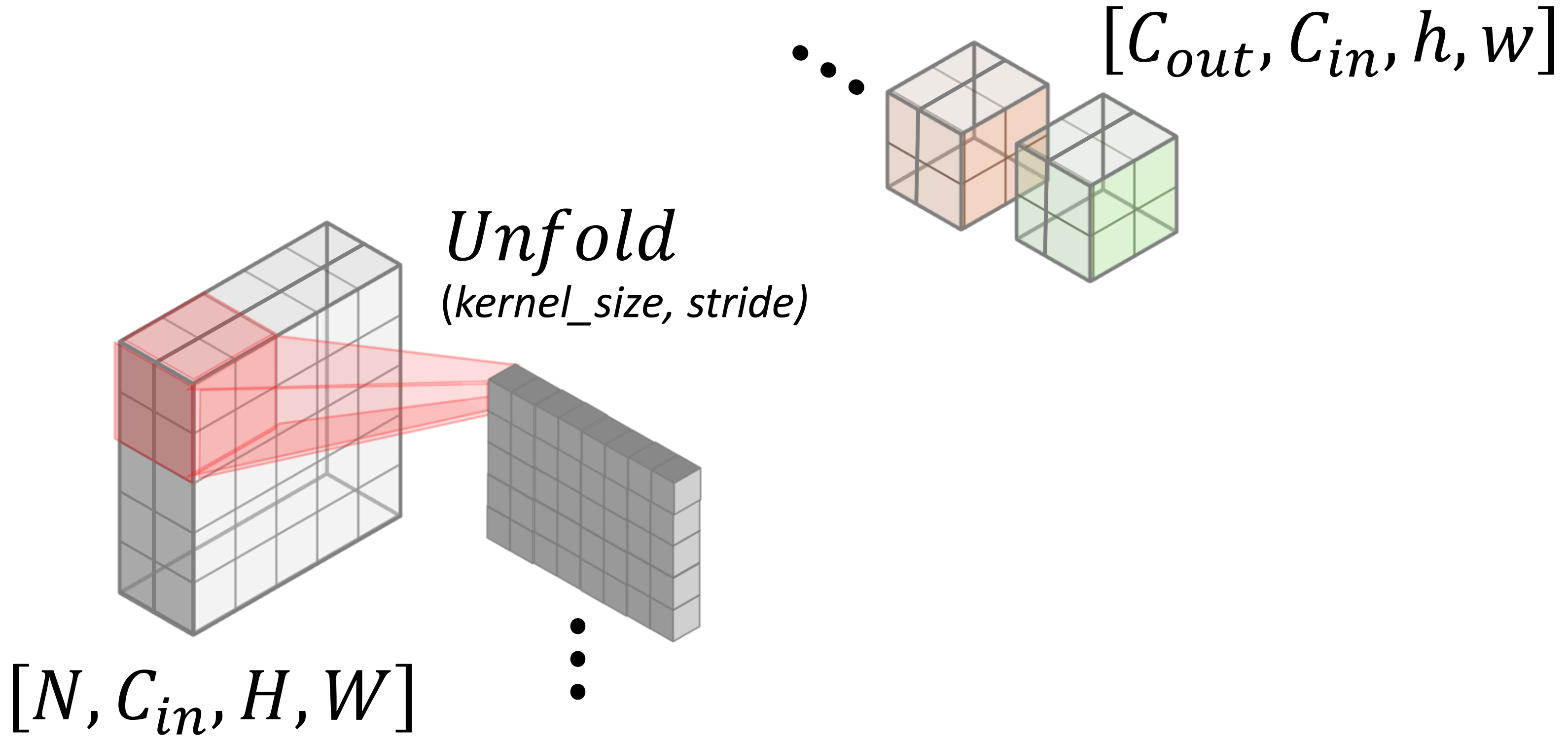
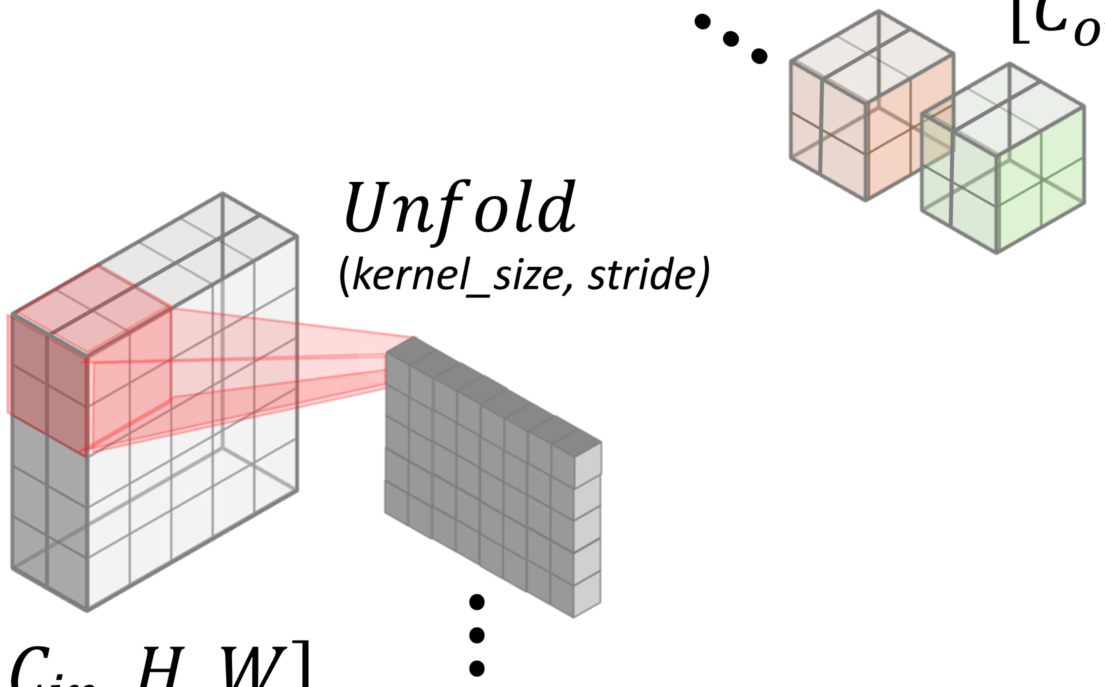


A note about the implementation of conv

$[C_{out}, C_{in}, h, w]$

$Unfold$

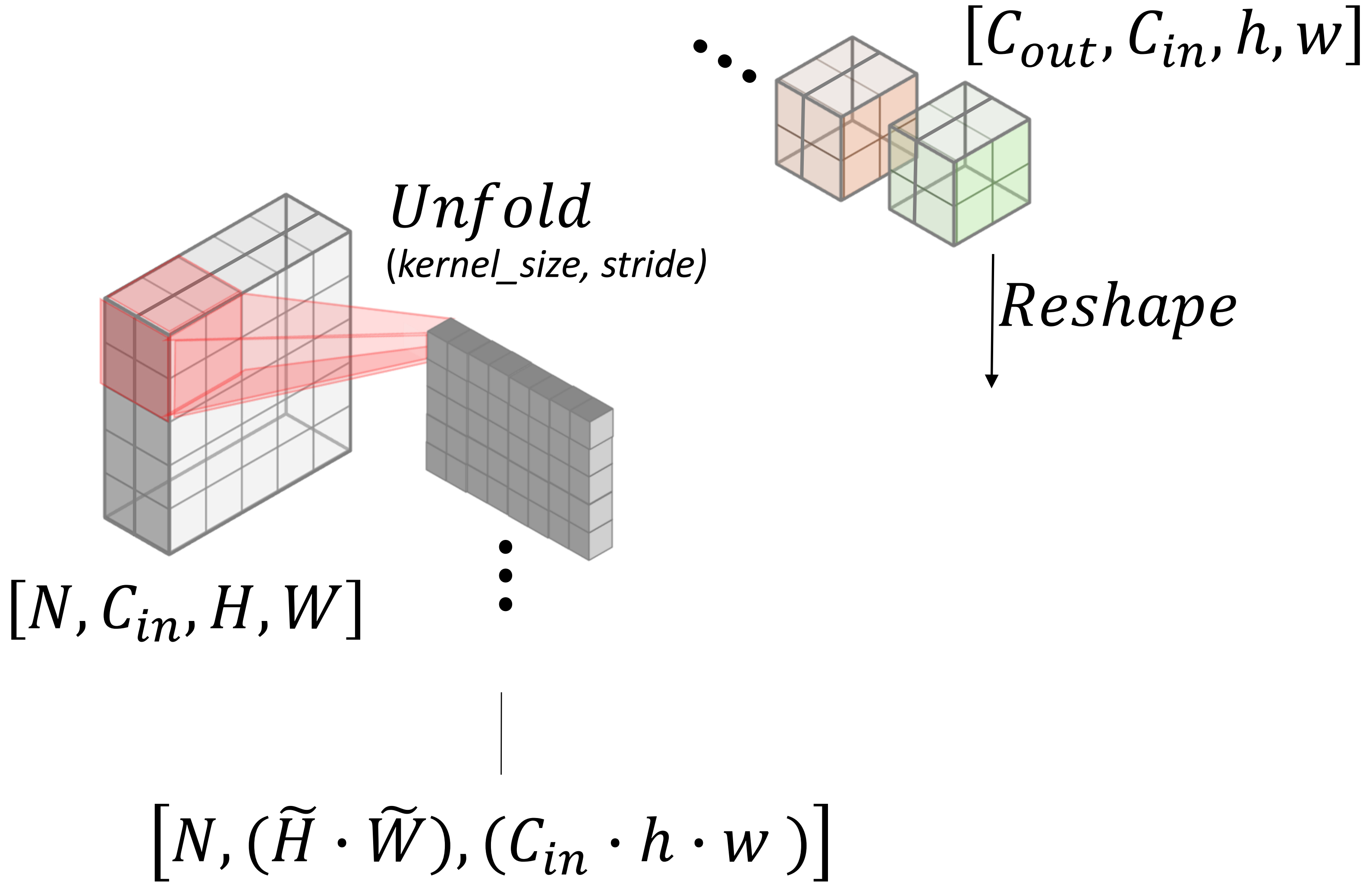
(*kernel_size, stride*)



$[N, C_{in}, H, W]$

$[N, (\widetilde{H} \cdot \widetilde{W}), (C_{in} \cdot h \cdot w)]$

A note about the implementation of conv



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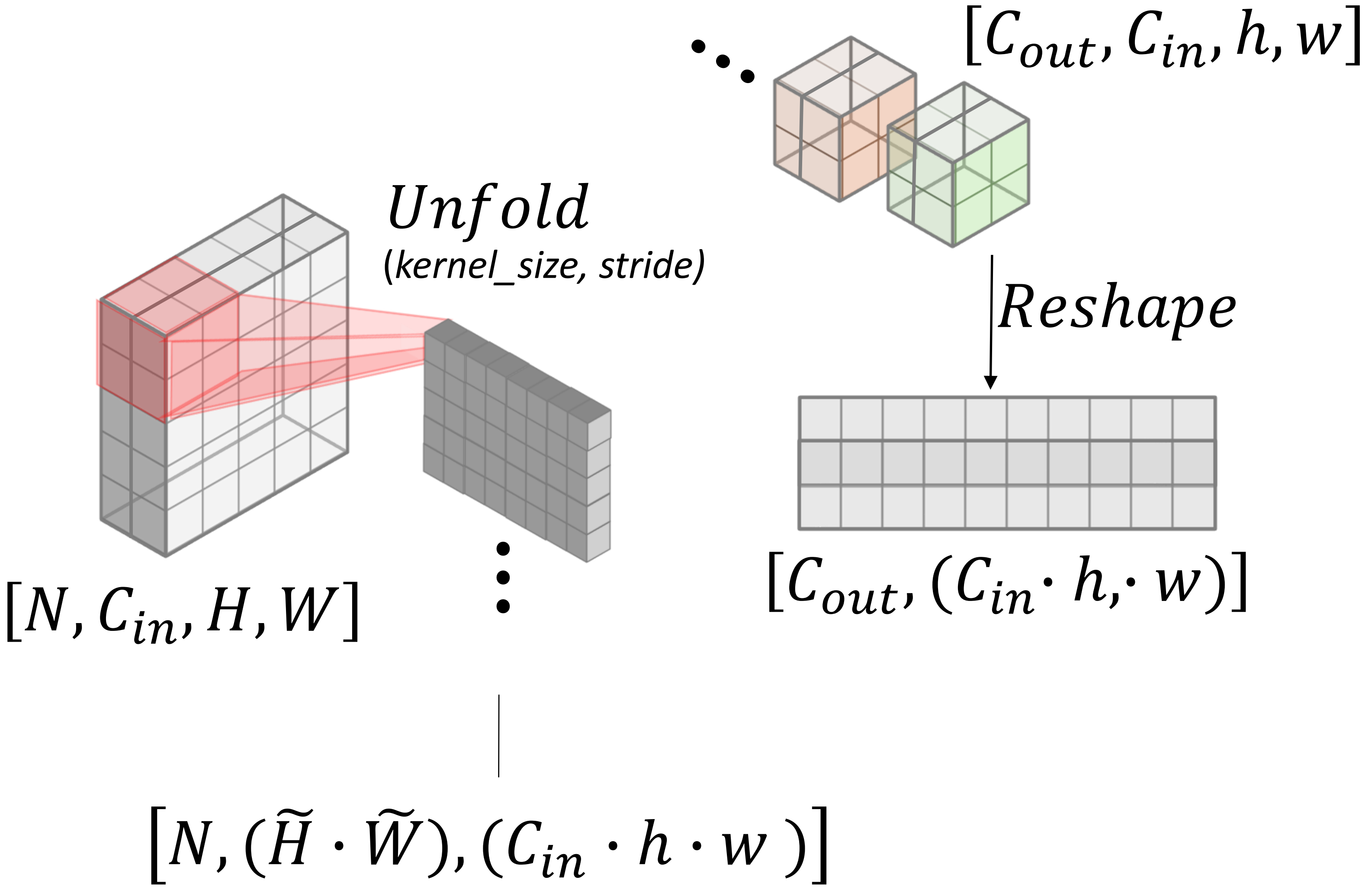

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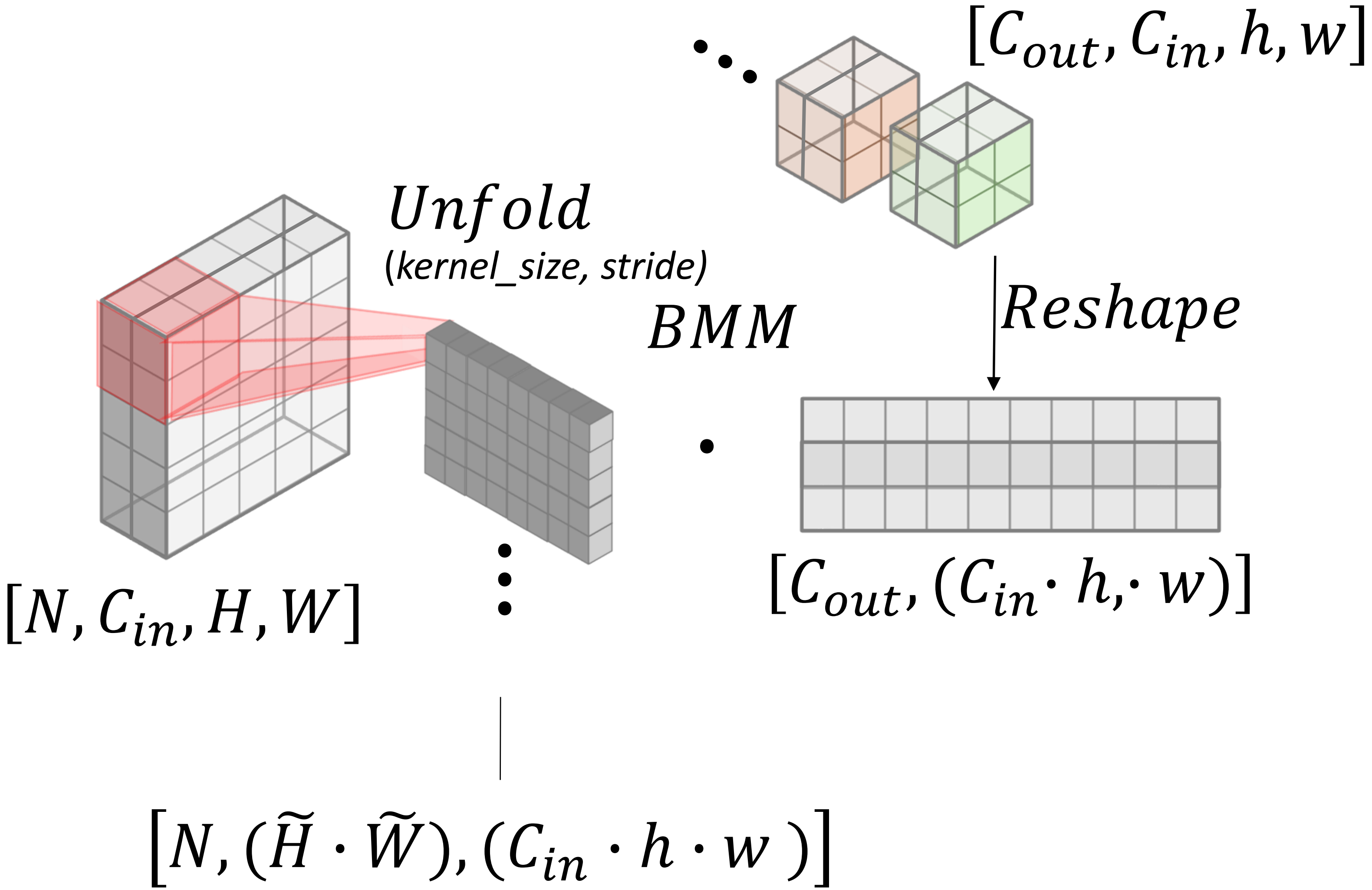

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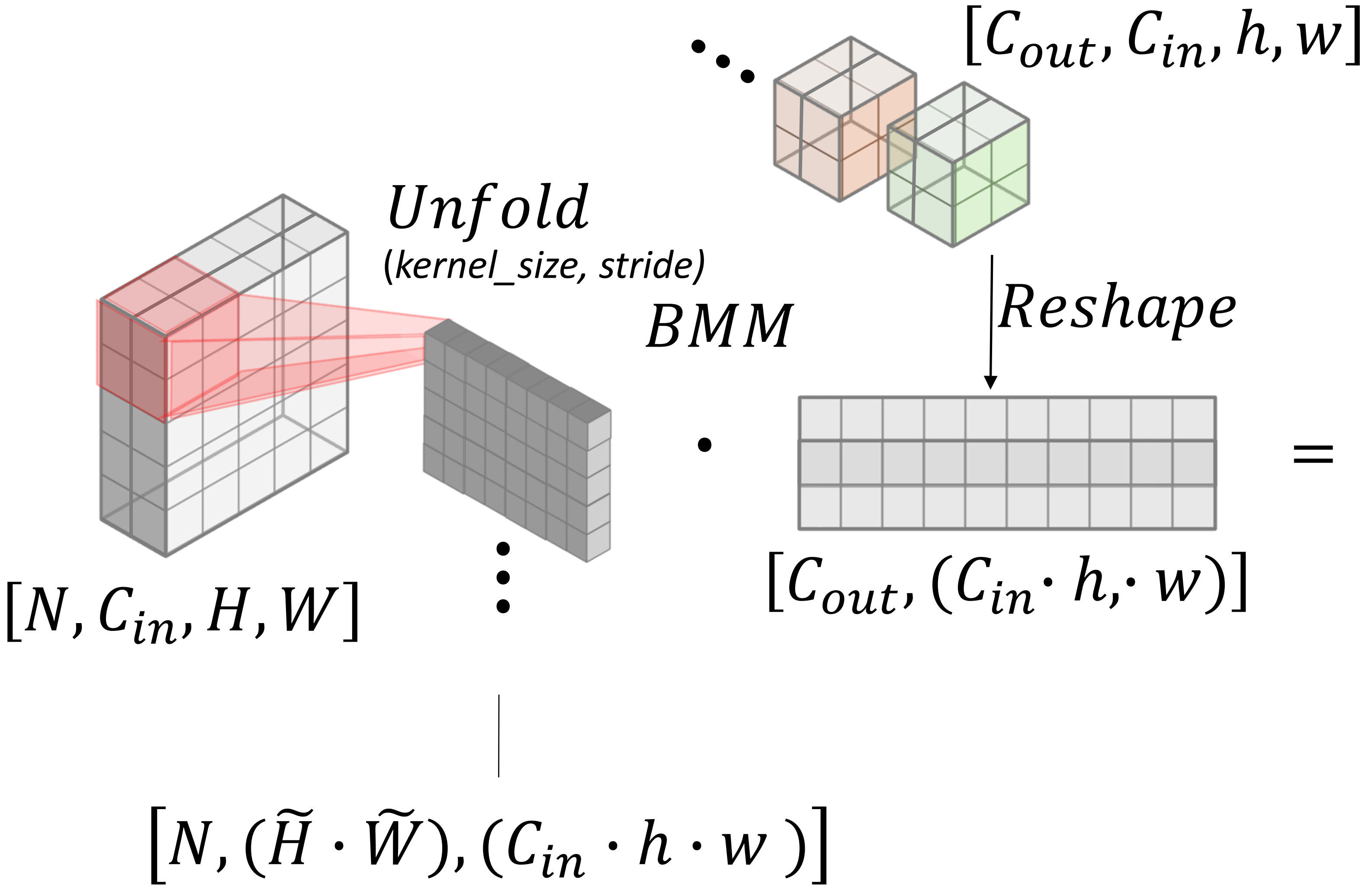

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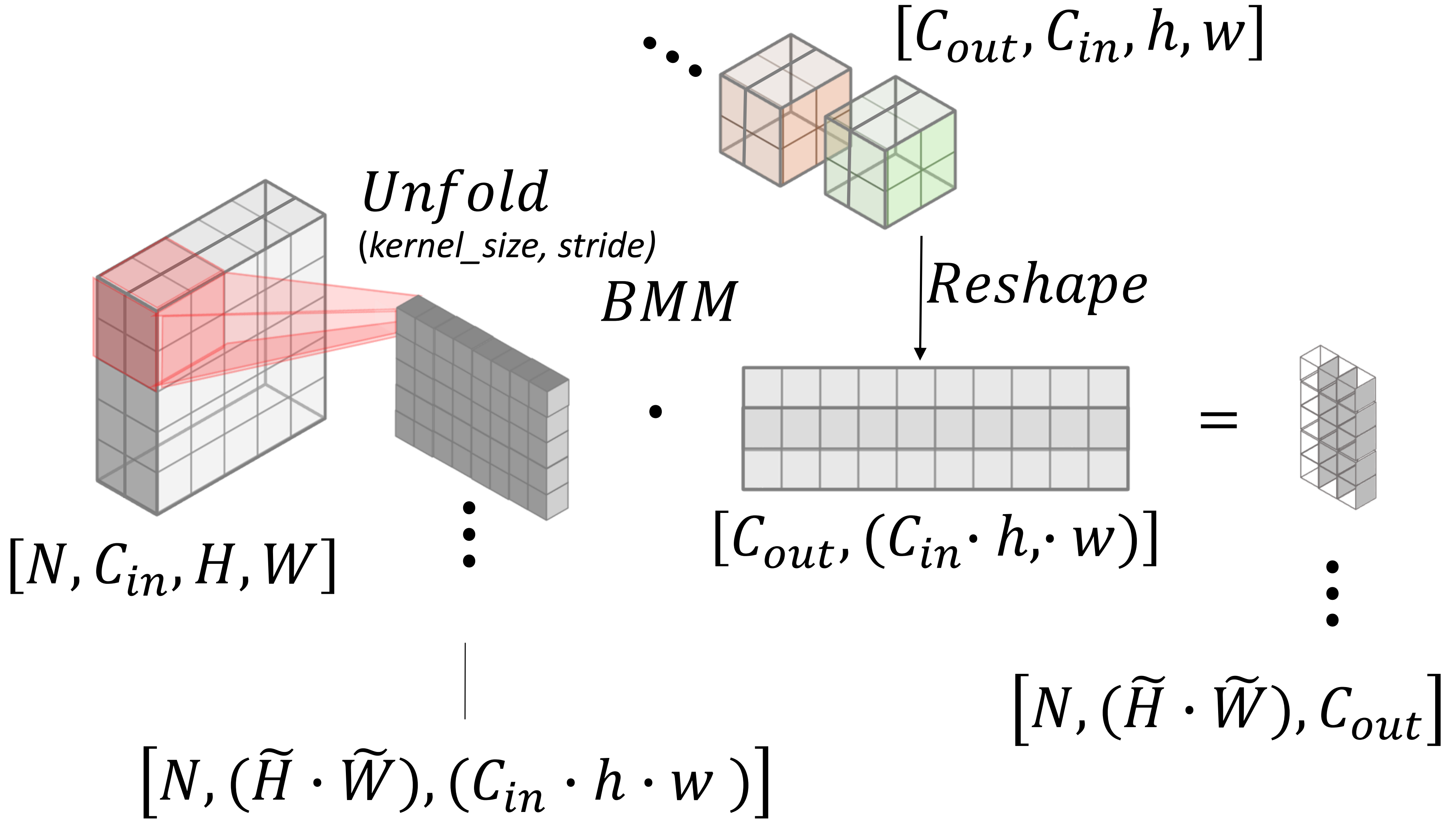

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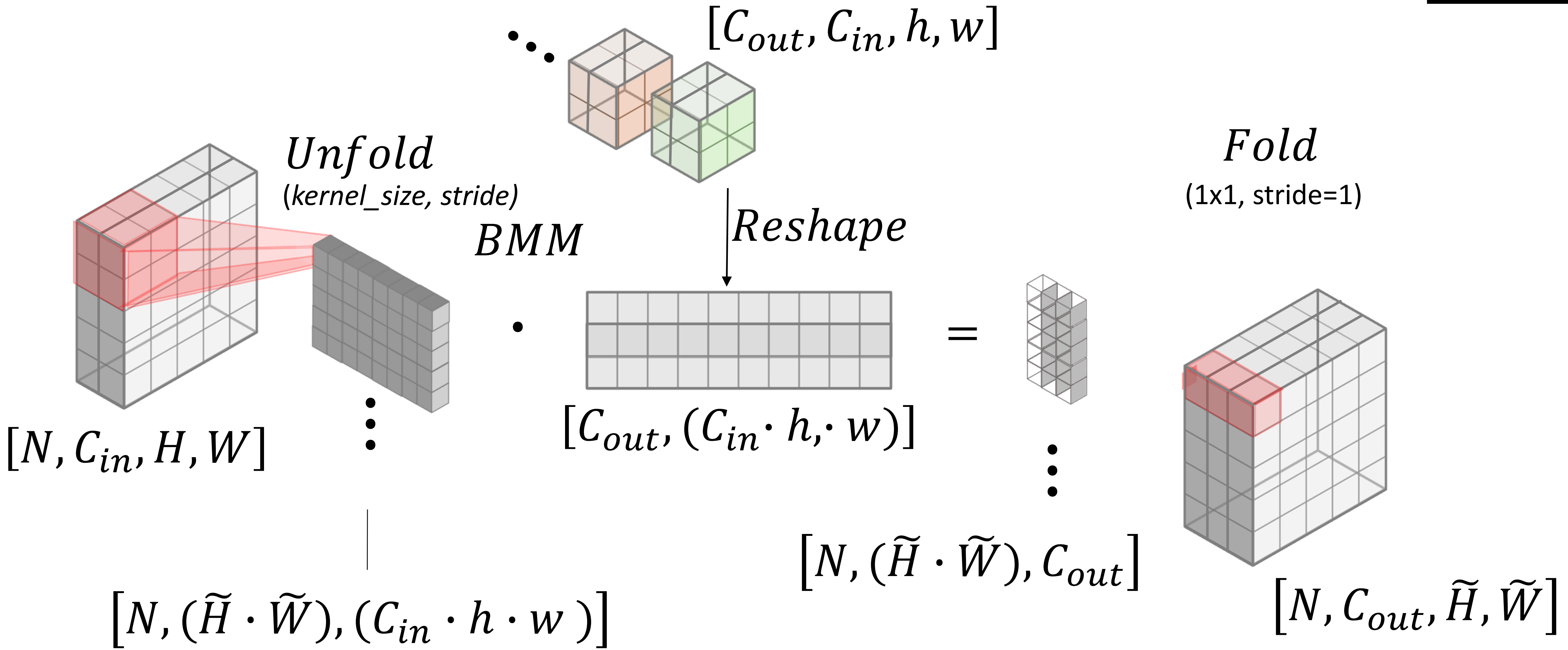

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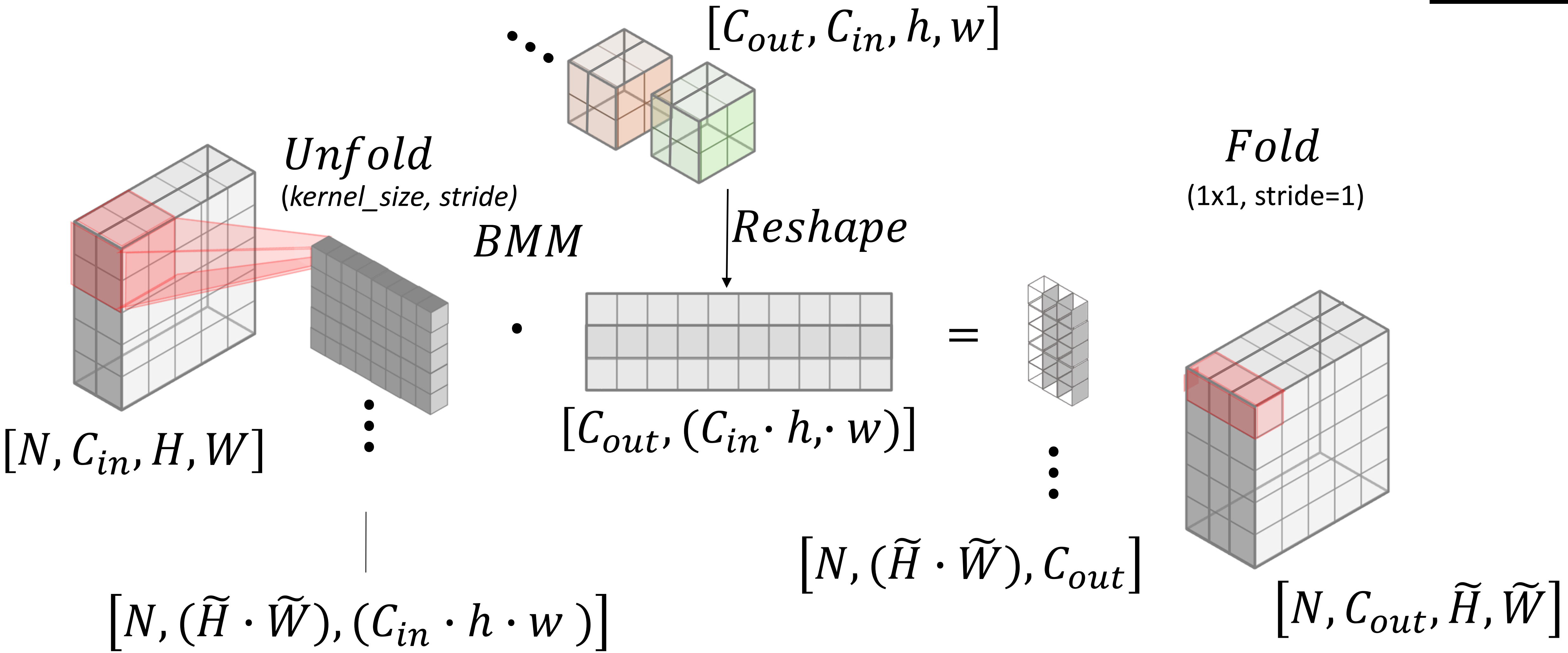

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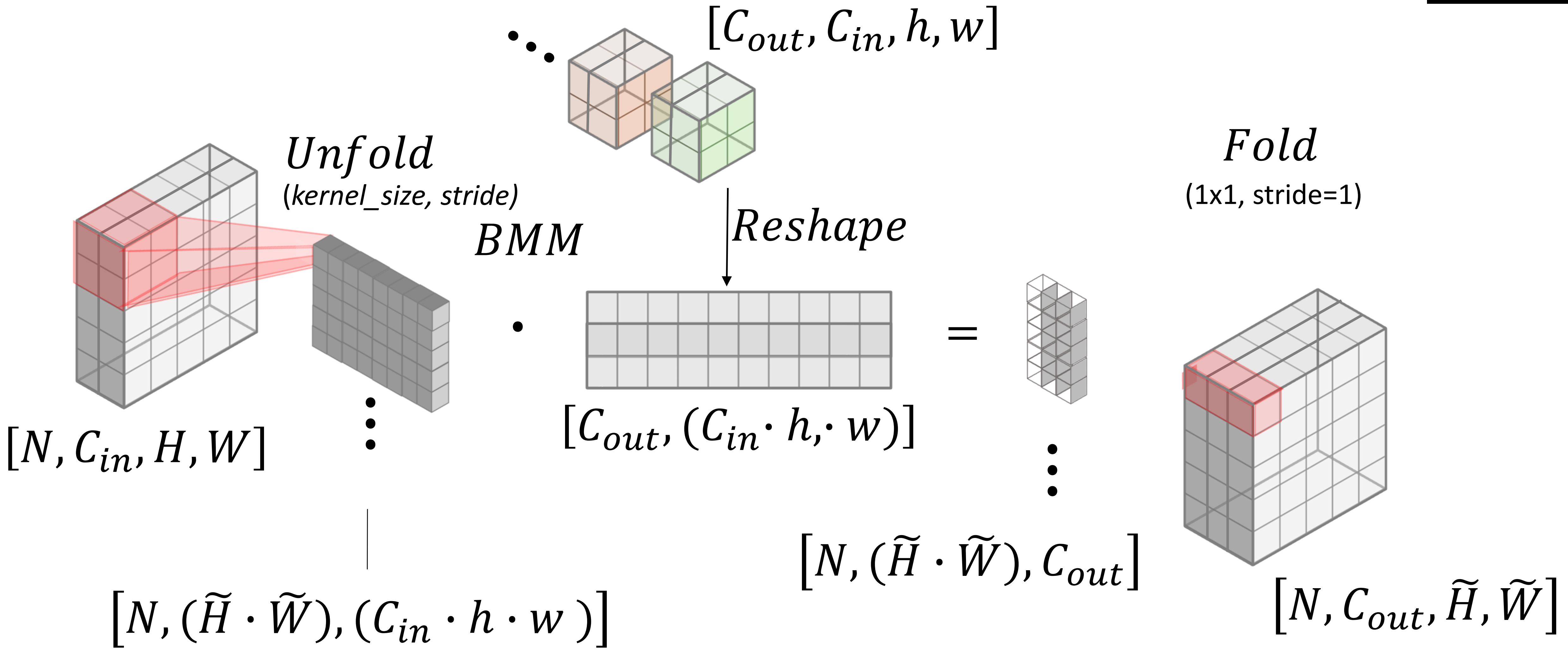

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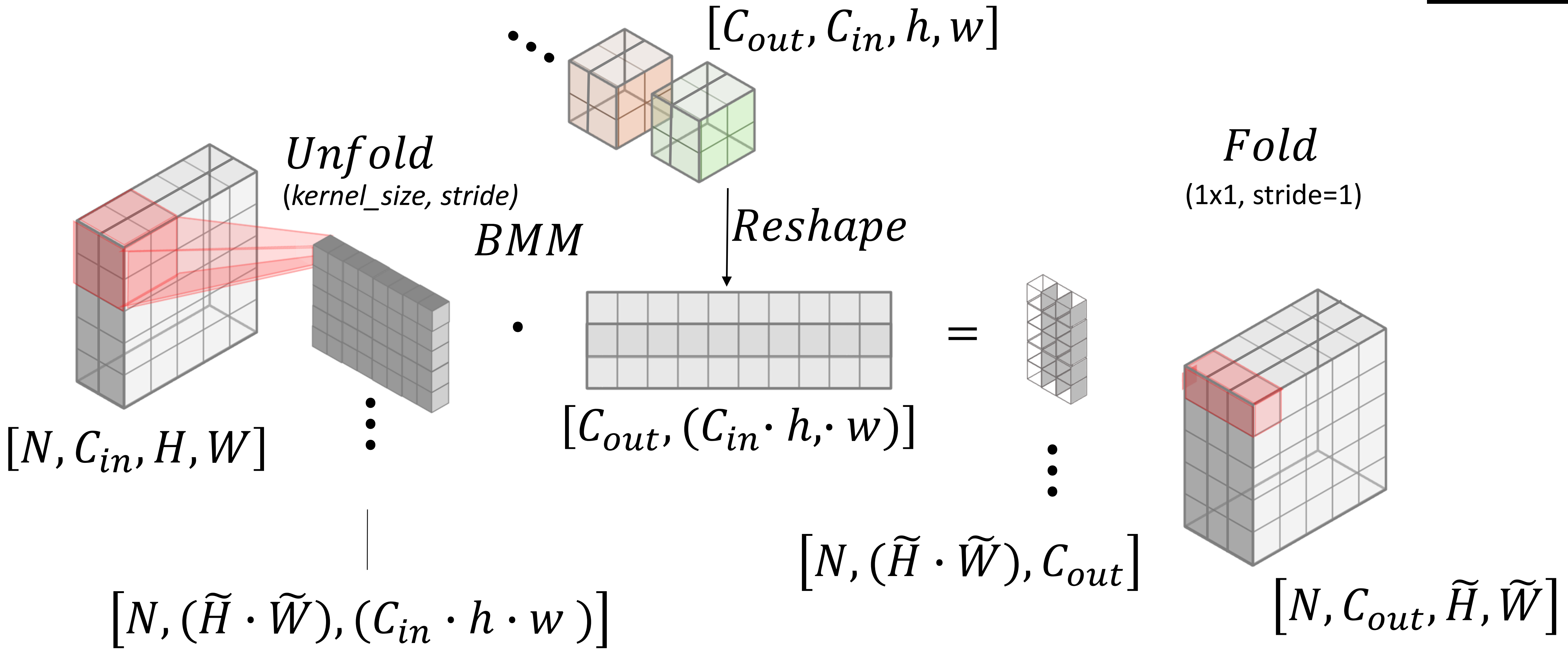

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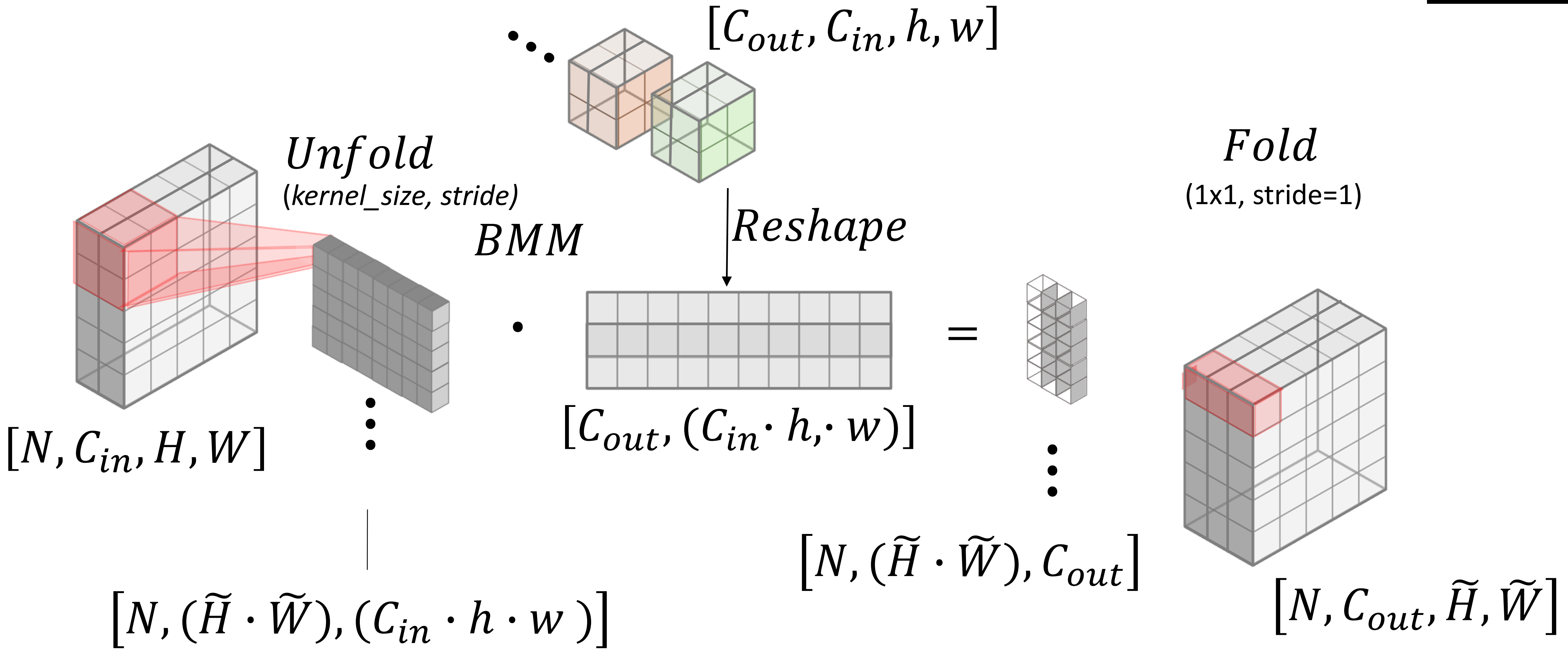

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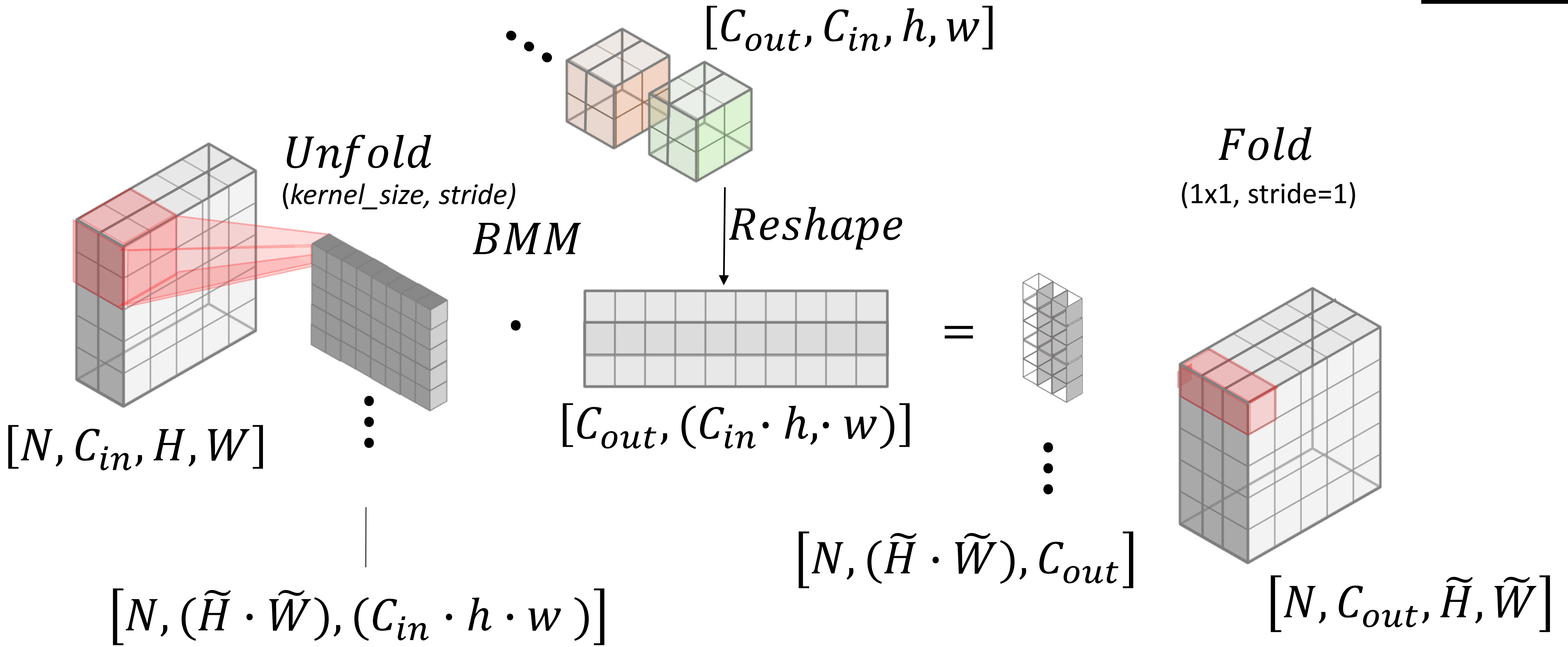

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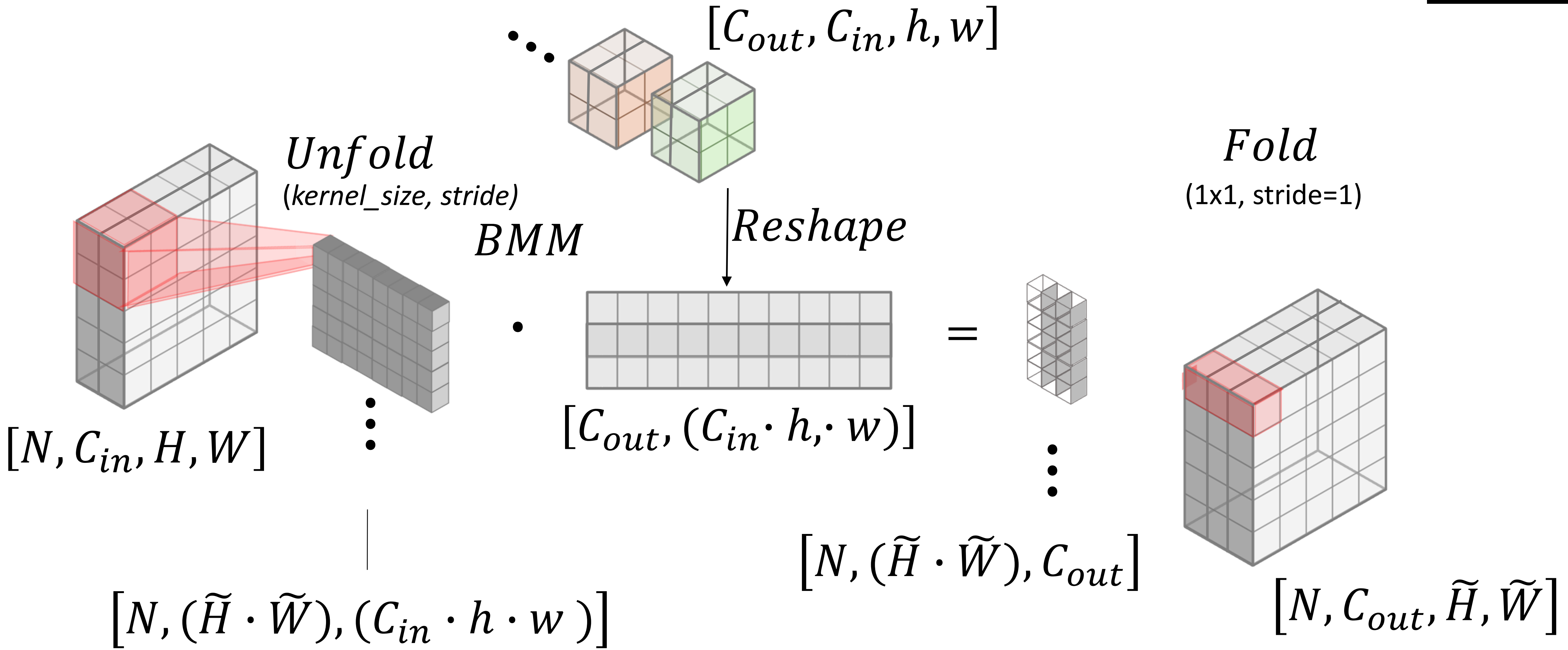

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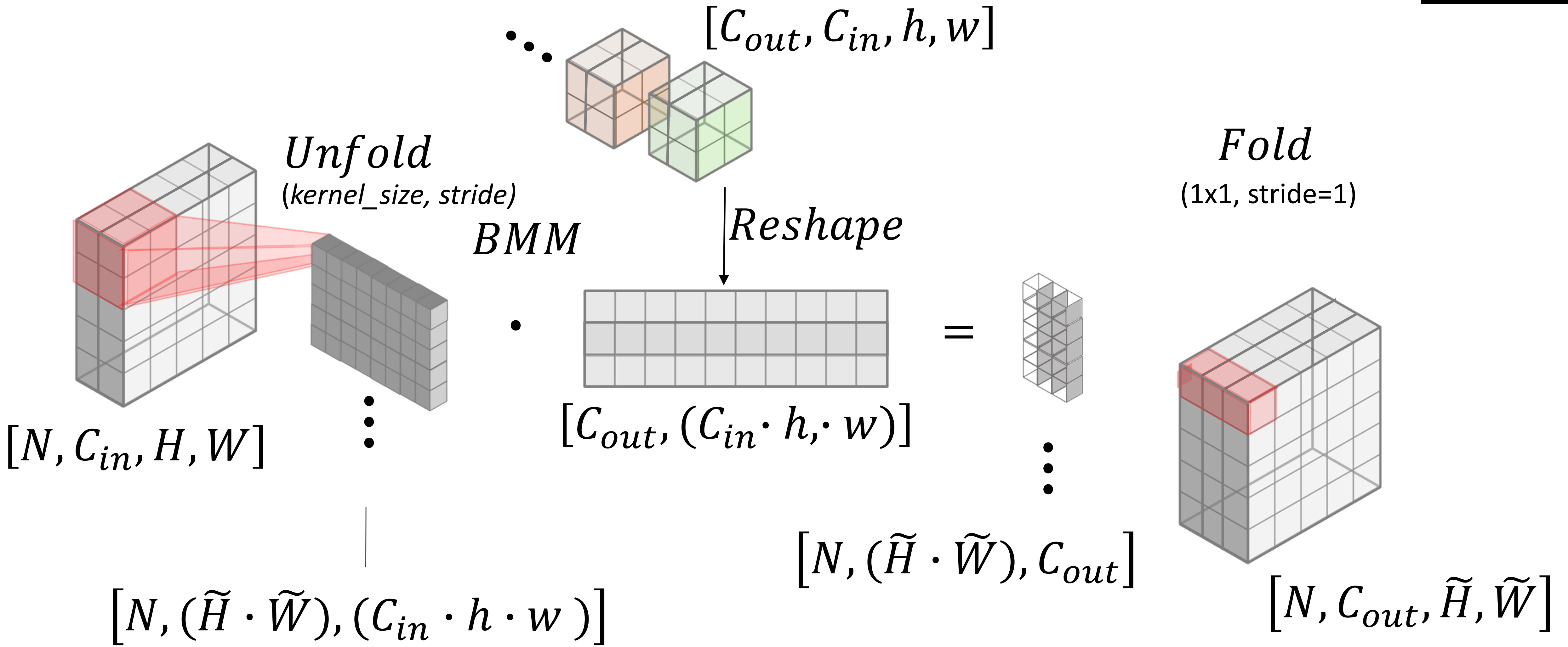

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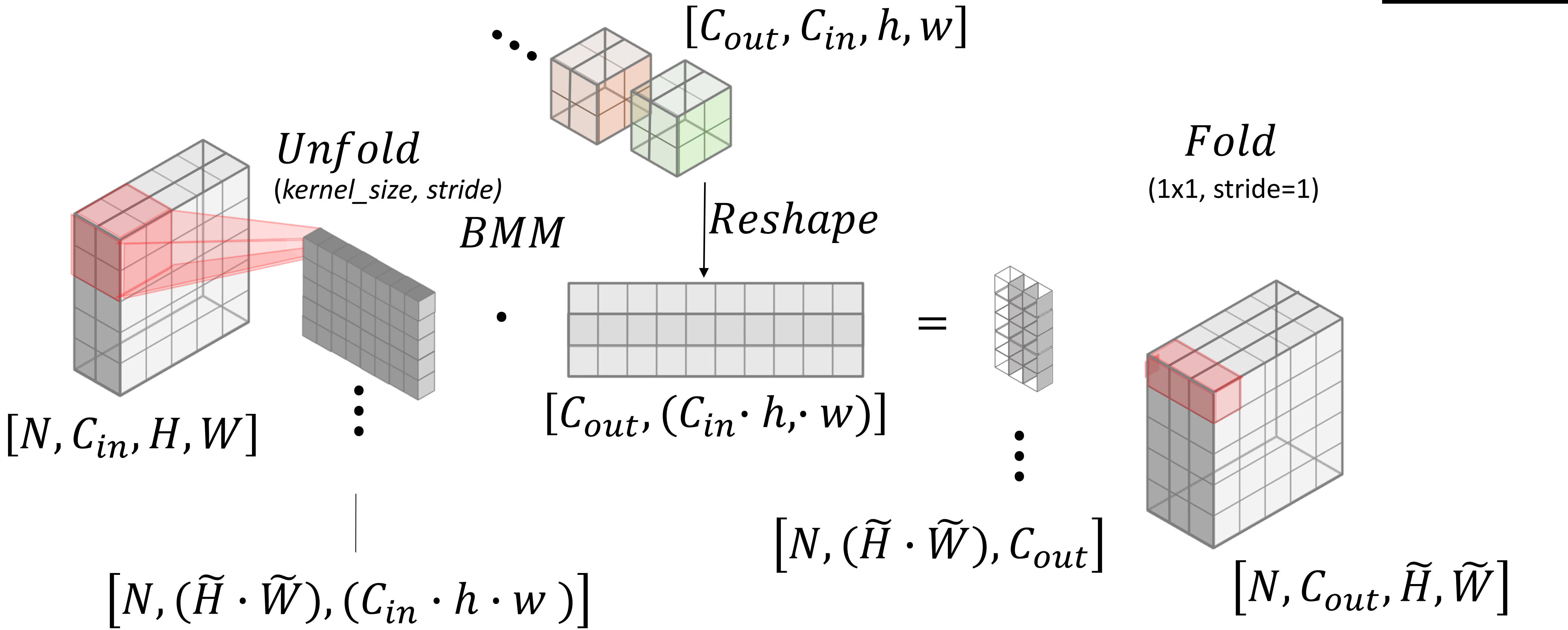

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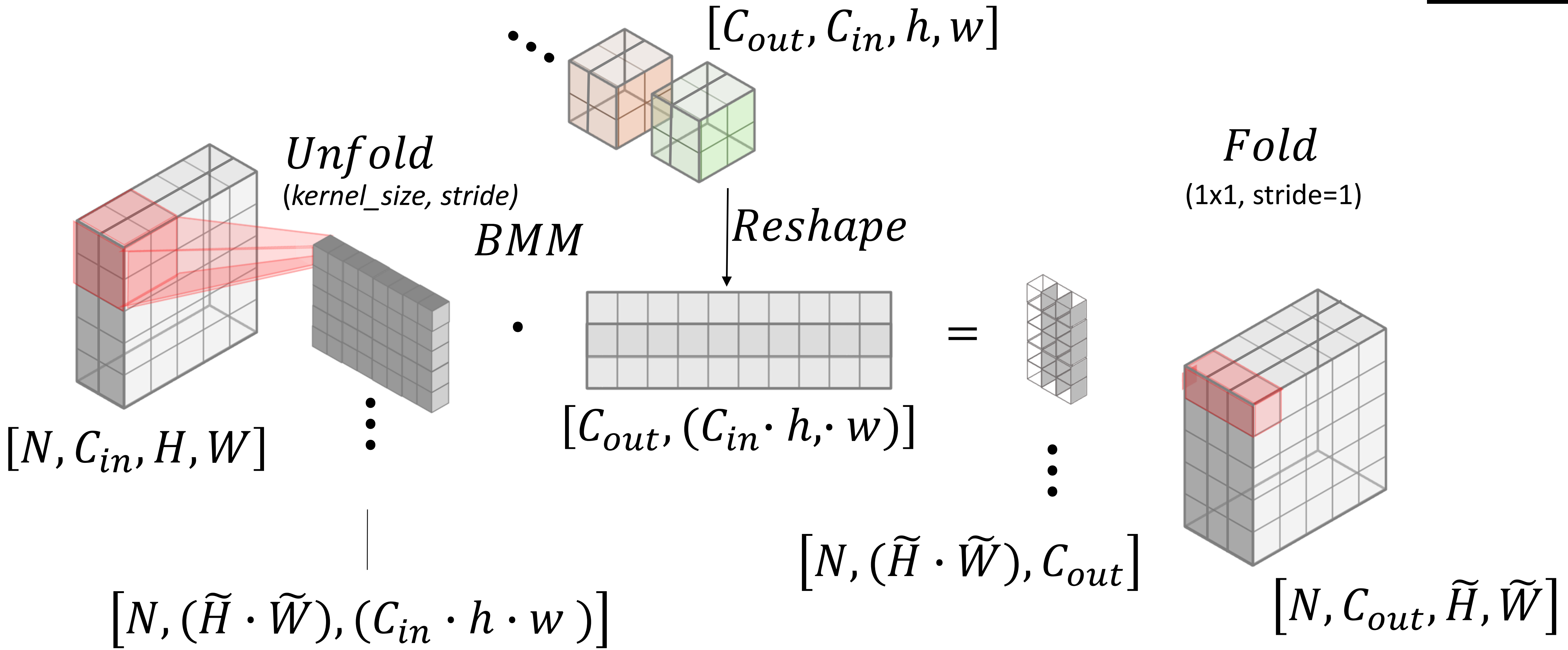
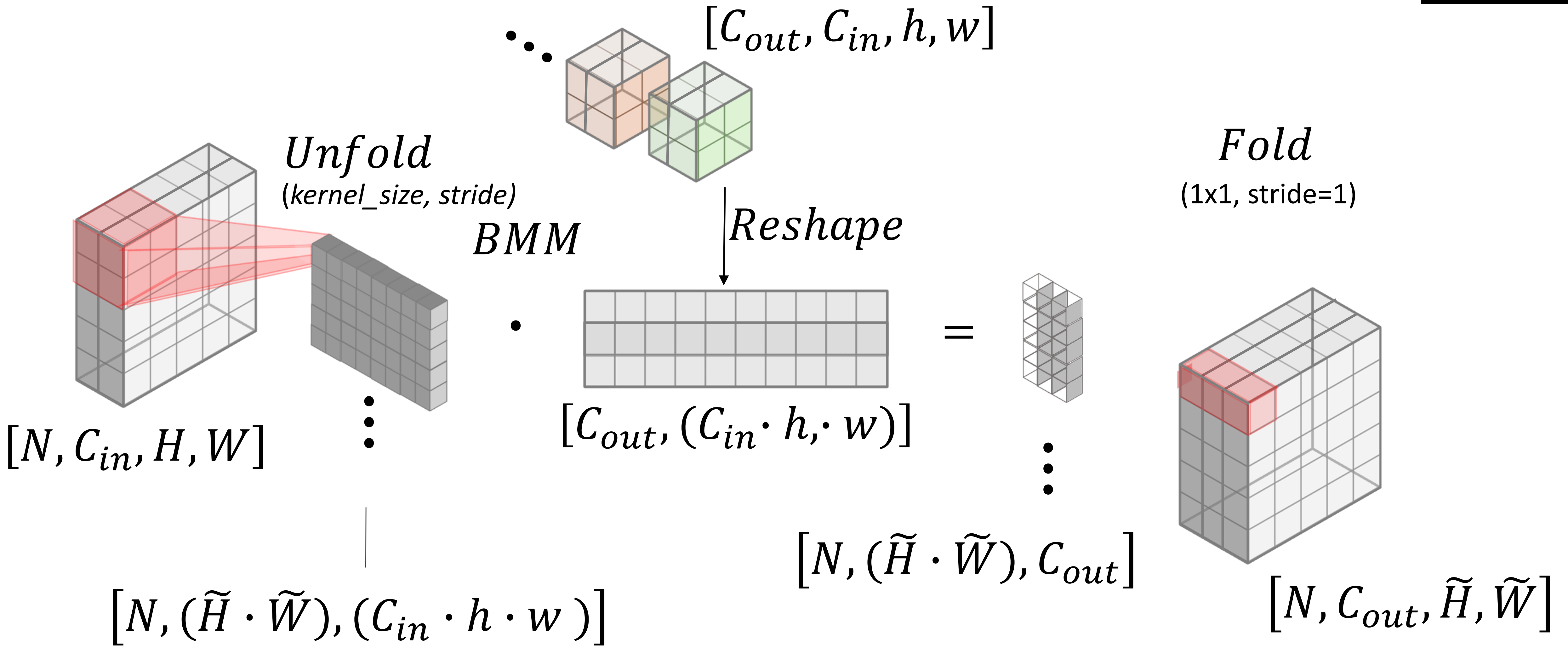
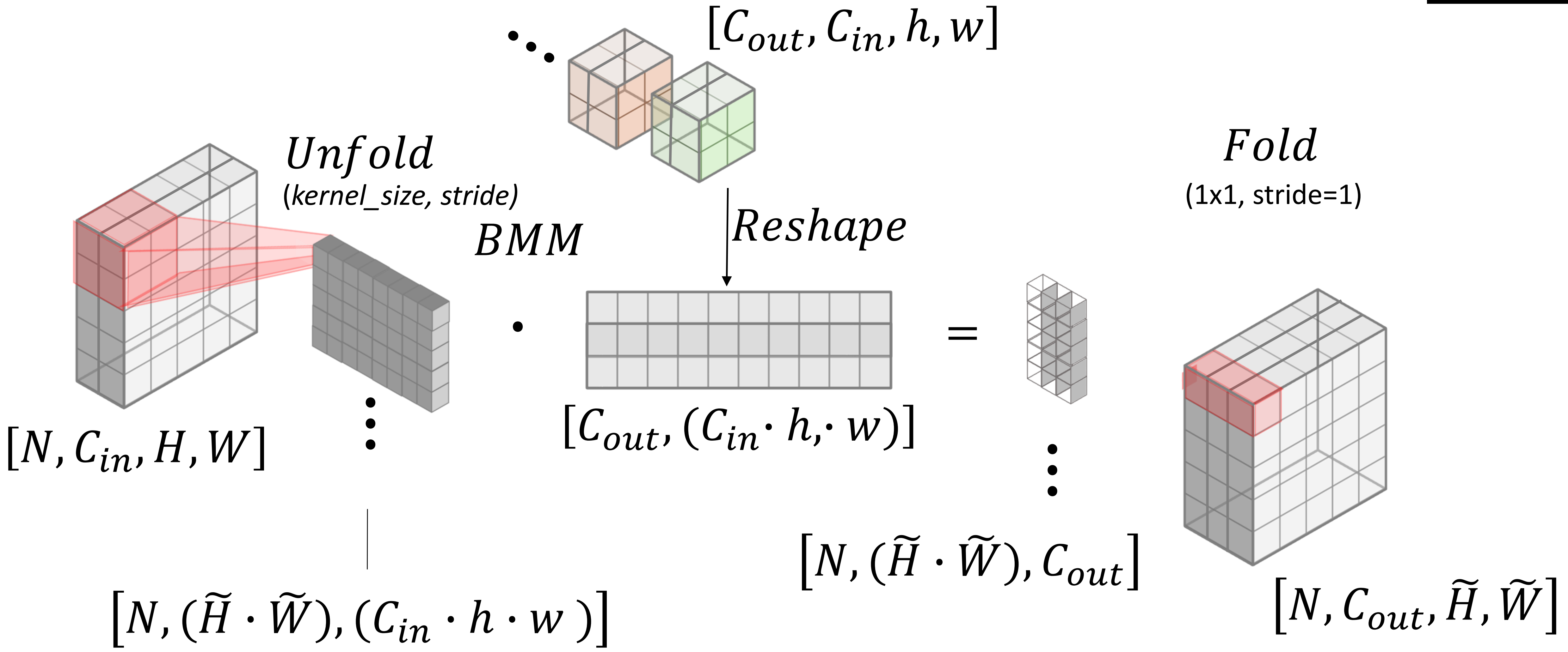


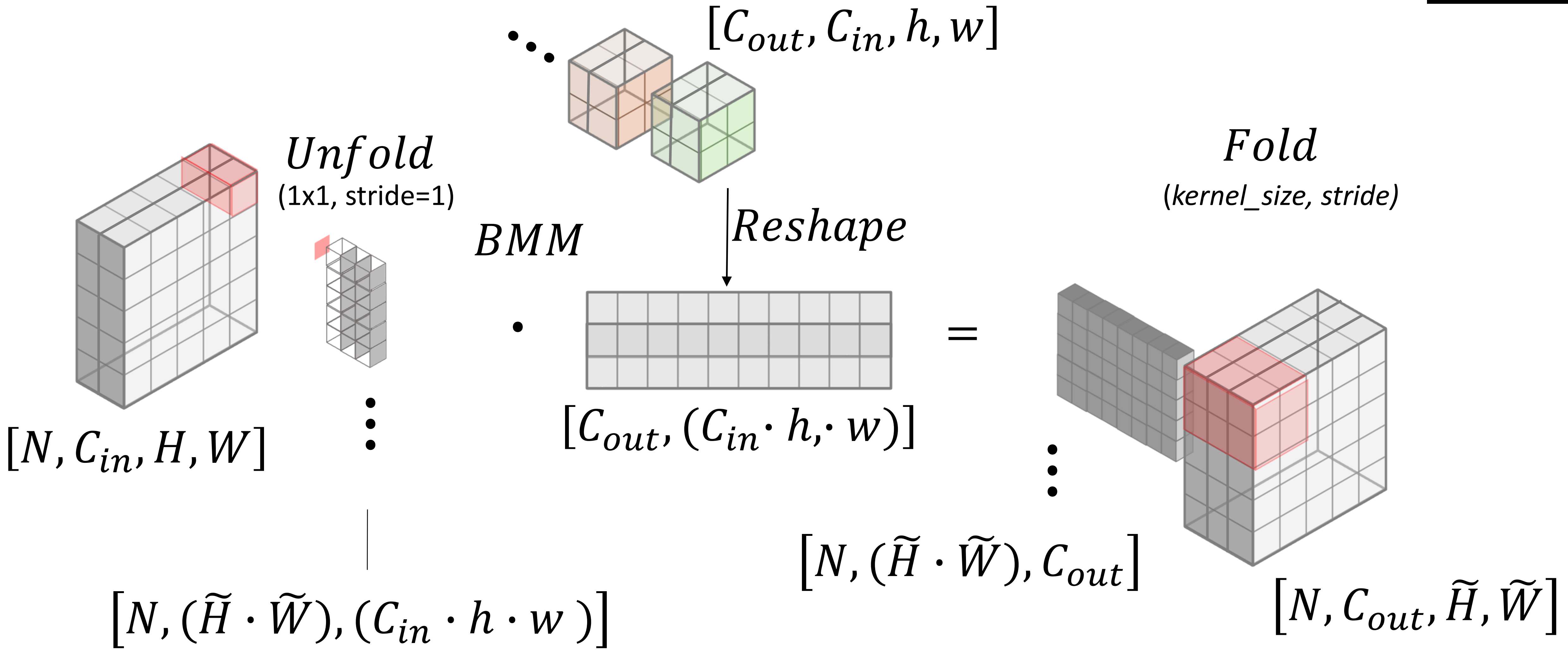
A note about the implementation of conv



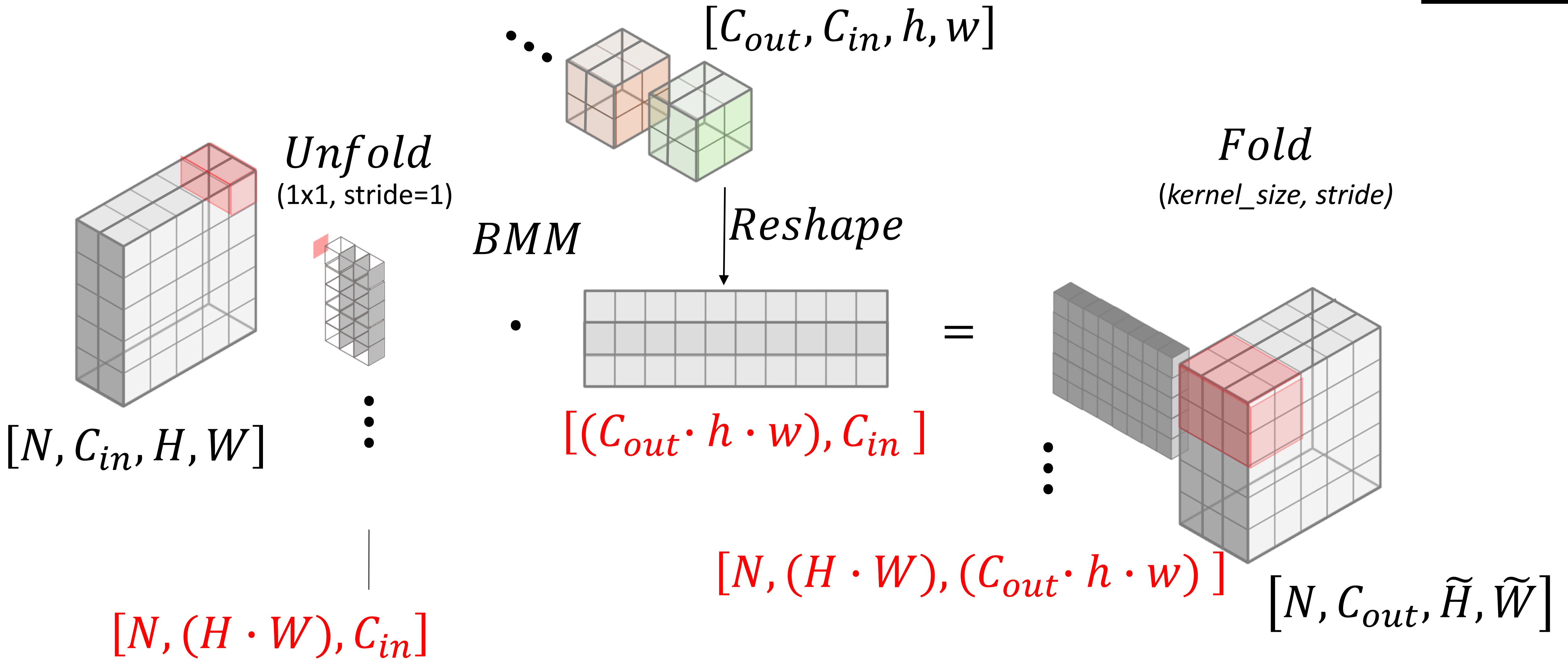
A note about the implementation of conv *TRANSPOSED*



A note about the implementation of conv *TRANSPOSED*



A note about the implementation of conv *TRANSPOSED*



Q: How do you backprop a Conv? (1D, single channel)

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<u>For derivative of loss w.r.t all neurons</u>:
Transposed Conv with the same filter!

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For derivative of loss w.r.t all neurons:
Transposed Conv with the same filter!

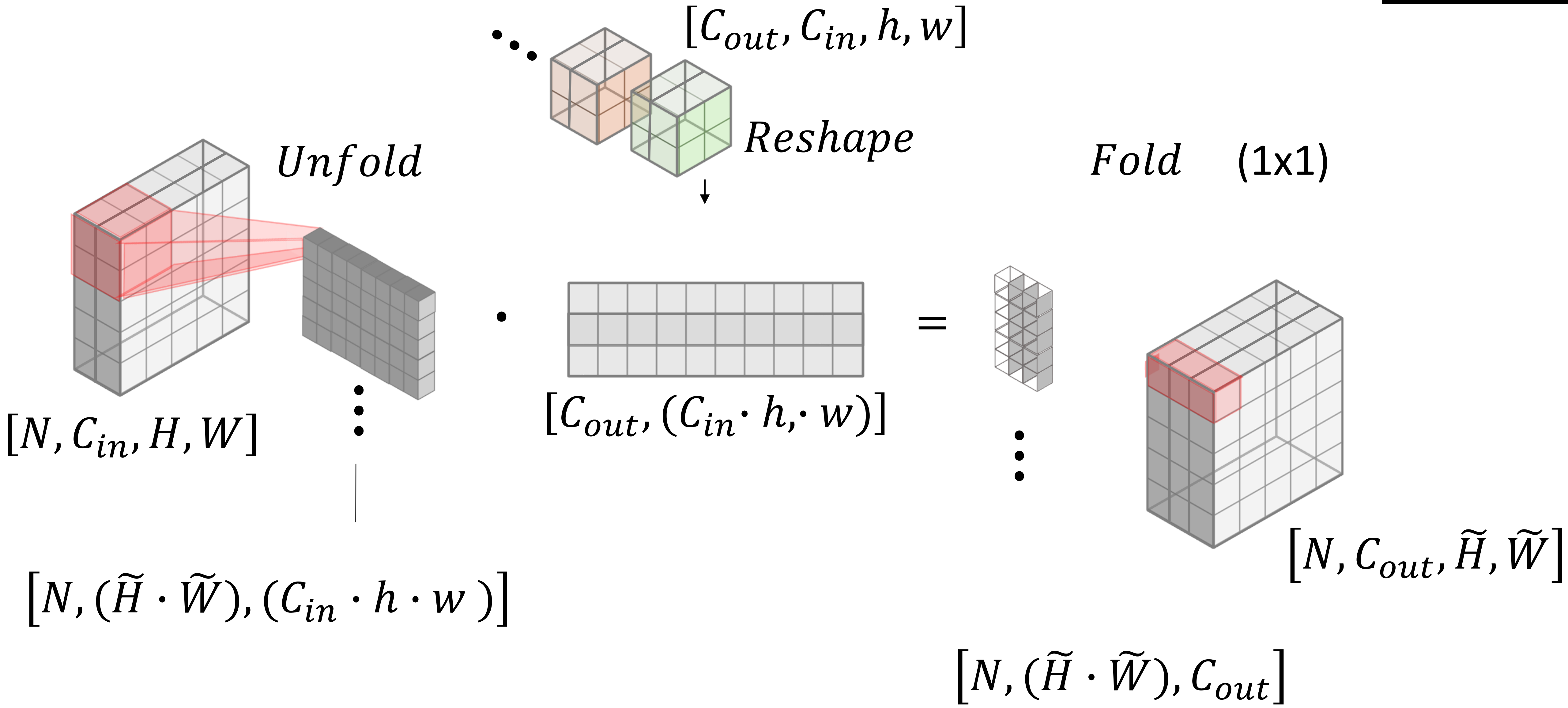
(Conv is a special case of linear)

Q: How about Conv2D?

For derivative of loss w.r.t all neurons:
1. Transpose dims of filter c_{in} , c_{out} (as in FC)
2. Transposed Conv2D with the modified filter!

(Think of a conv as a linear layer applied to each patch separately, going from c_{in} to c_{out})

A note about the implementation of conv - BACKWARD



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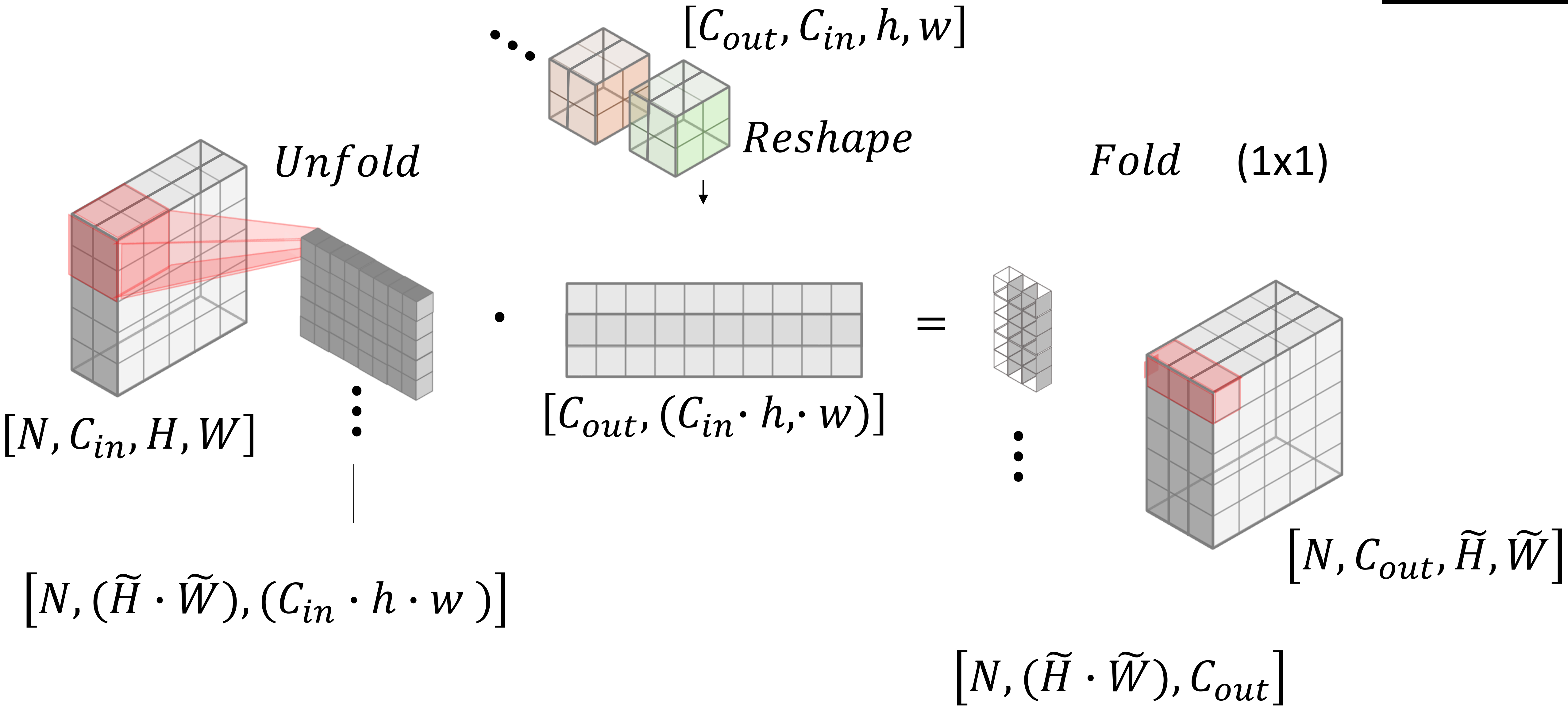

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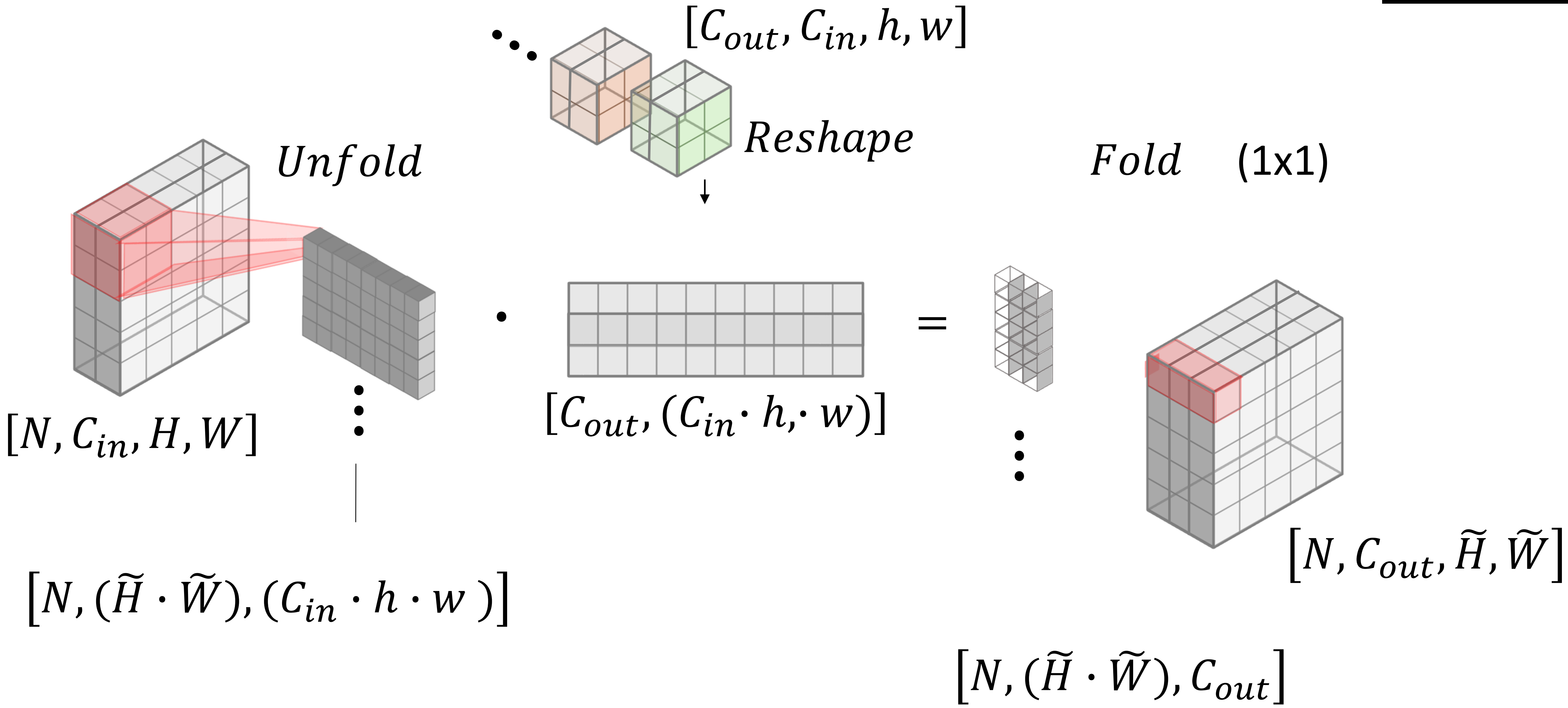

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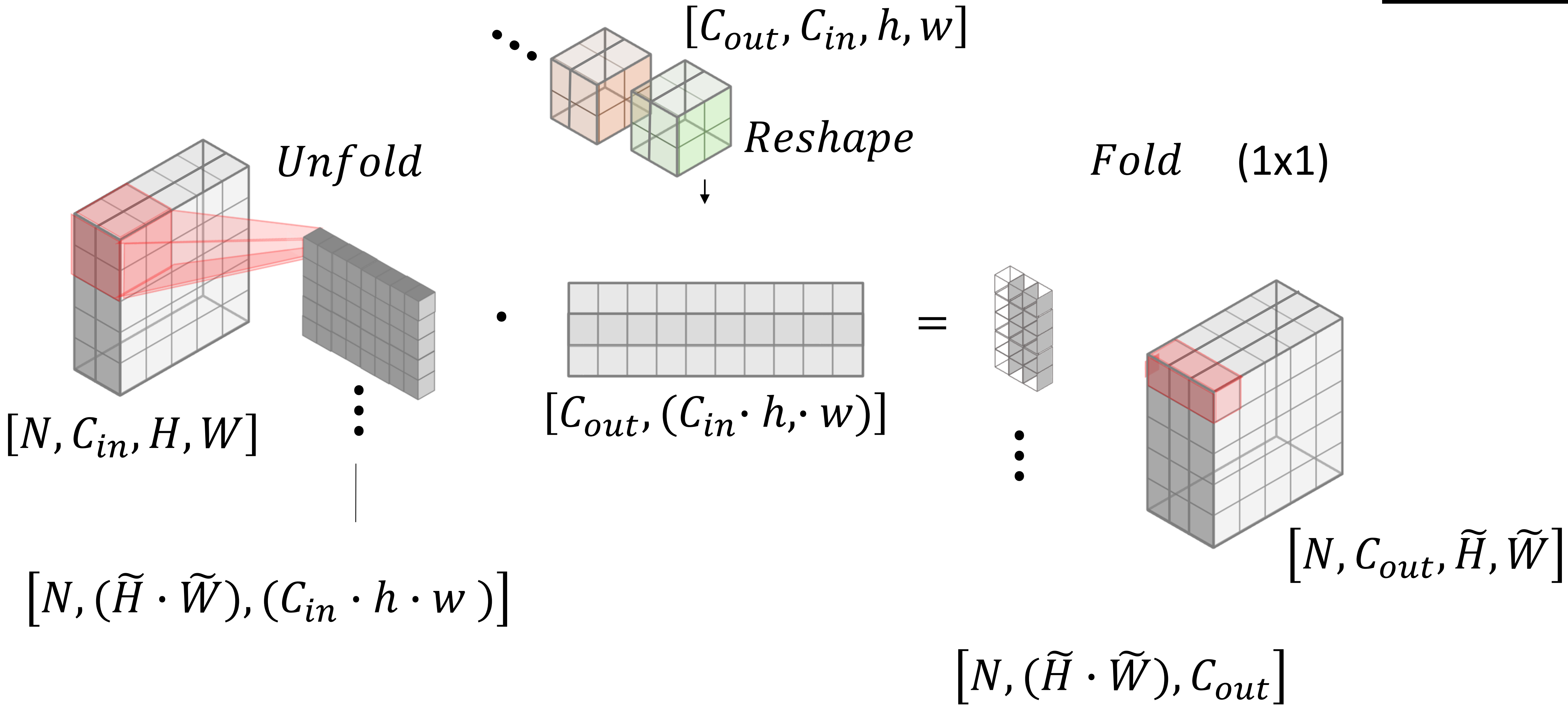

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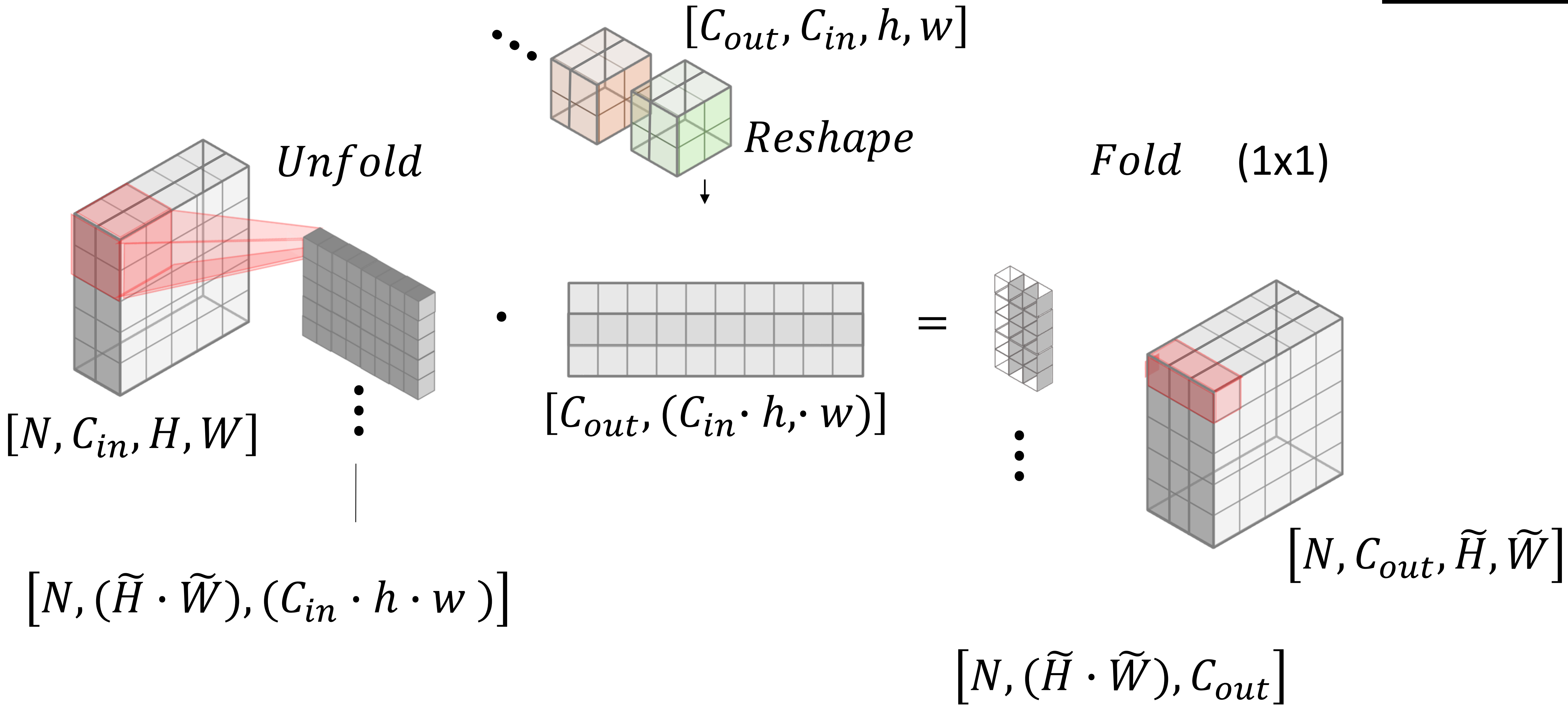

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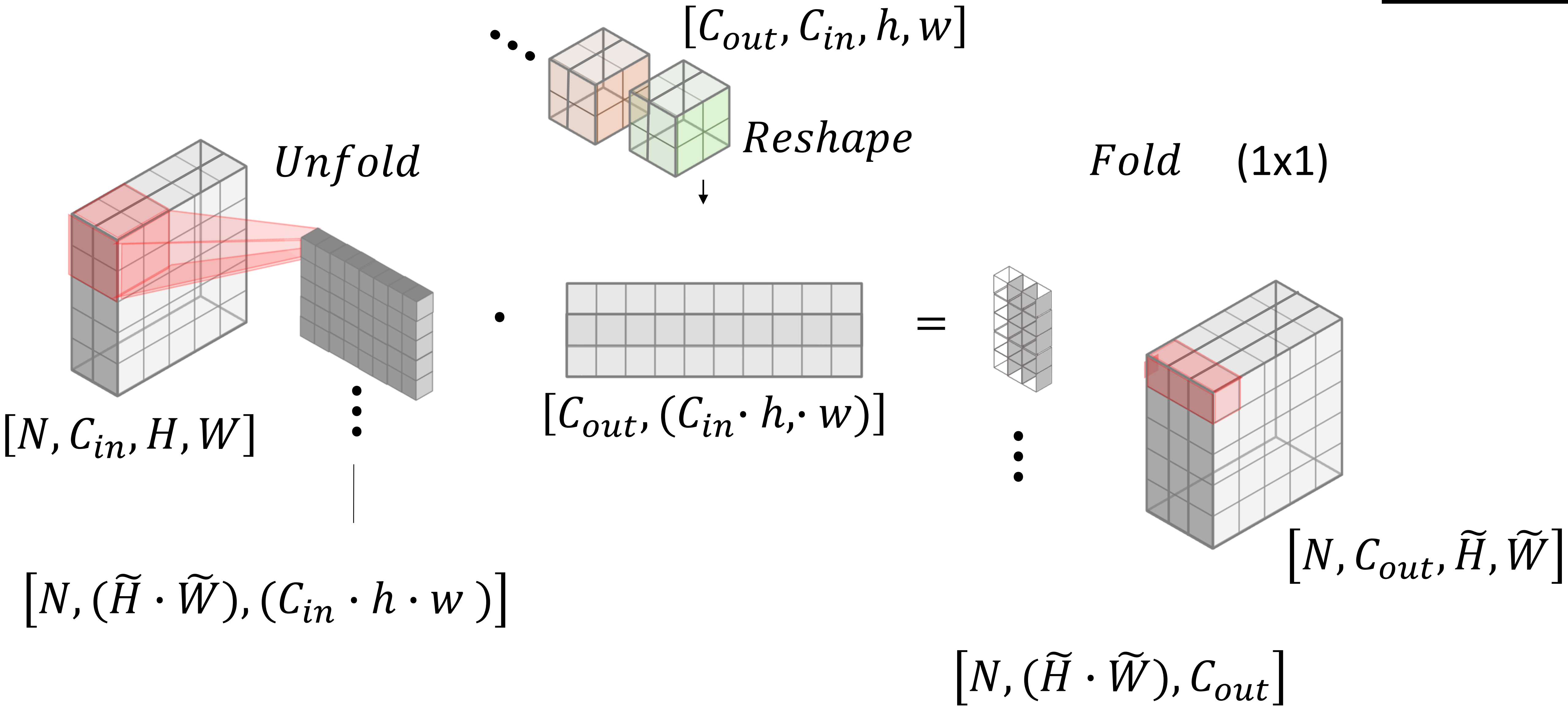

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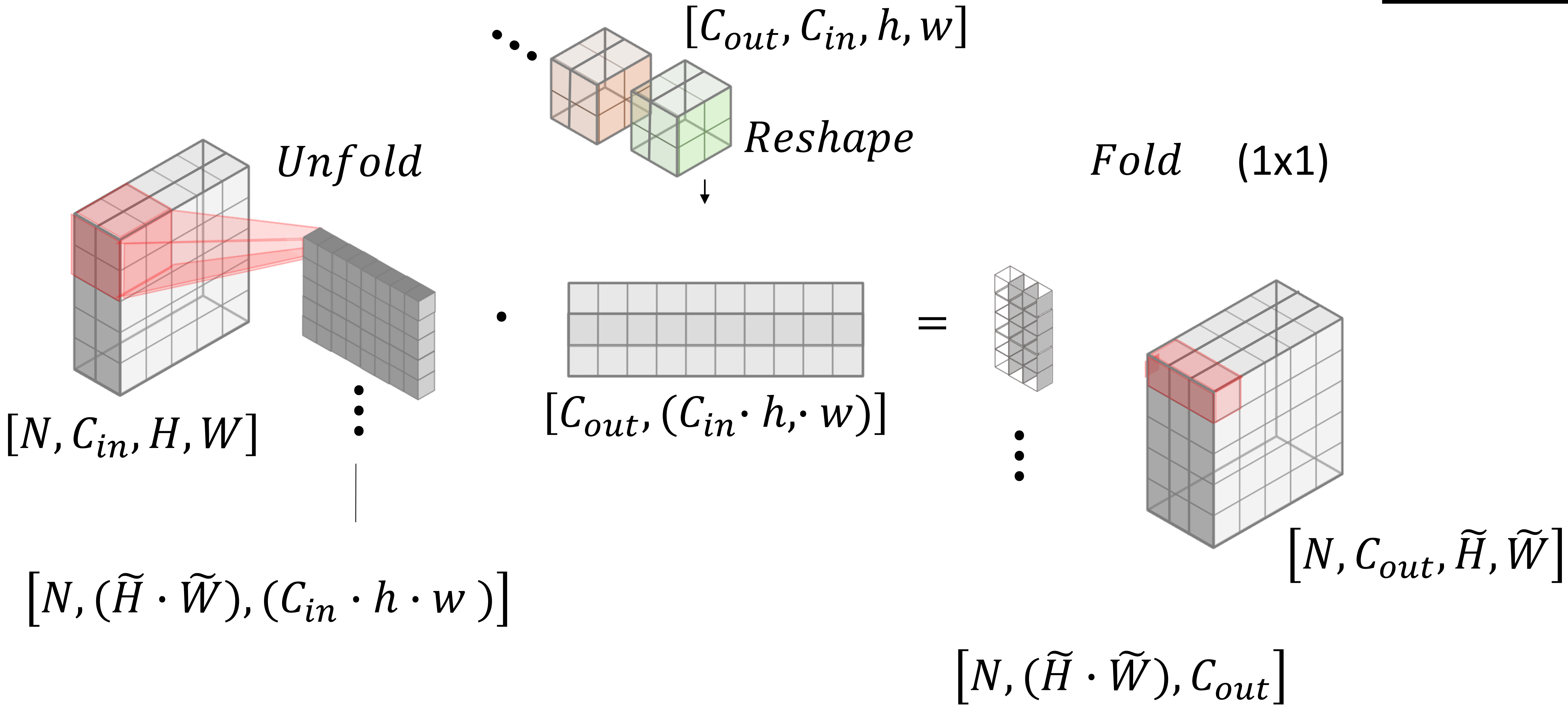

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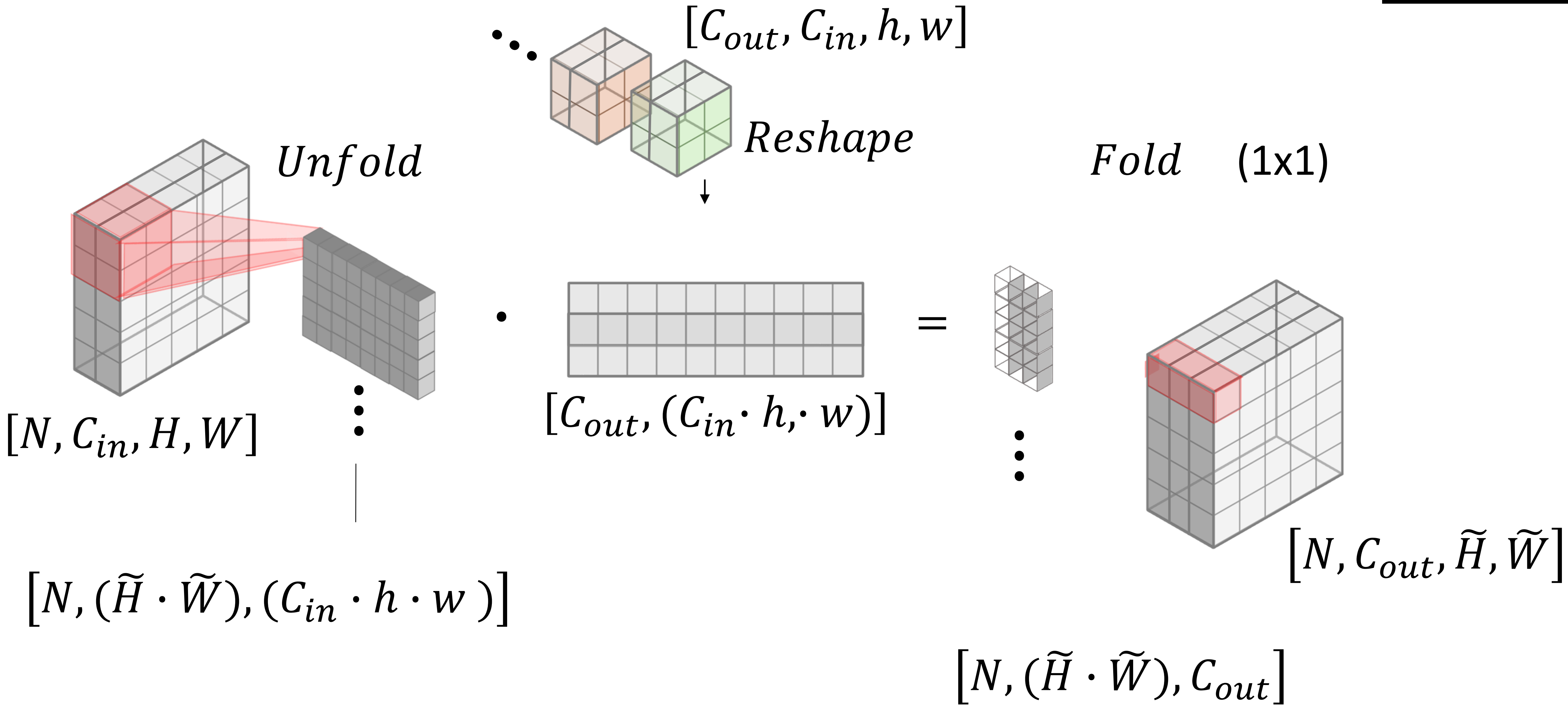

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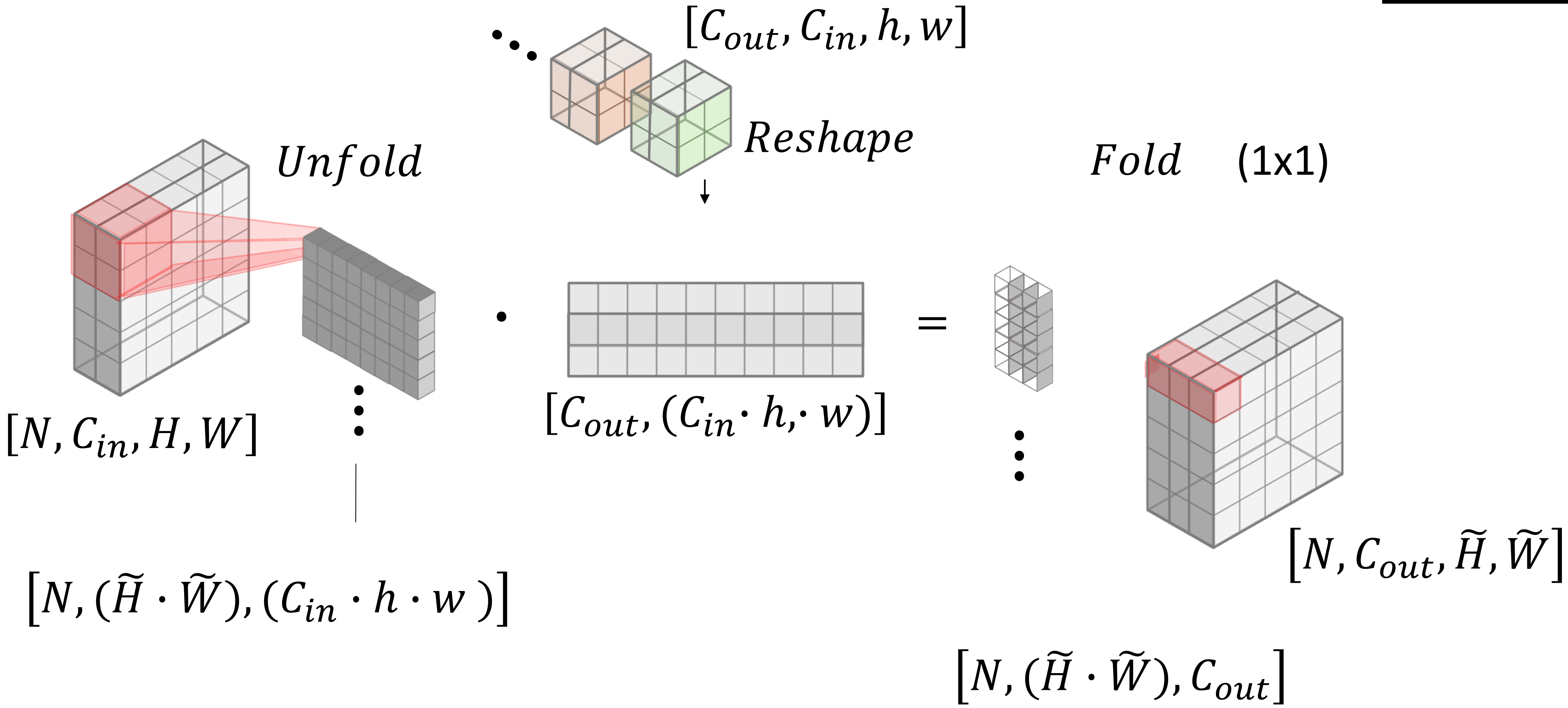

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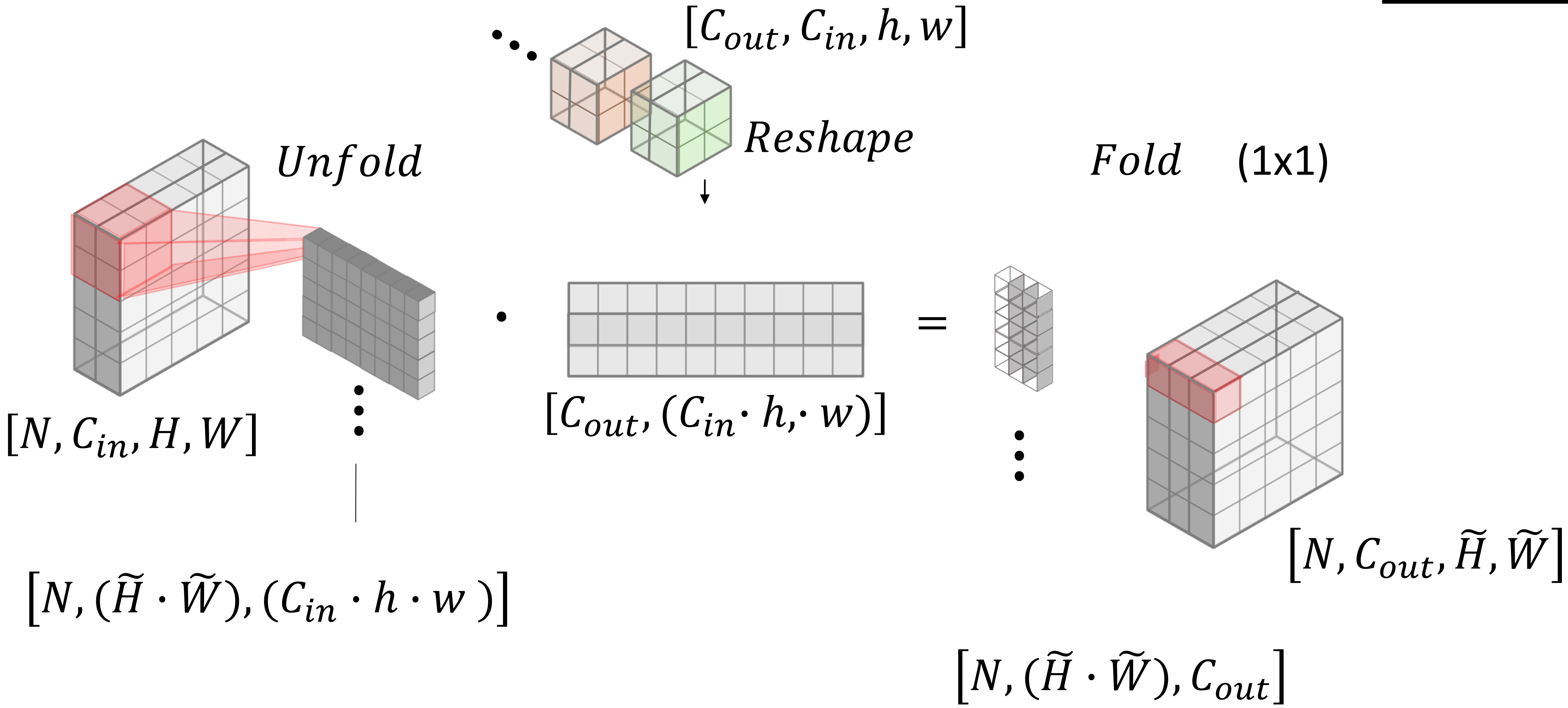

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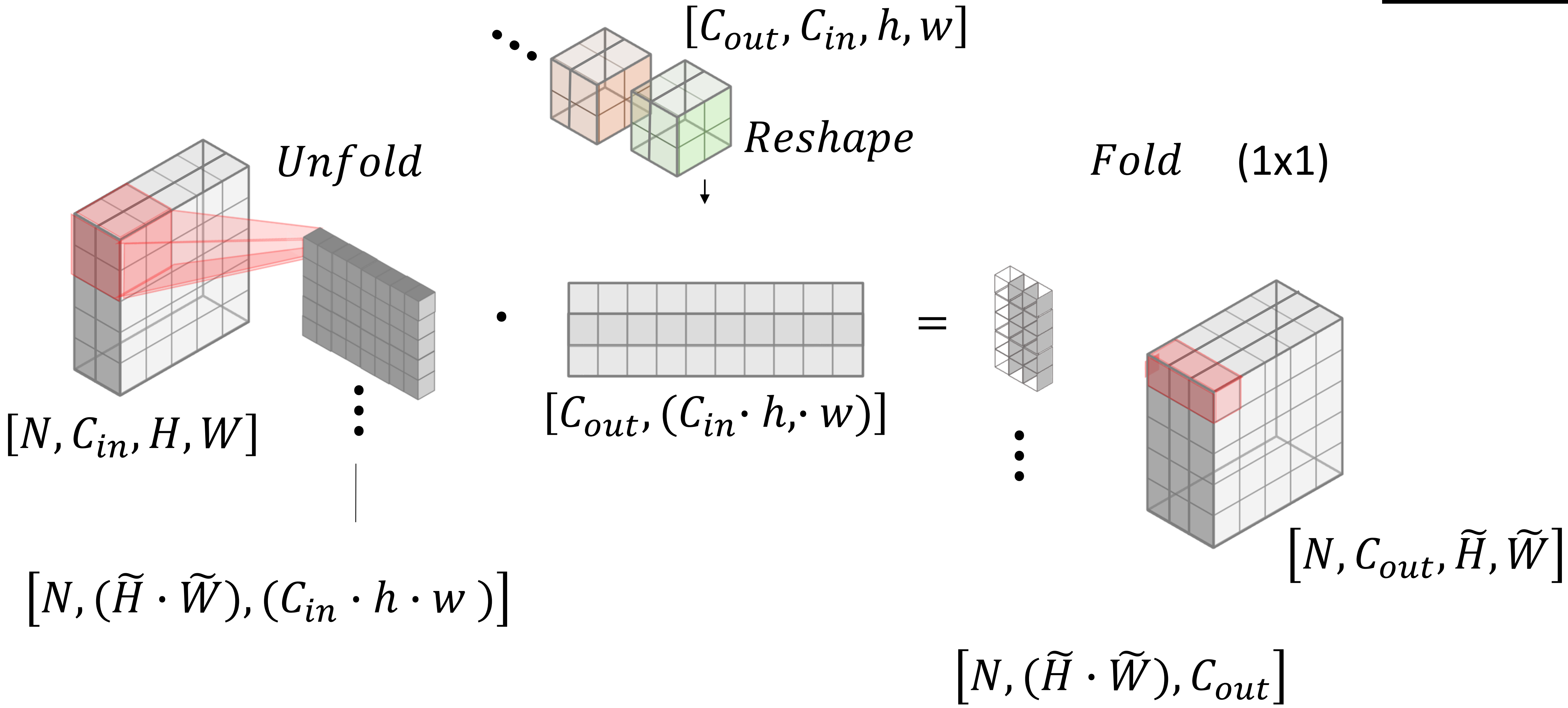

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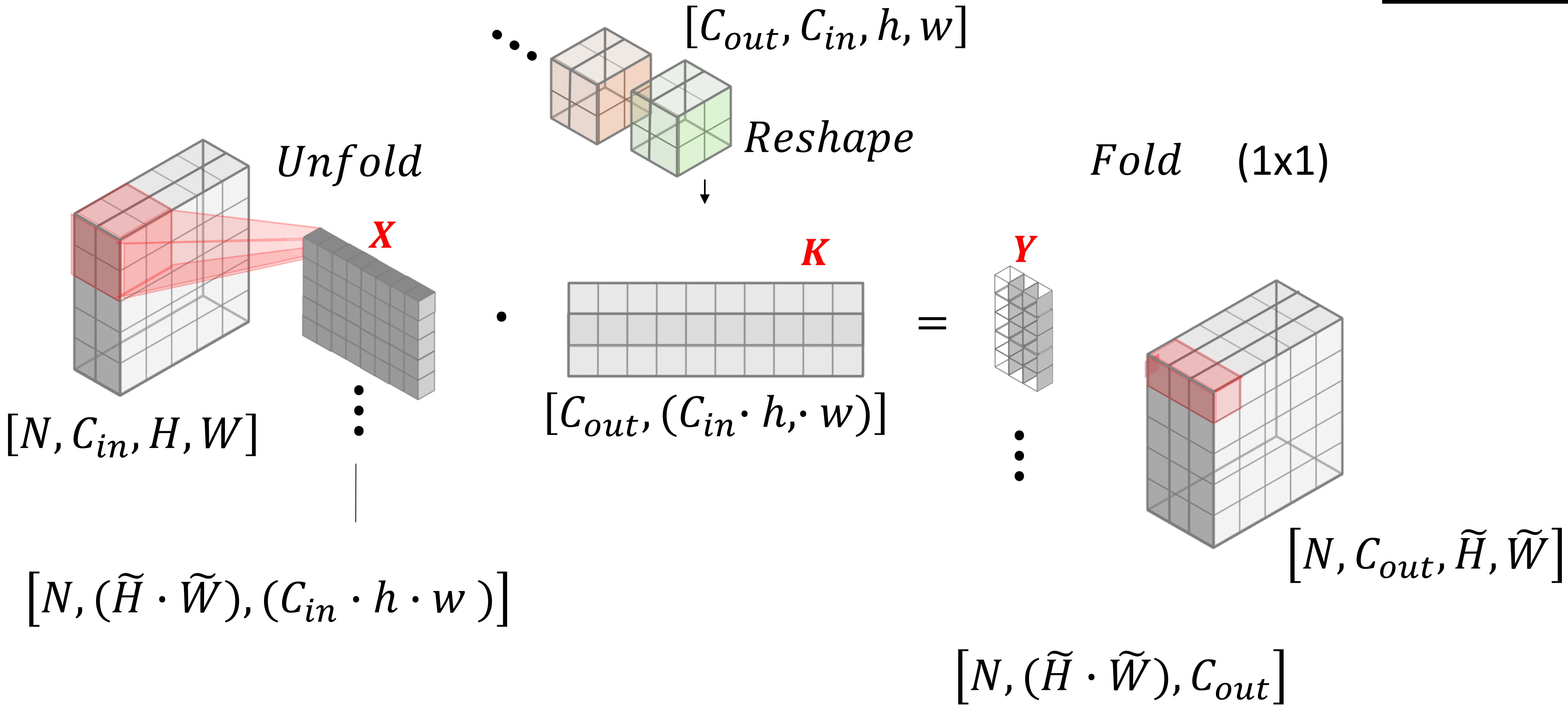
[redacted]



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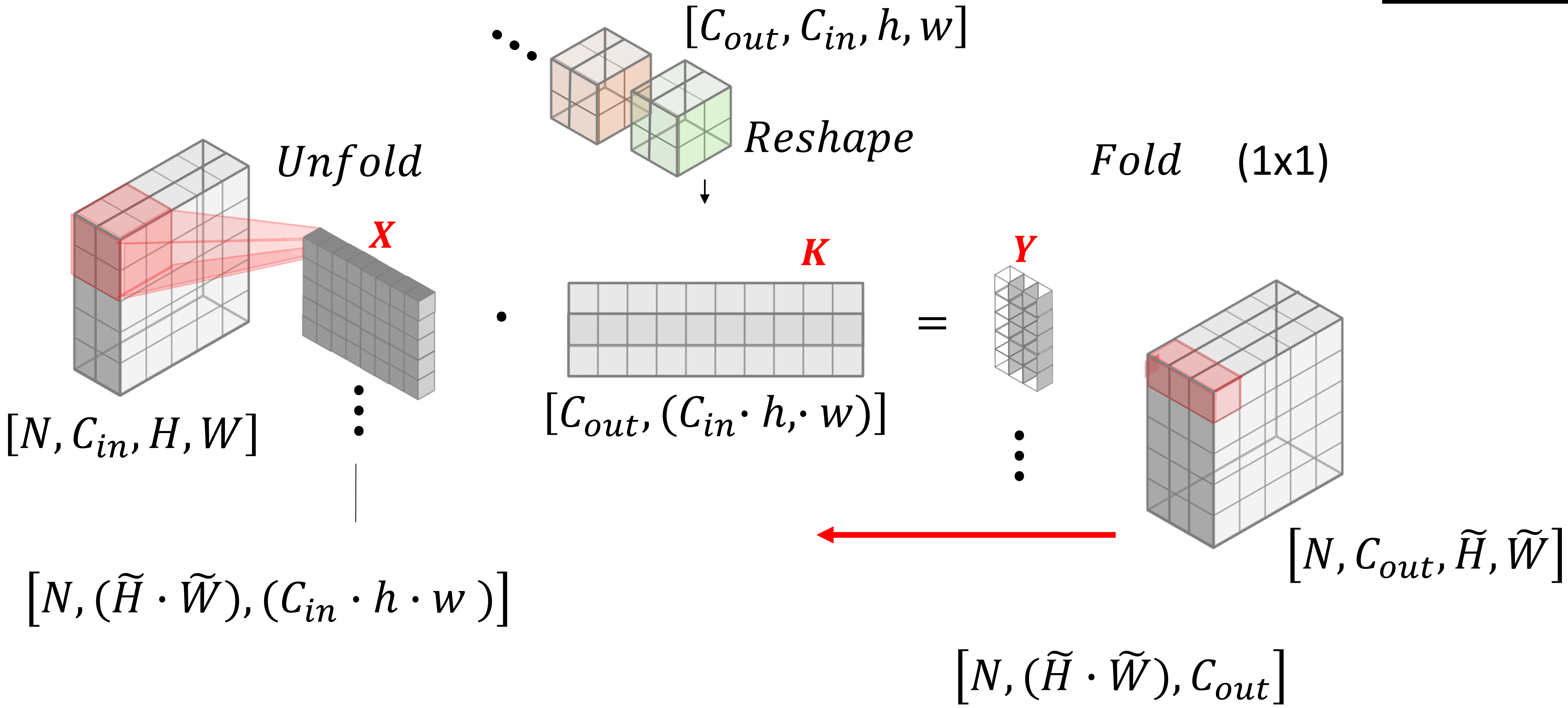

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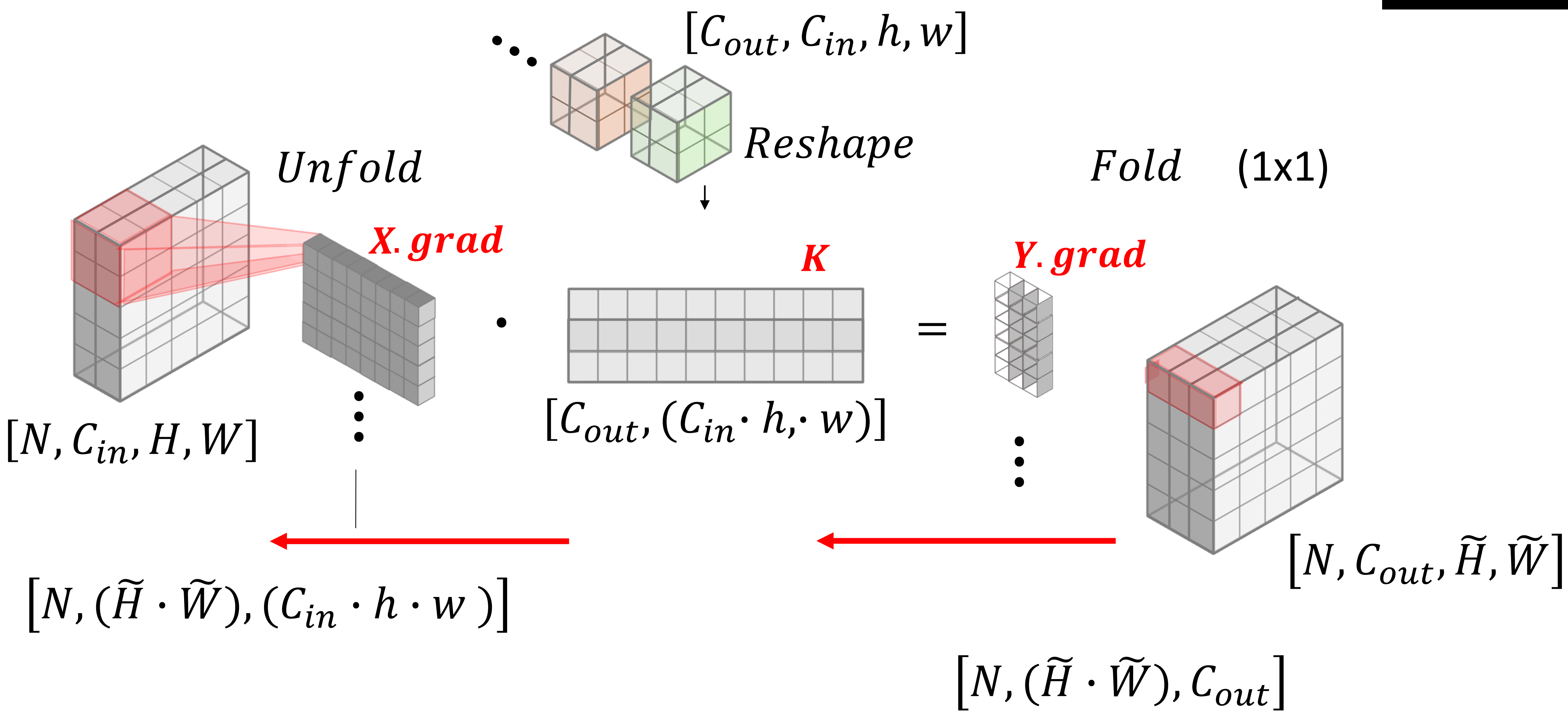

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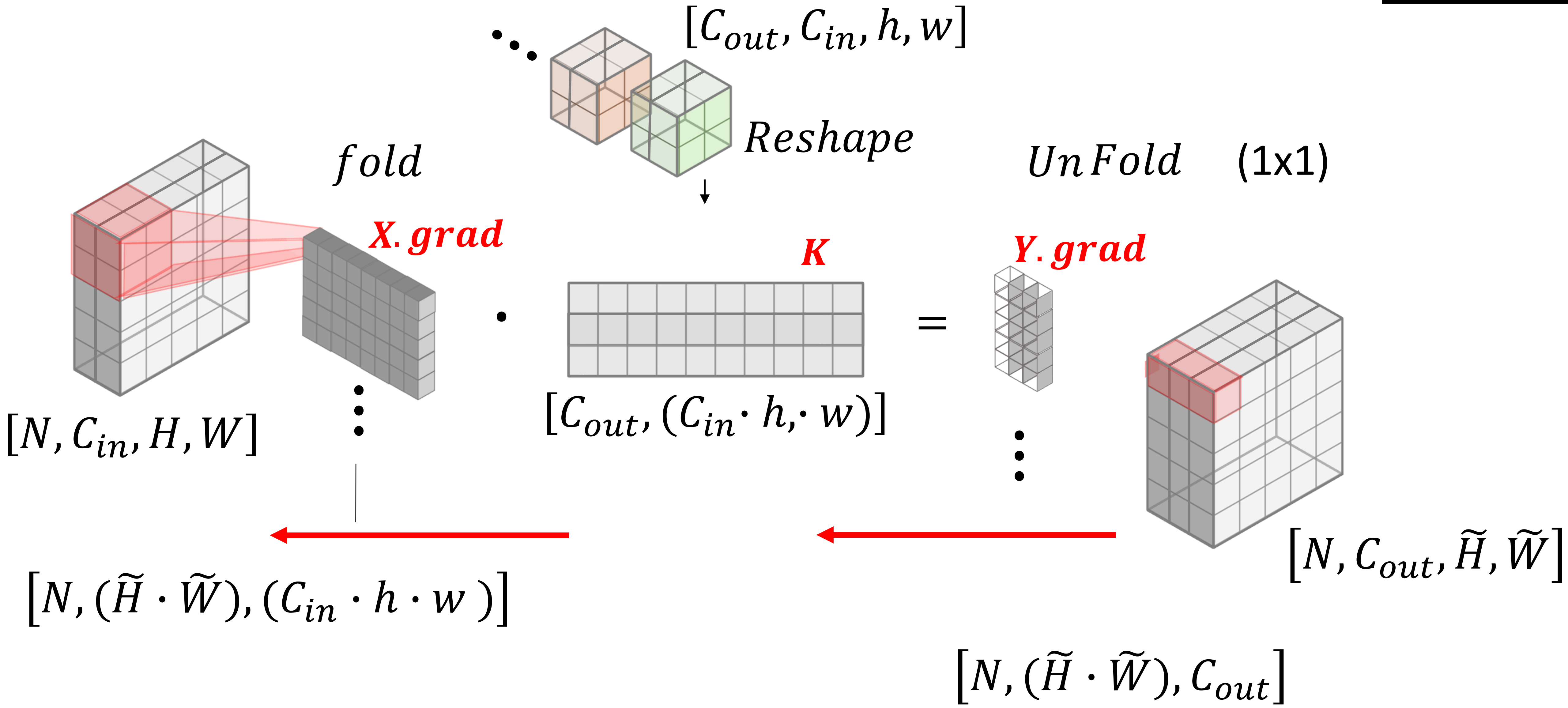

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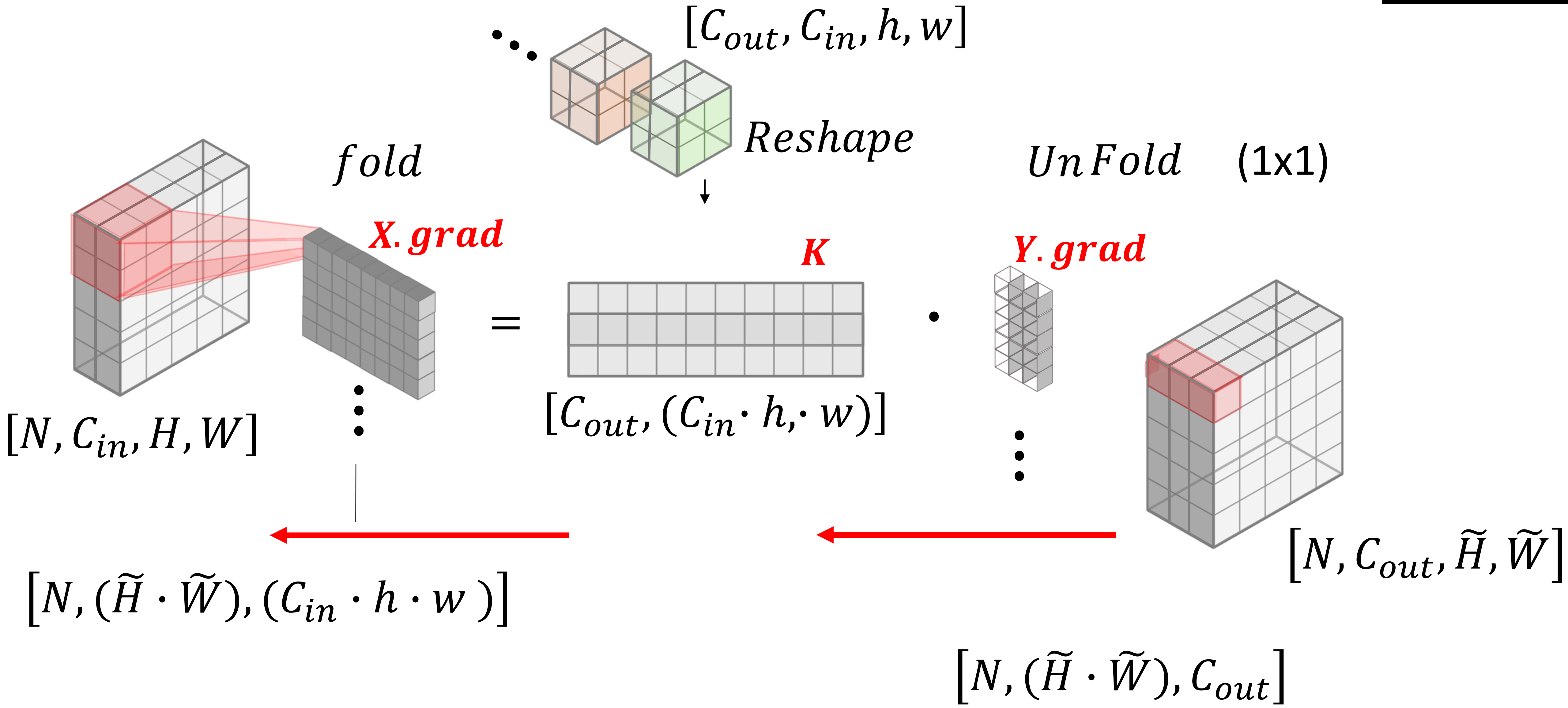

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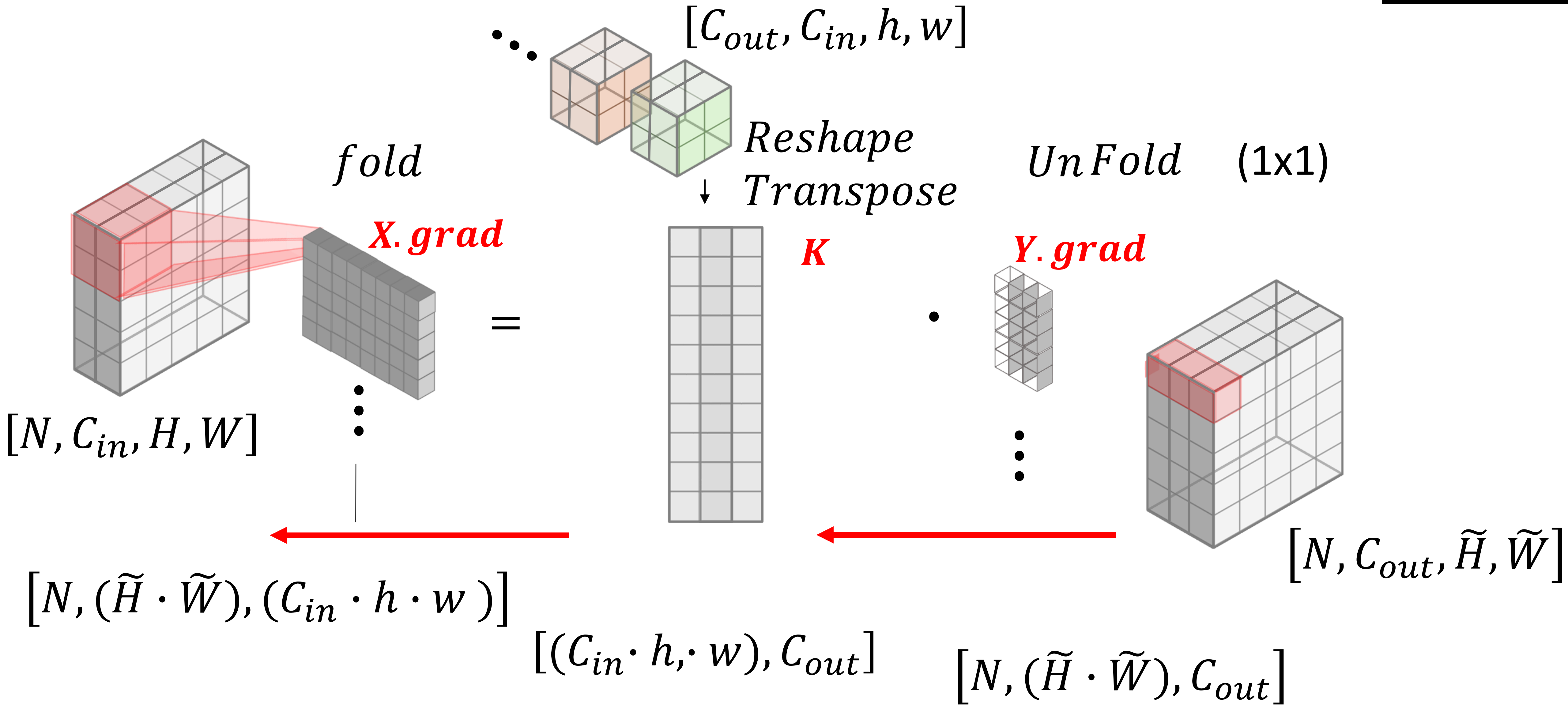

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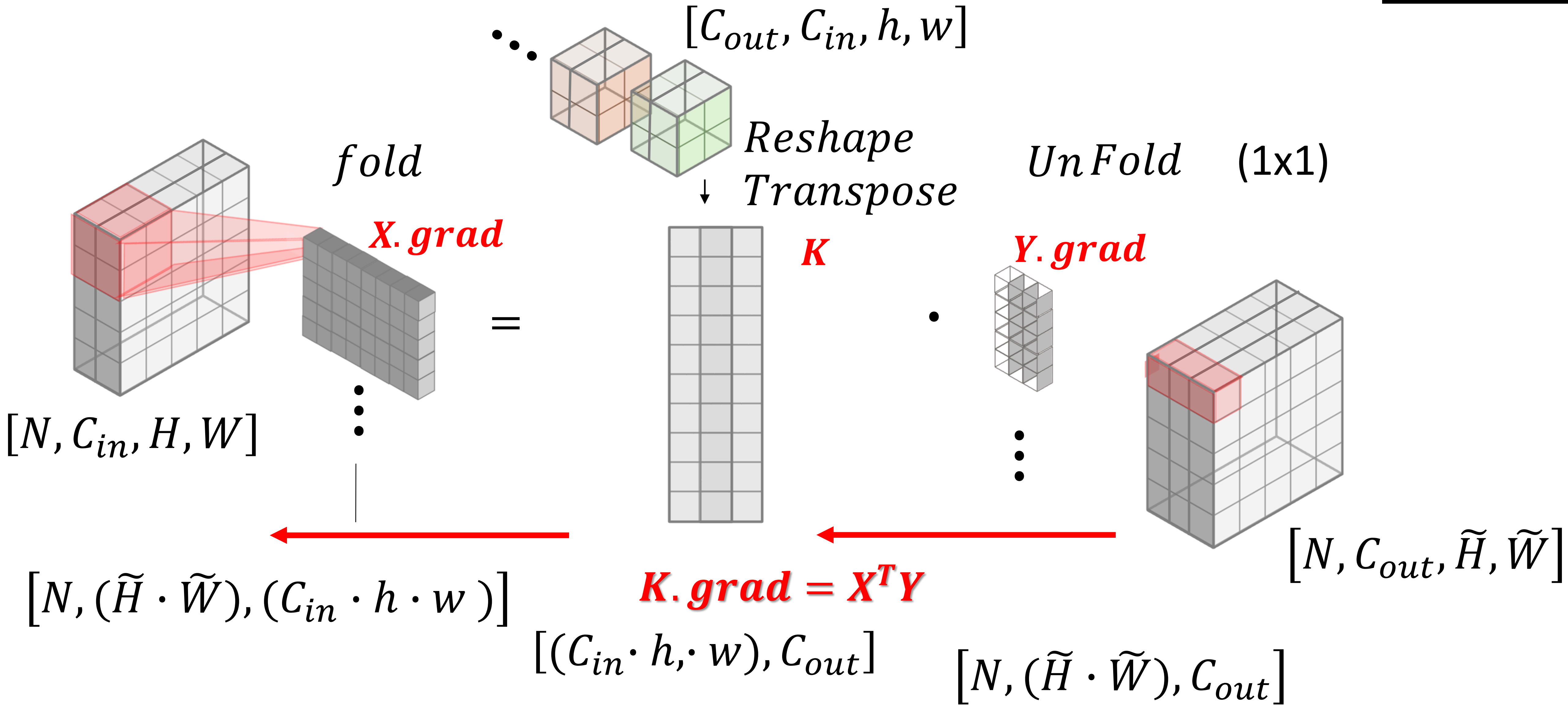

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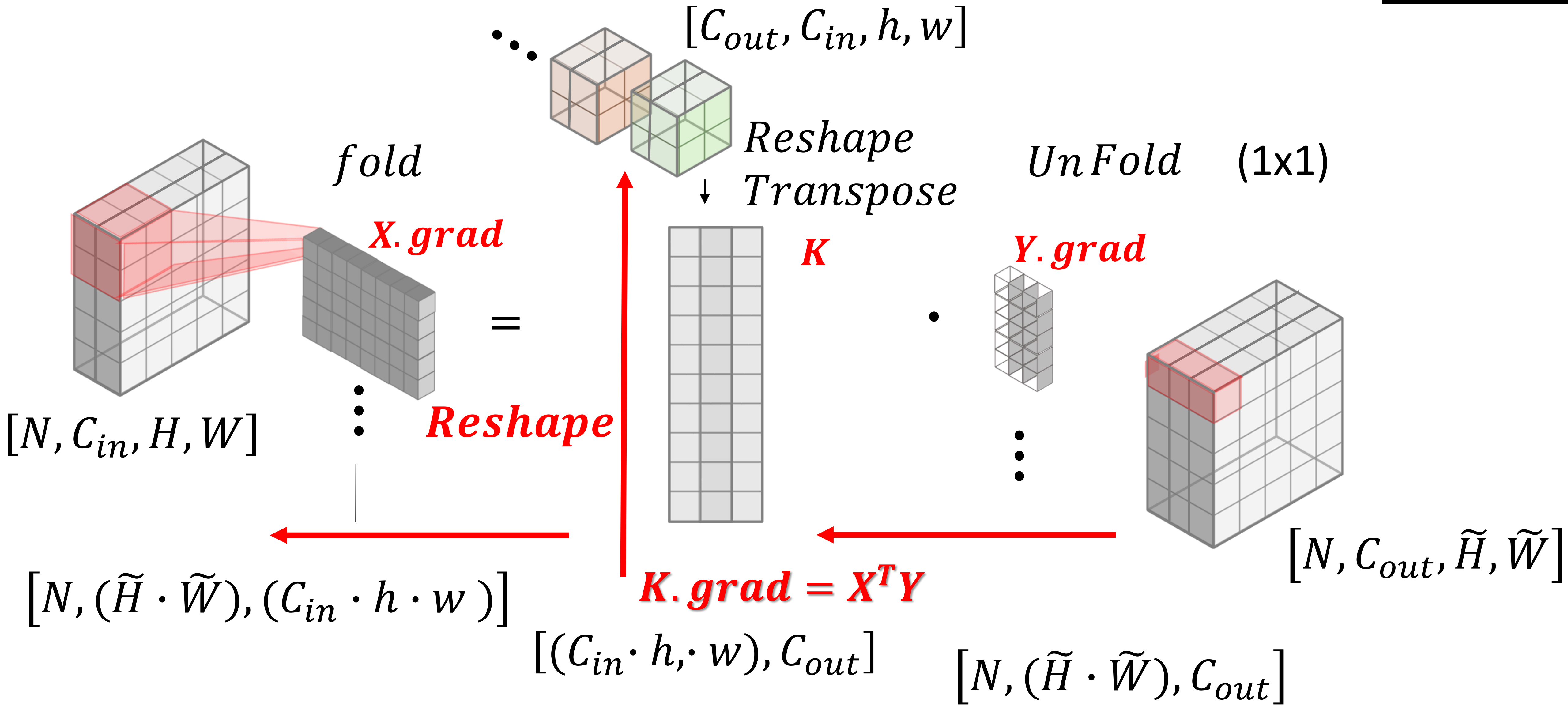
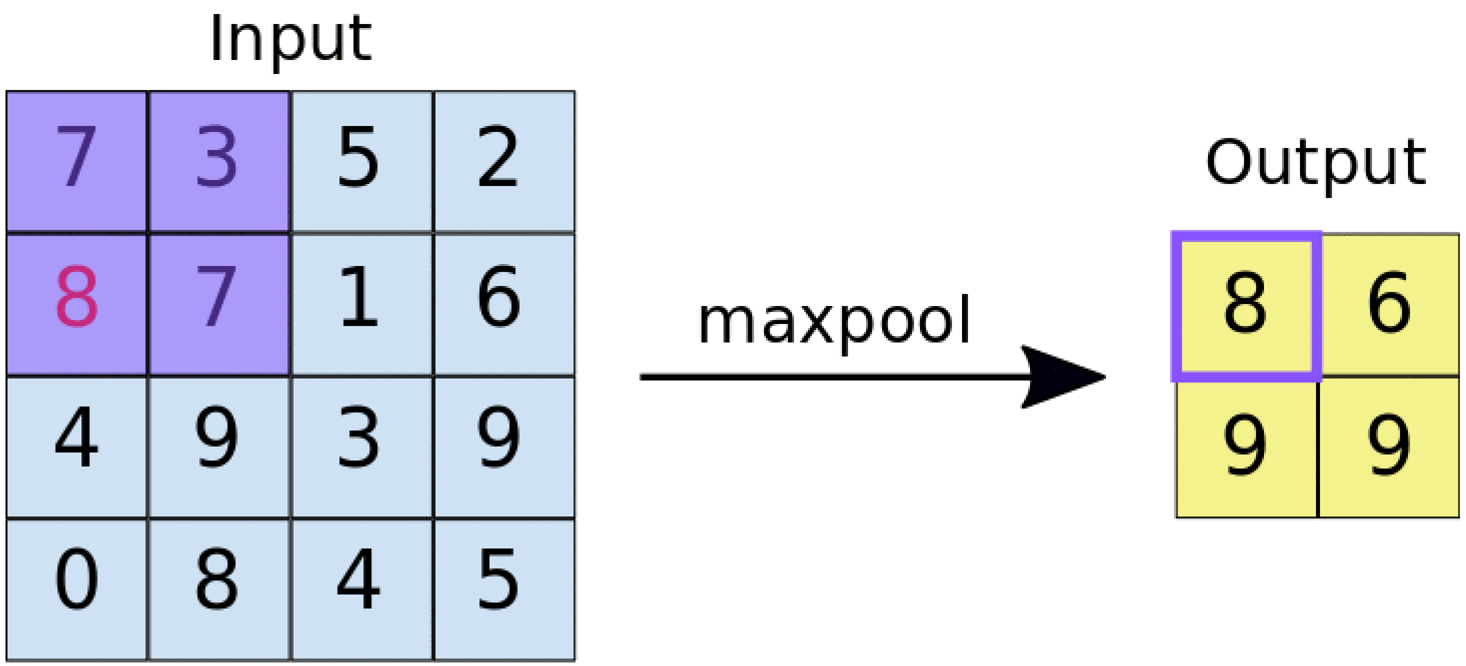


Max Pooling



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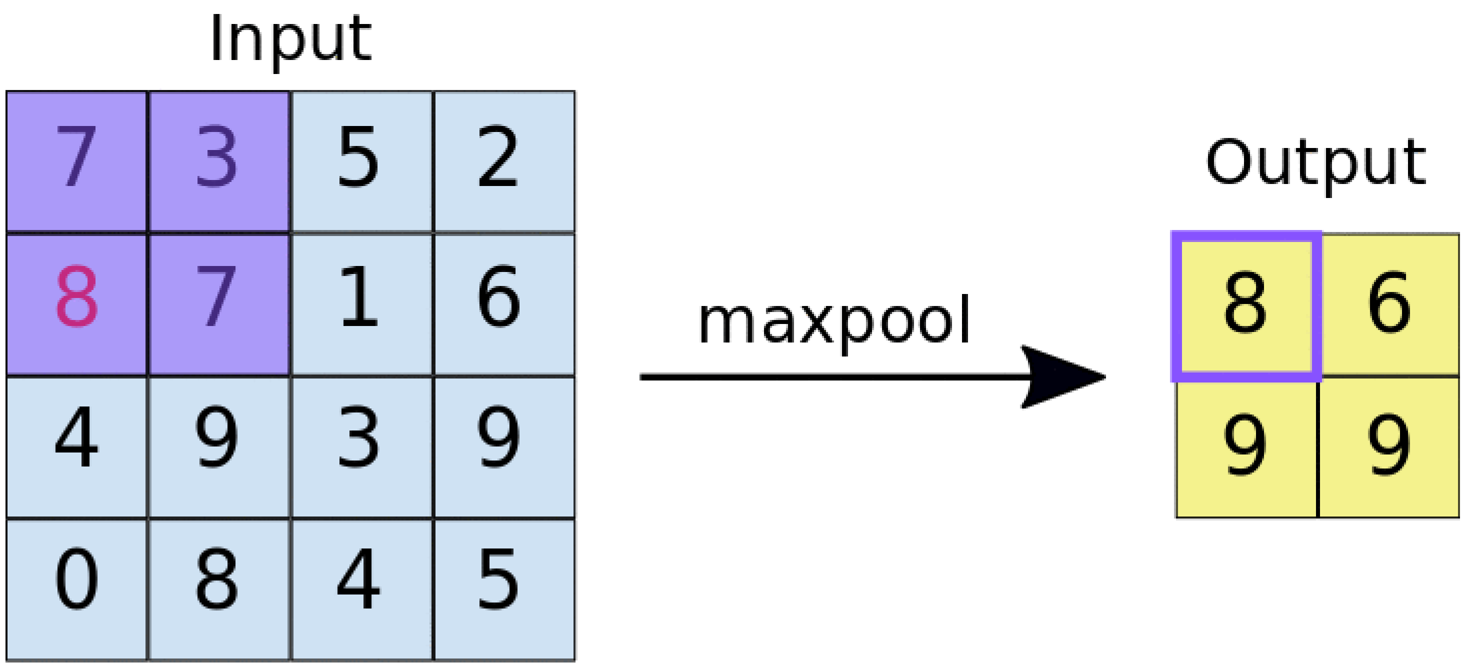
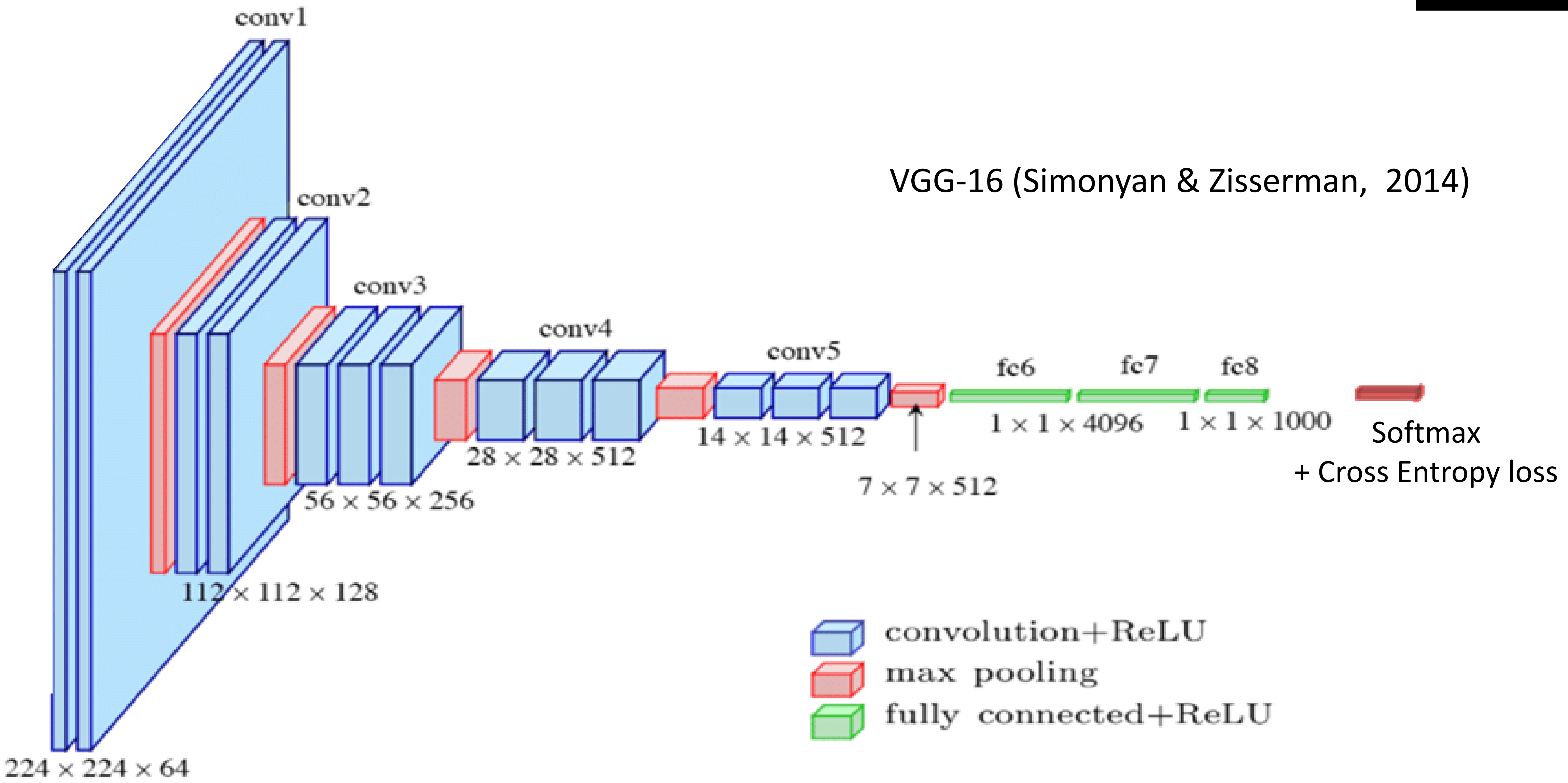


- Usually stride=win-size, but not always.
- Each channel separately.

ConvNet Example



VGG-16 (Simonyan & Zisserman, 2014)

More special Convs!

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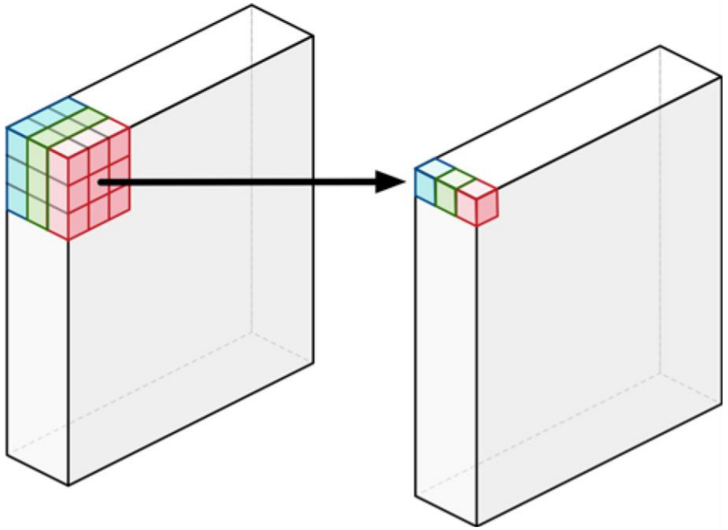
Depthwise Conv



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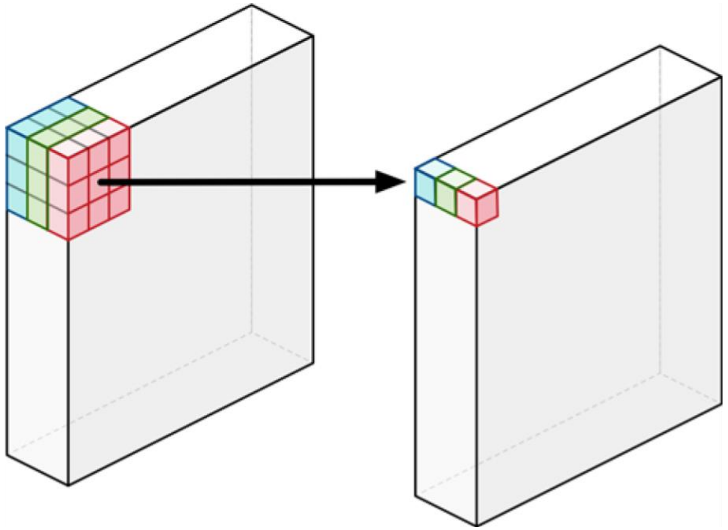
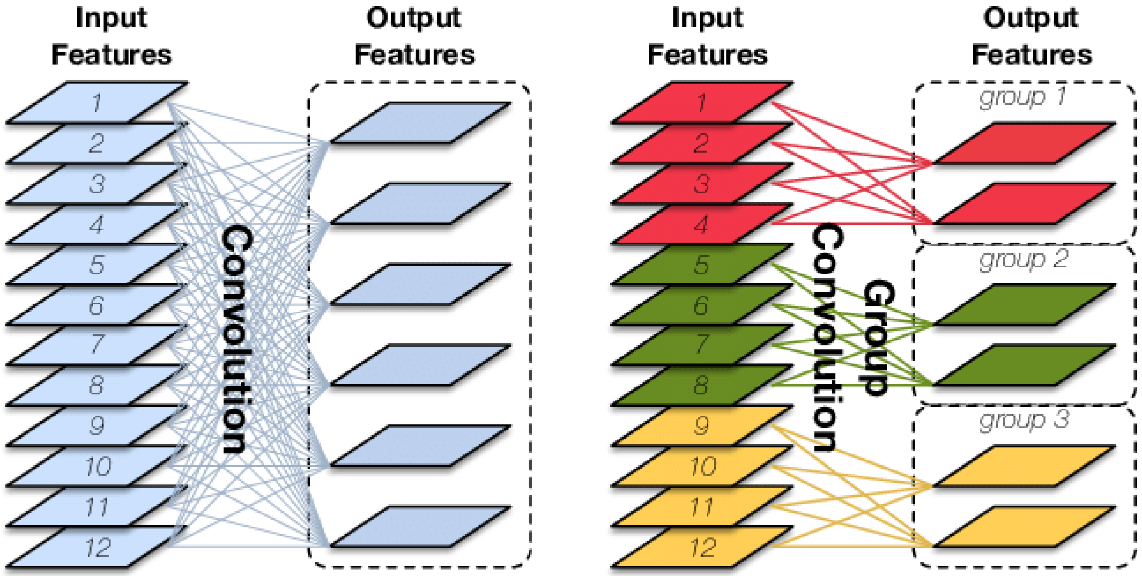


Group Conv (Krihzevsky 2012)



More special Convs!

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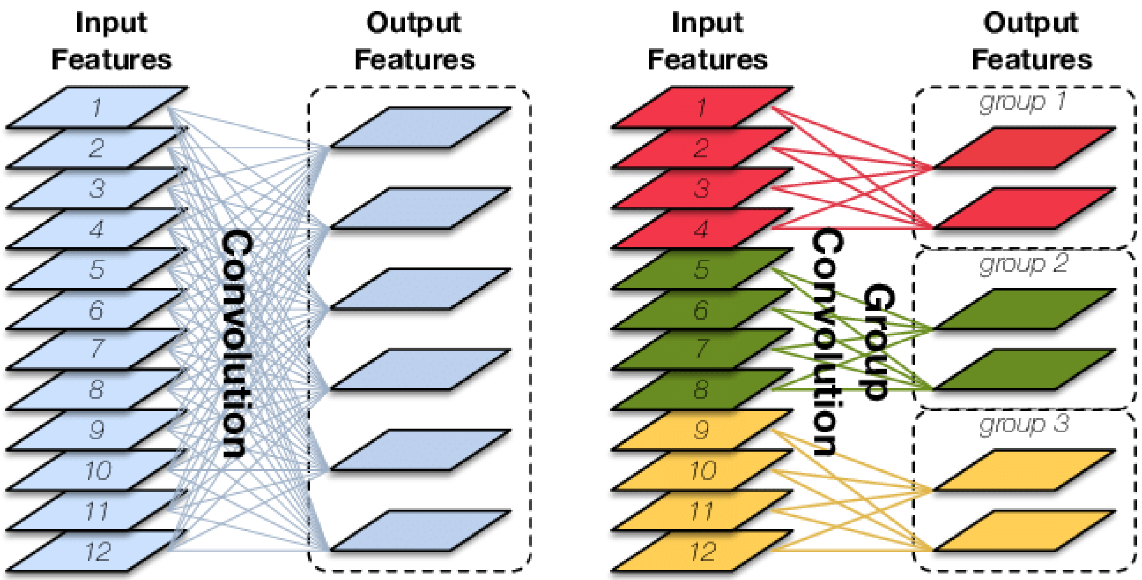

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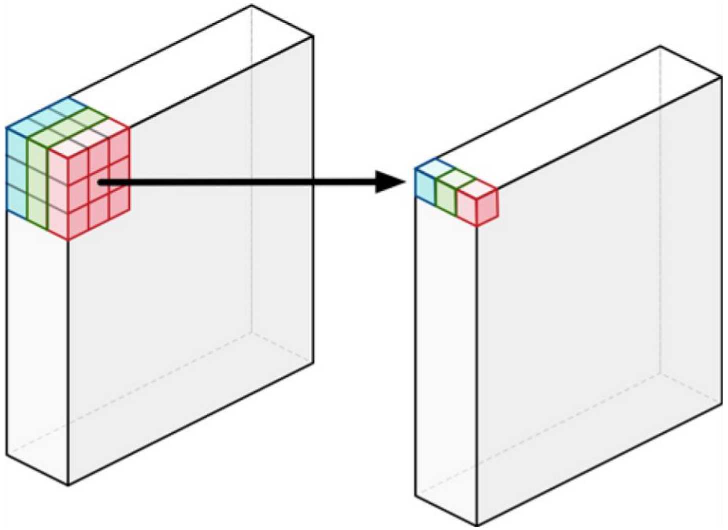
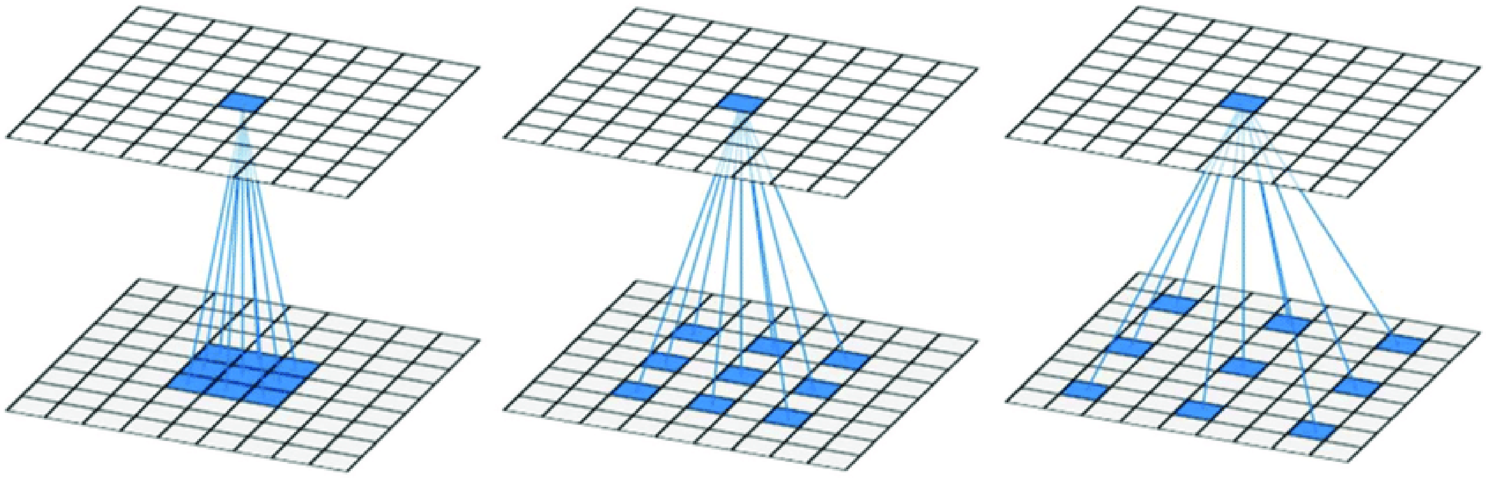


Dilated Conv (Yu&Koltun 2016)



dilation=1 dilation=2 dilation=3

No Tutorial this week! (sigd)

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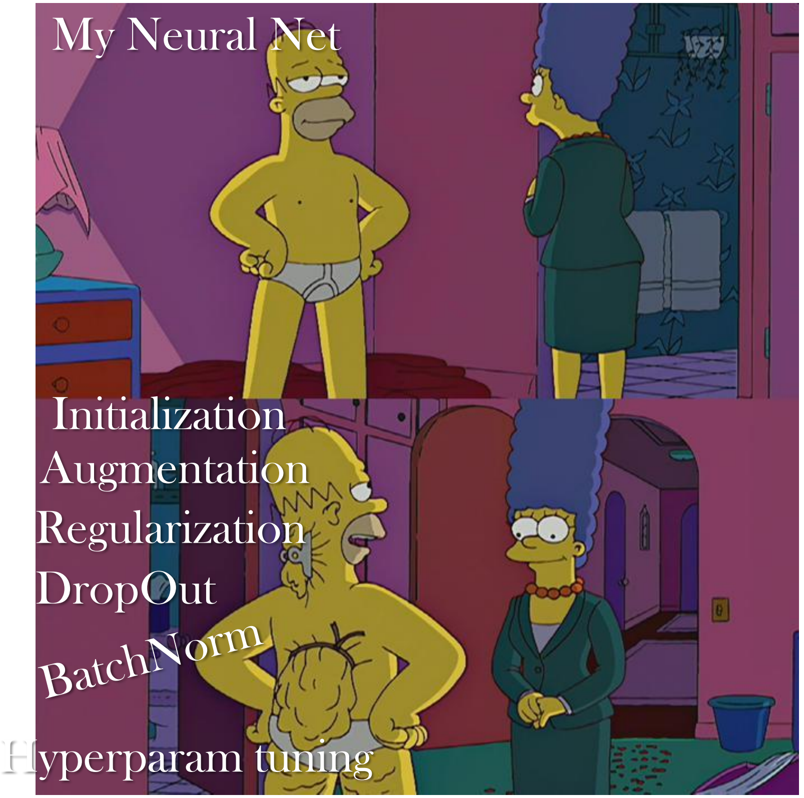
Next week's lecture:

Shai Bagon

Practical Training



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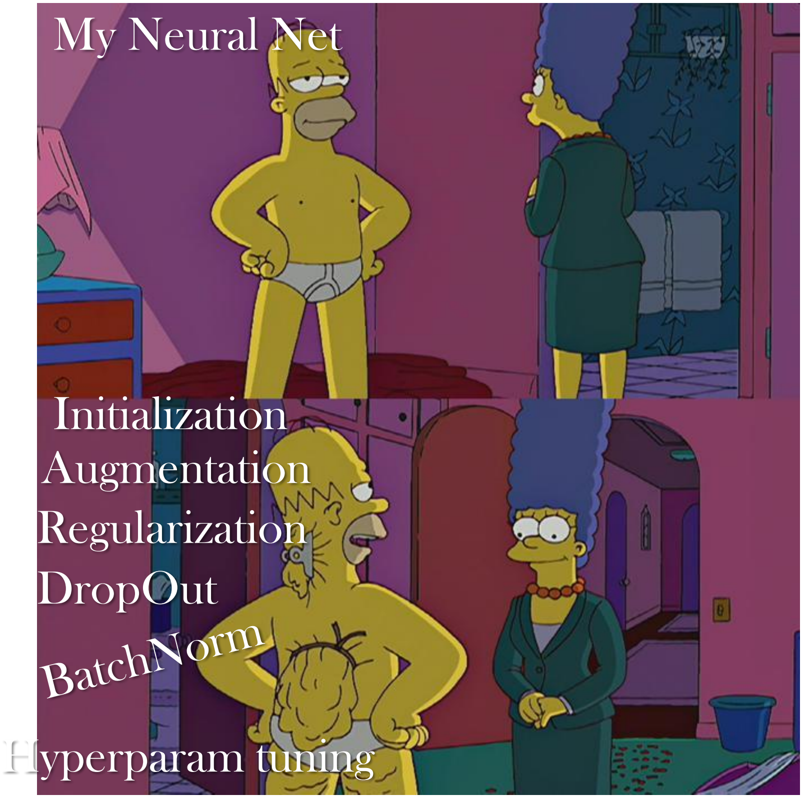

Dror Moran

Next week's tutorial:
CNN Architectures