

# Learning for vision III

## Convolutional networks

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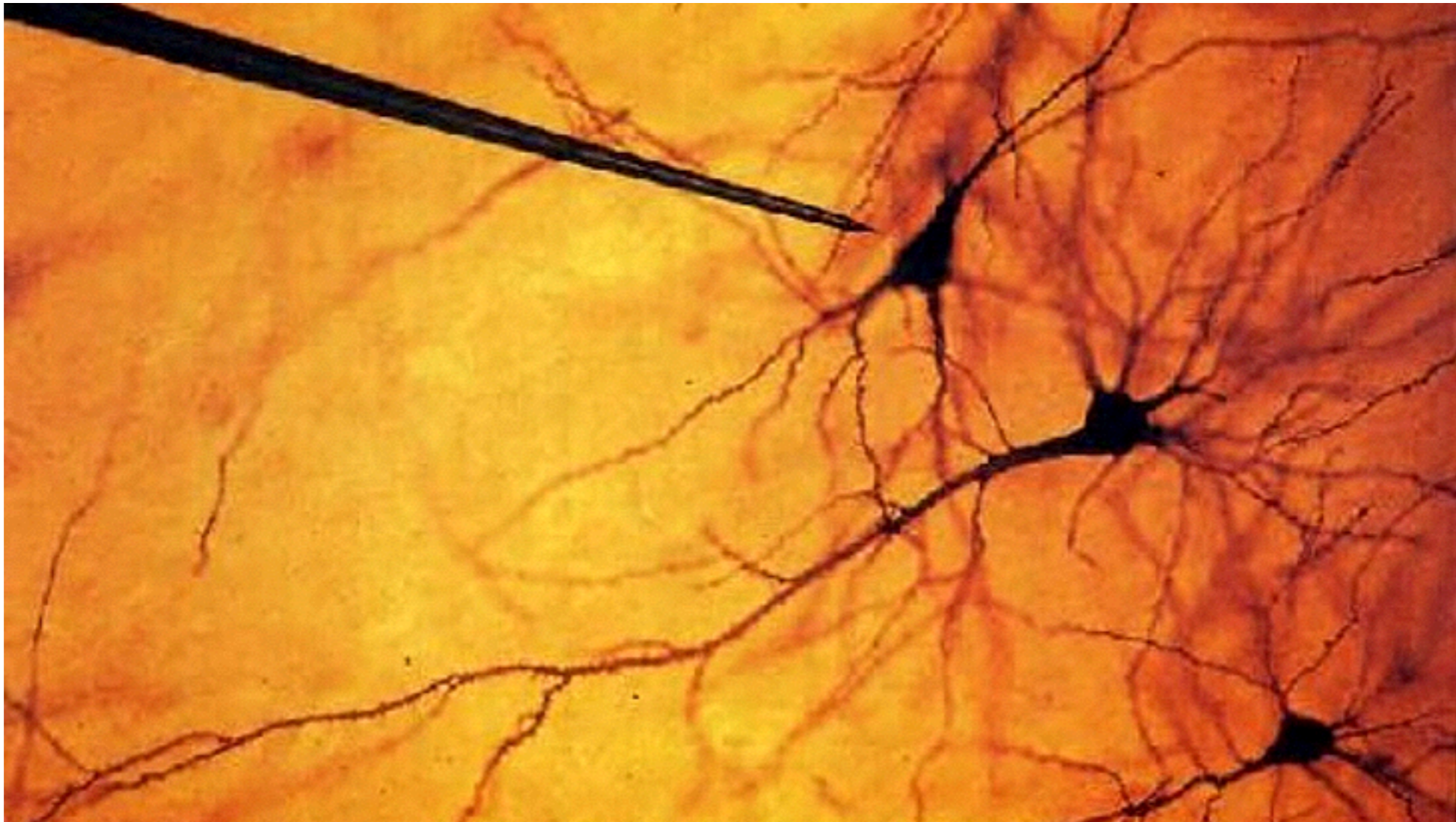


# Outline

- Avoid overfitting by search for the NN model suitable for image processing [Hubel and Wiesel 1960].
- Feedforward and Backprop in ConvNets.



# The Tungsten Electrode [Hubel-Science-1957]



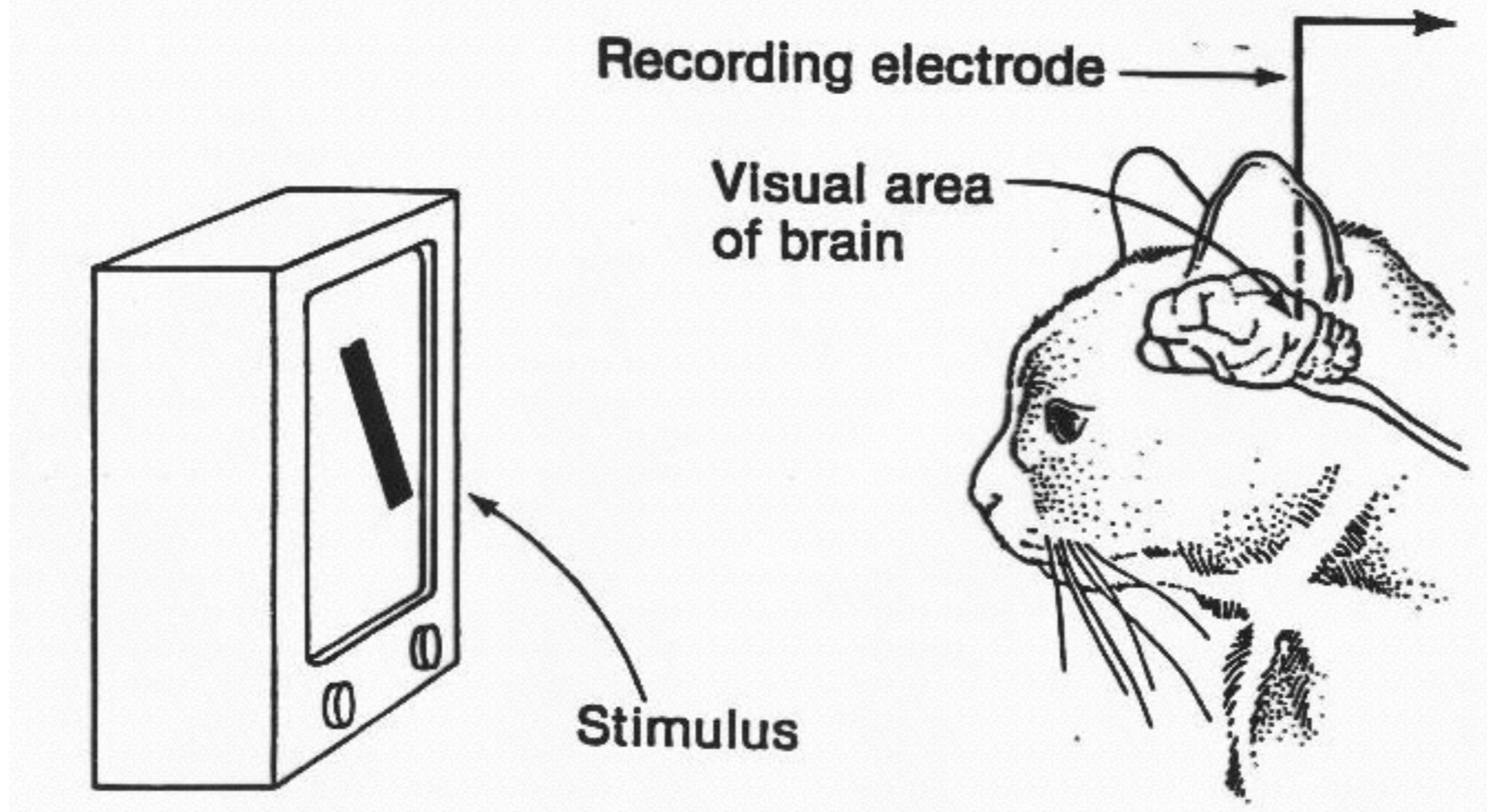
<http://braintour.harvard.edu/archives/portfolio-items/hubel-and-wiesel>

- Device capable to record signal from a single neuron



[Hubel and Wiesel 1959]

Electrical signal  
from brain



- Experiment with anaesthetised paralysed cat
- Recording of electrical signal reveals:
  1. Nearby neurons process information from nearby visual fields (topographical map).
  2. Neurons with similar function organized into columns
  3. Neurons are sensitive to edges and its orientation



[Hubel and Wiesel 1960]



<https://knowingneurons.com/2014/10/29/hubel-and-wiesel-the-neural-basis-of-visual-perception/>

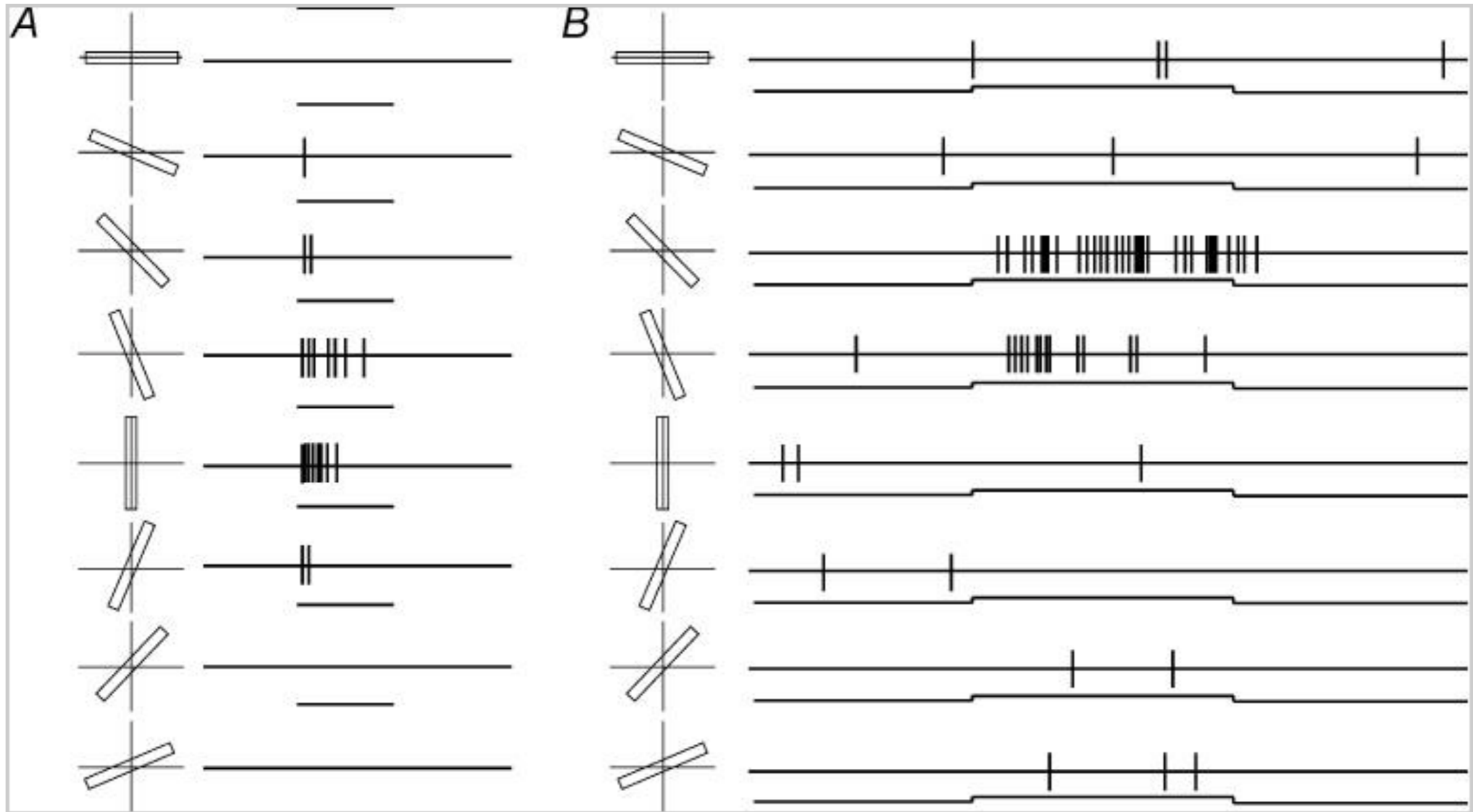


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[Hubel and Wiesel 1960]

paralysed cat

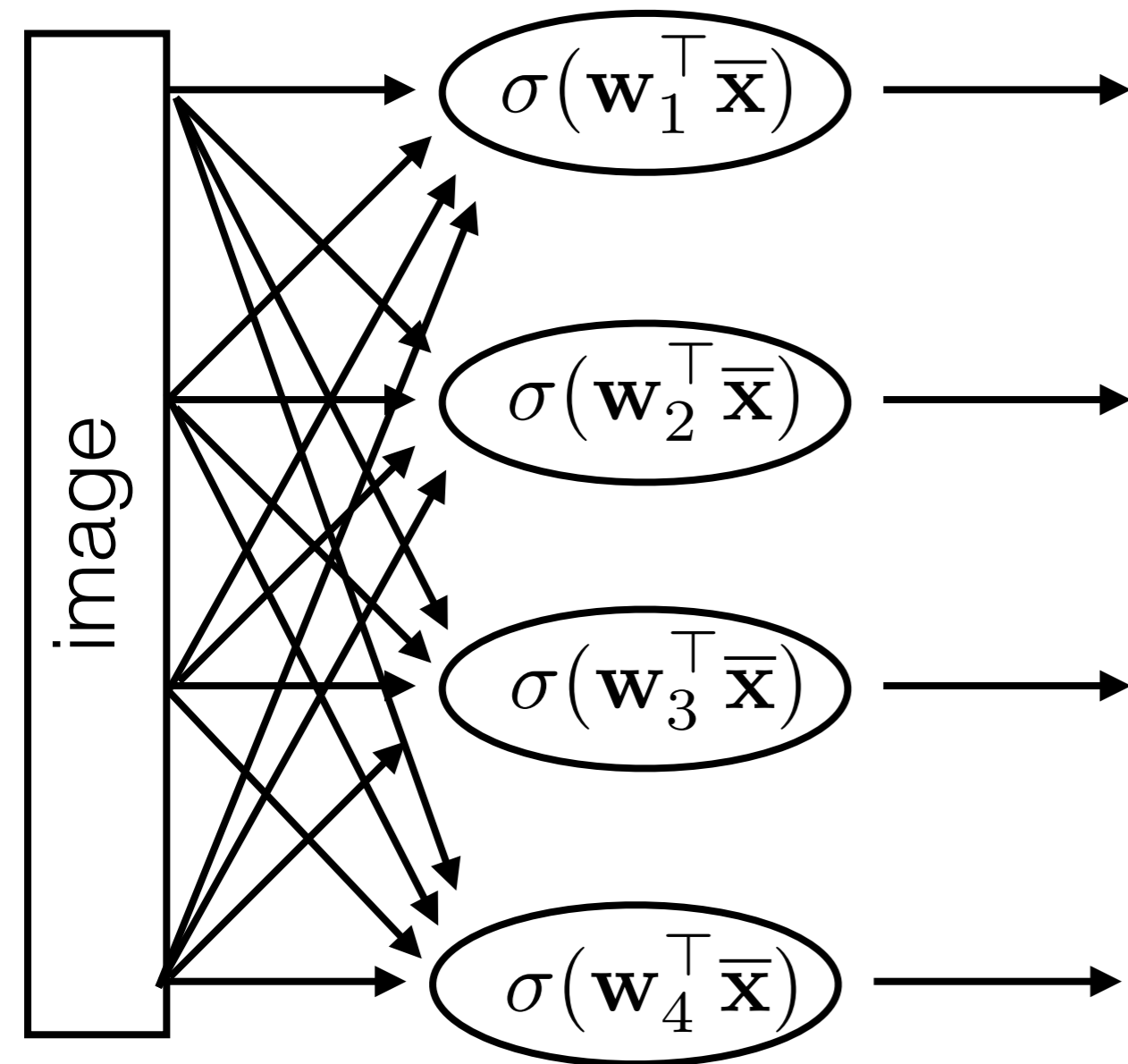
awake monkey



<https://knowingneurons.com/2014/10/29/hubel-and-wiesel-the-neural-basis-of-visual-perception/>



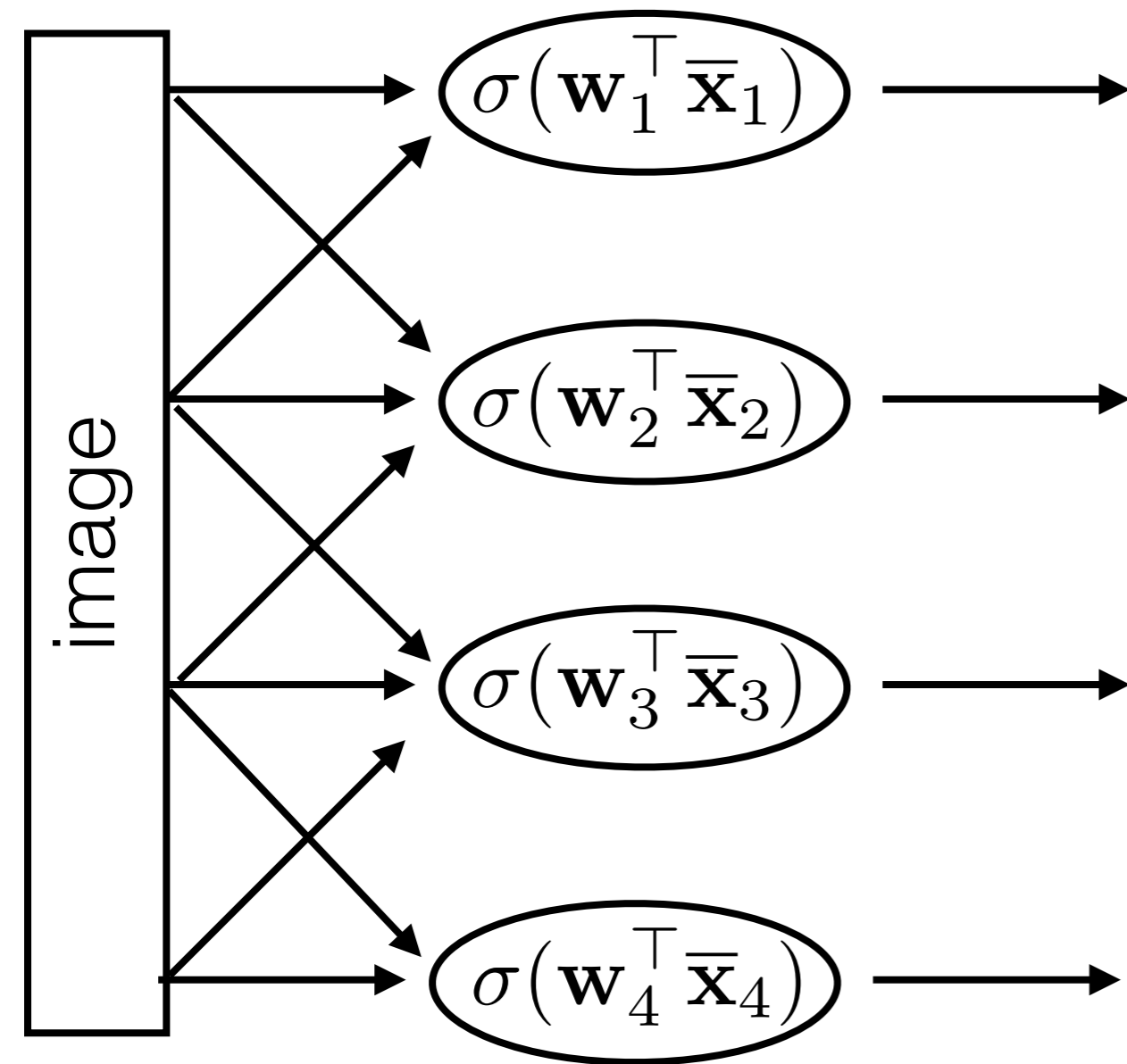
1. Nearby neurons process information from nearby visual field (topographical map).



- Processing of visual information in cortex is not fully connected.



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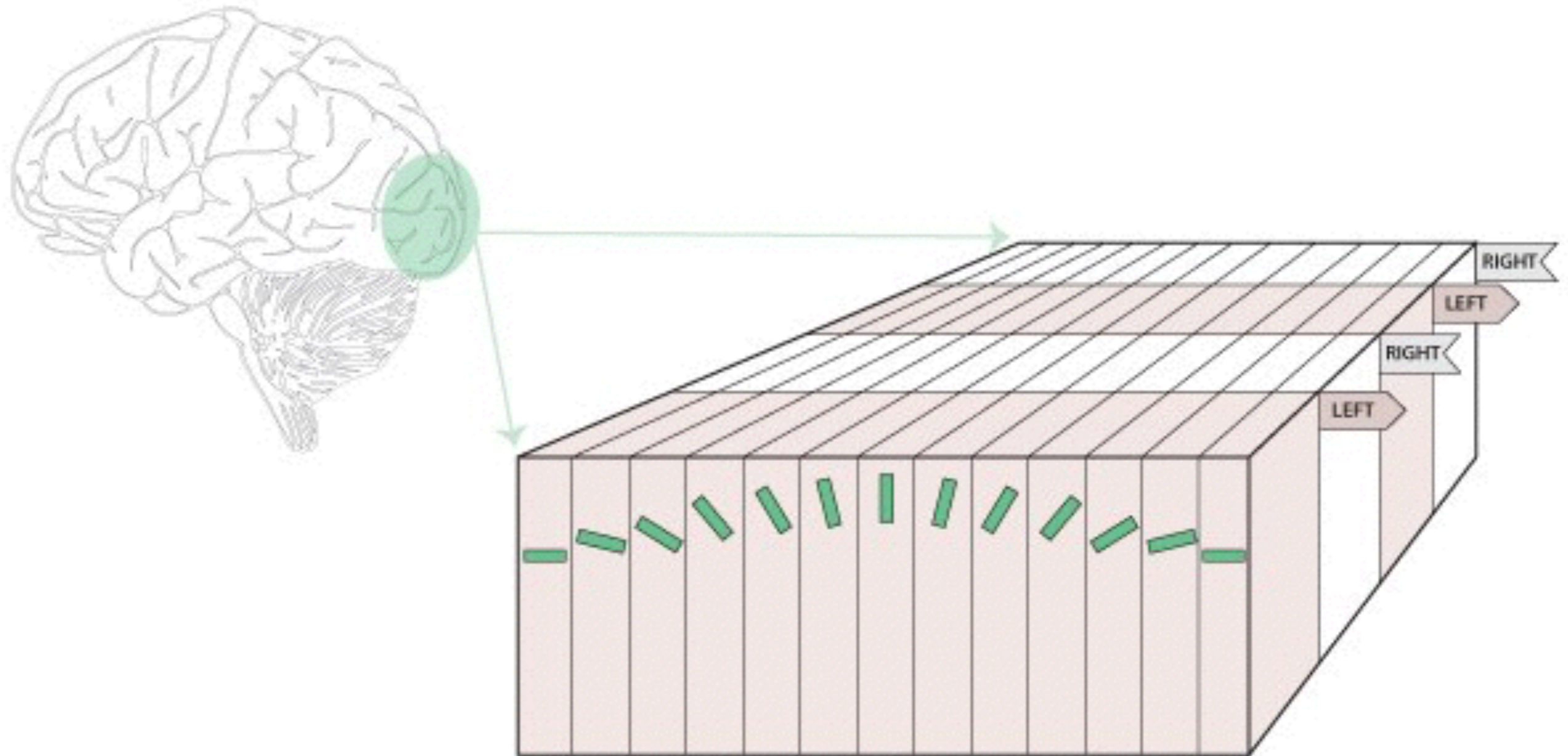


- What is dimensionality reduction for N-pixel image and n-dimensional spatial neighbourhood?





## 2. Neurons with similar function organized into columns

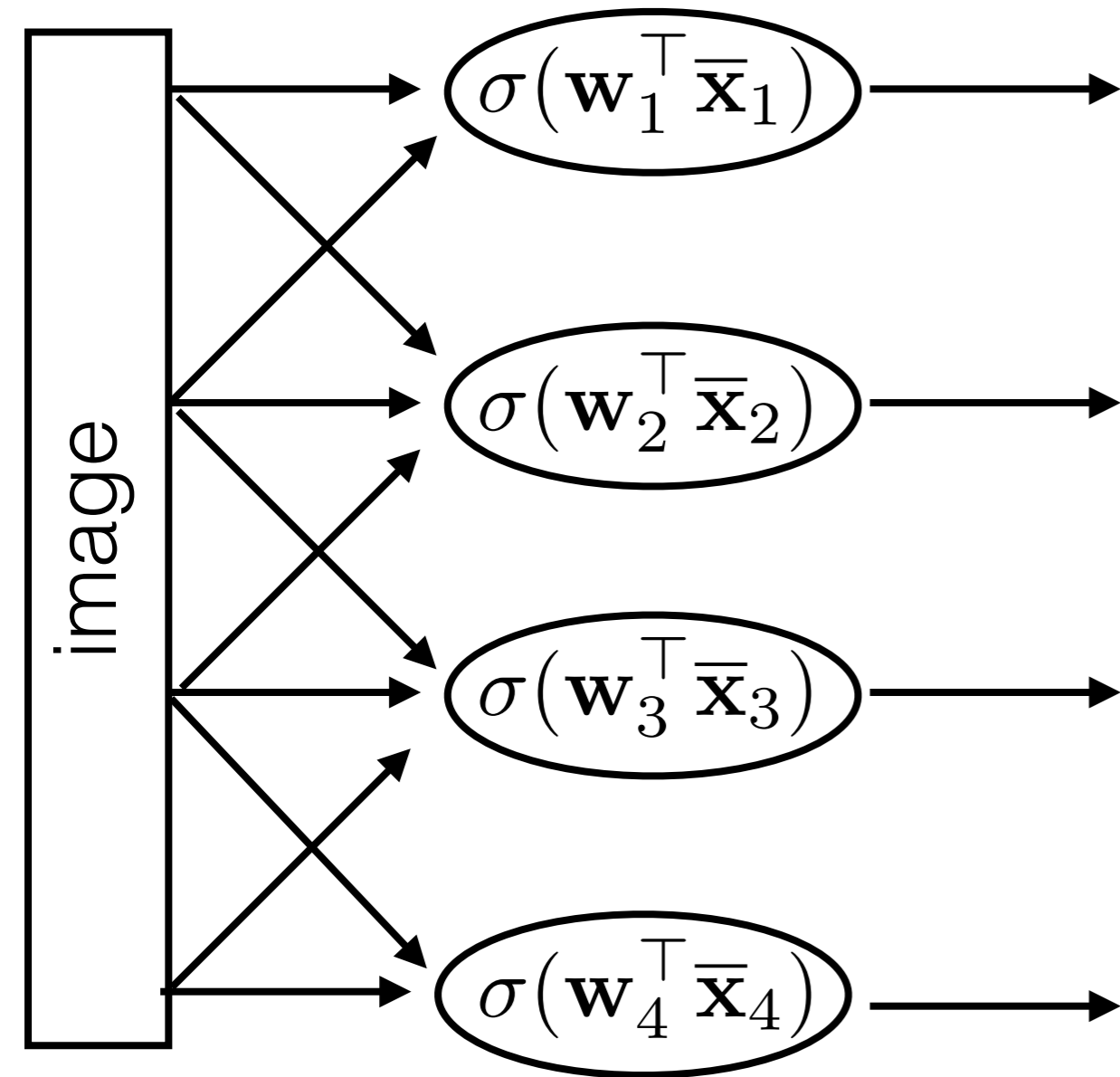


- There are neurons which detect an edge on the left and there are different neurons which detect the same edge on the right

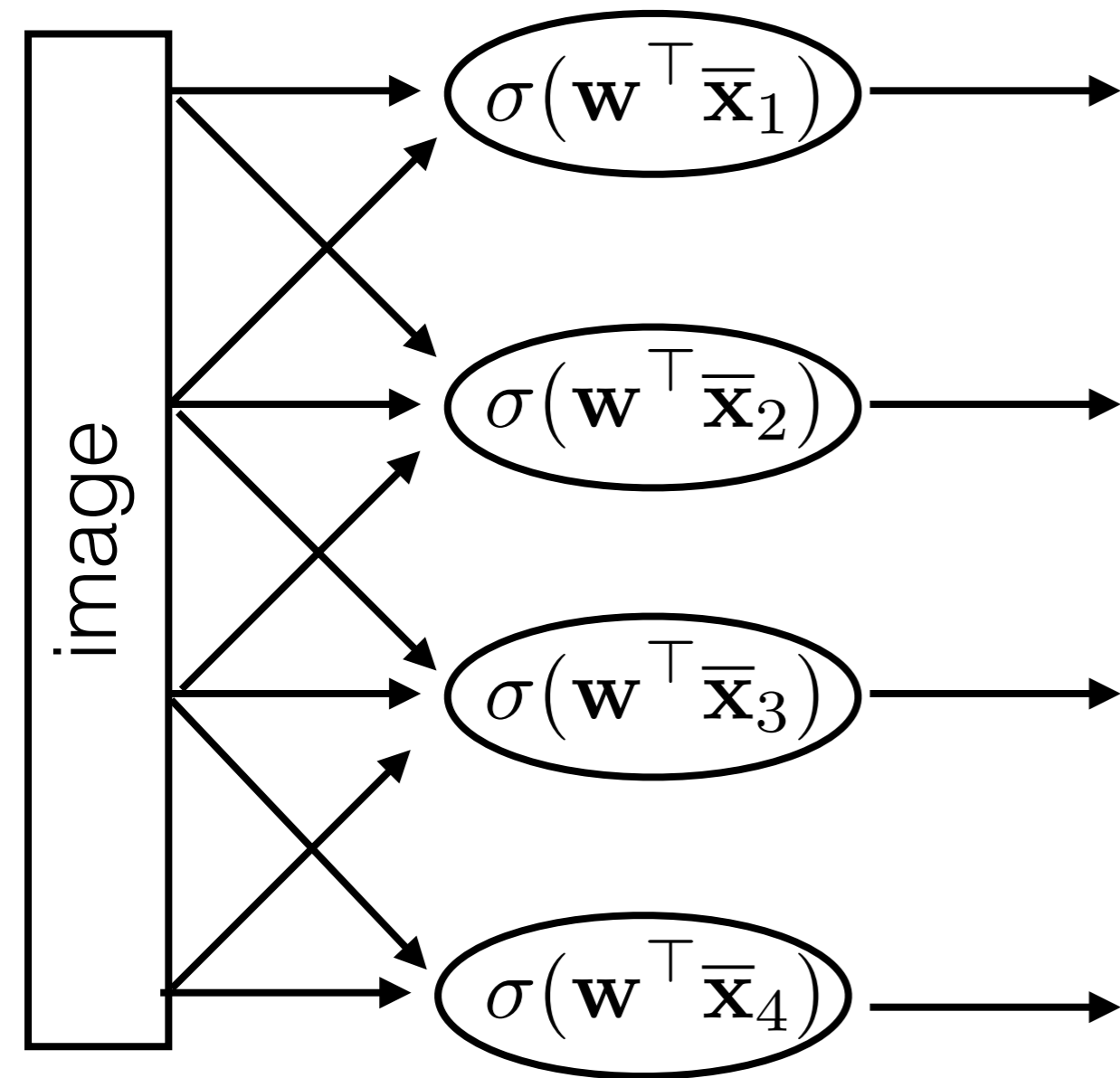
<https://knowingneurons.com/2014/10/29/hubel-and-wiesel-the-neural-basis-of-visual-perception/>



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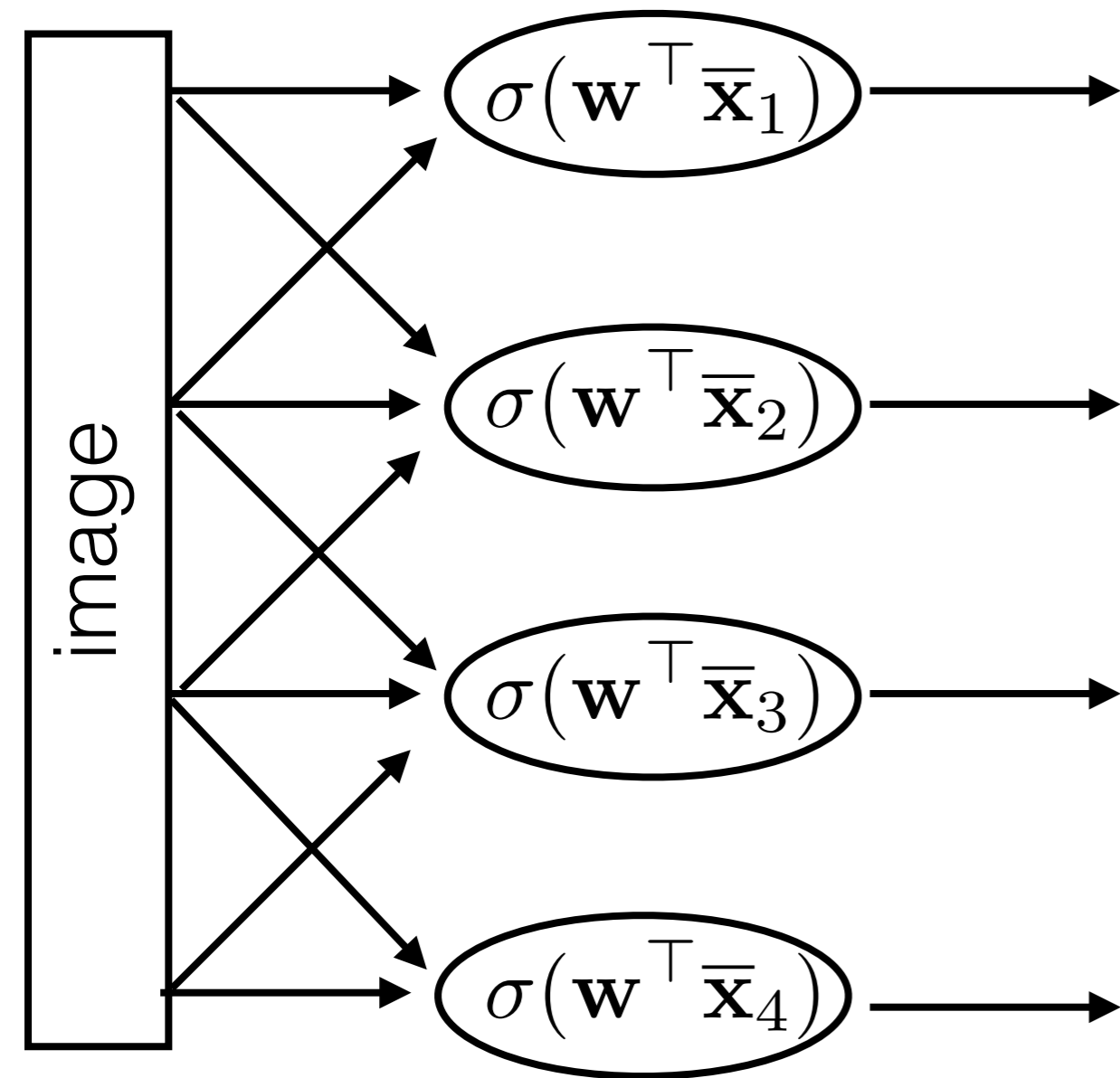
## 2. Neurons with similar function organized into columns



- What is dimensionality reduction for  $N$  pixel image and  $n$ -dimensional spatial neighbourhood?



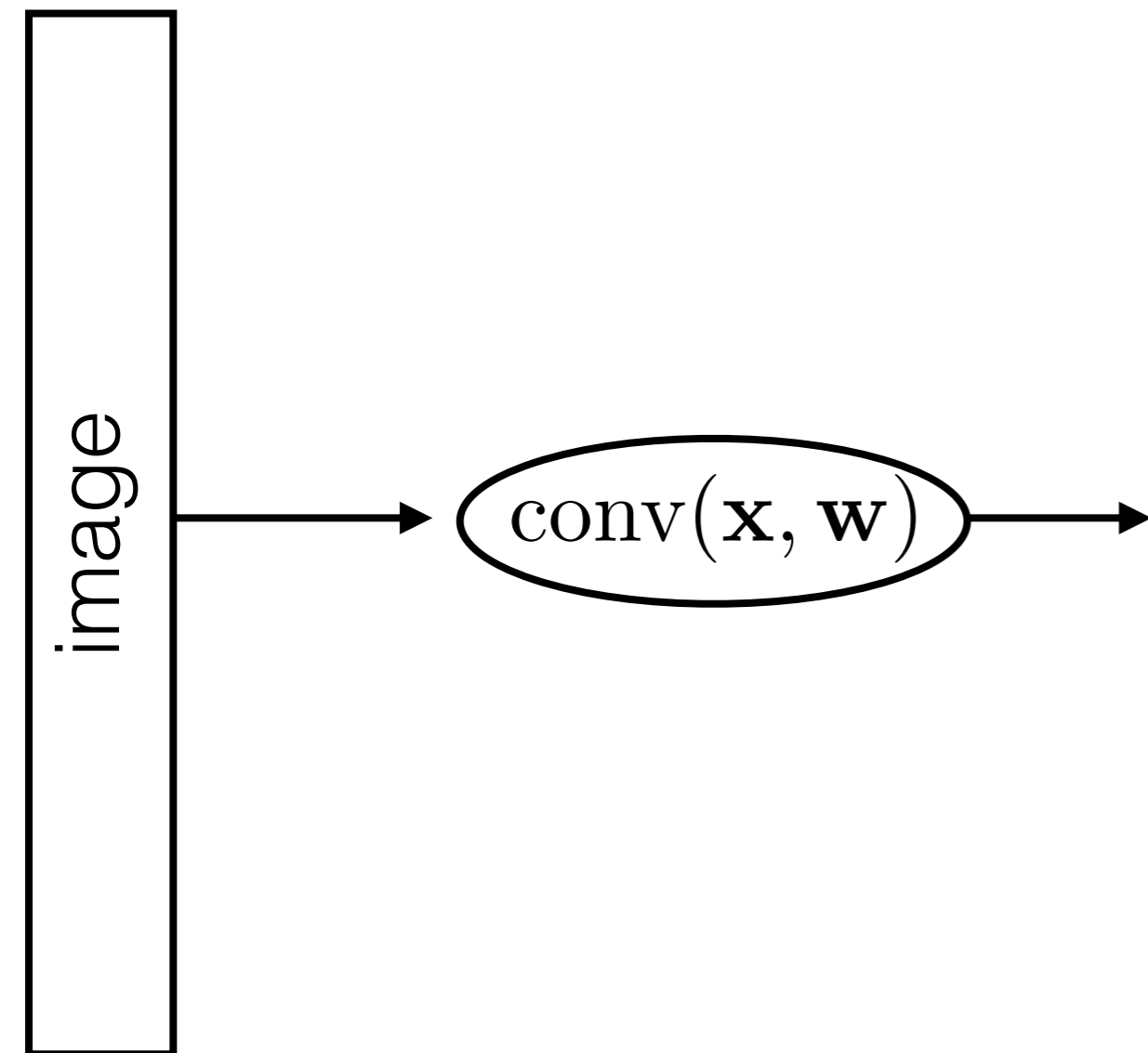
## 2. Neurons with similar function organized into columns



- $N^2$  vs  $n$  (it does not depend on the image resolution)
- It corresponds to convolution of image  $\mathbf{x}$  with kernel  $\mathbf{w}$  followed by activation function



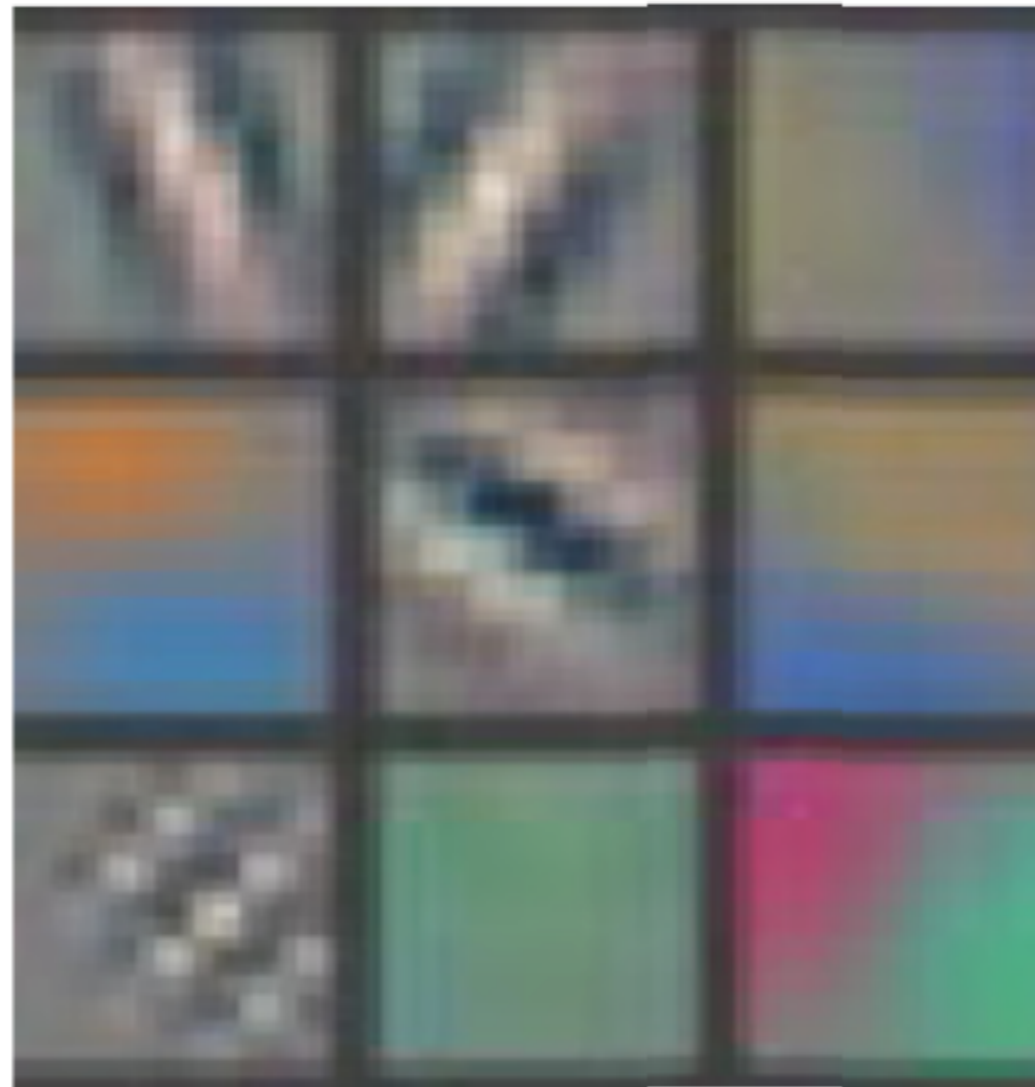
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3. Neurons are sensitive to edges and its orientation  
Inputs which maximized output of **layer 1**

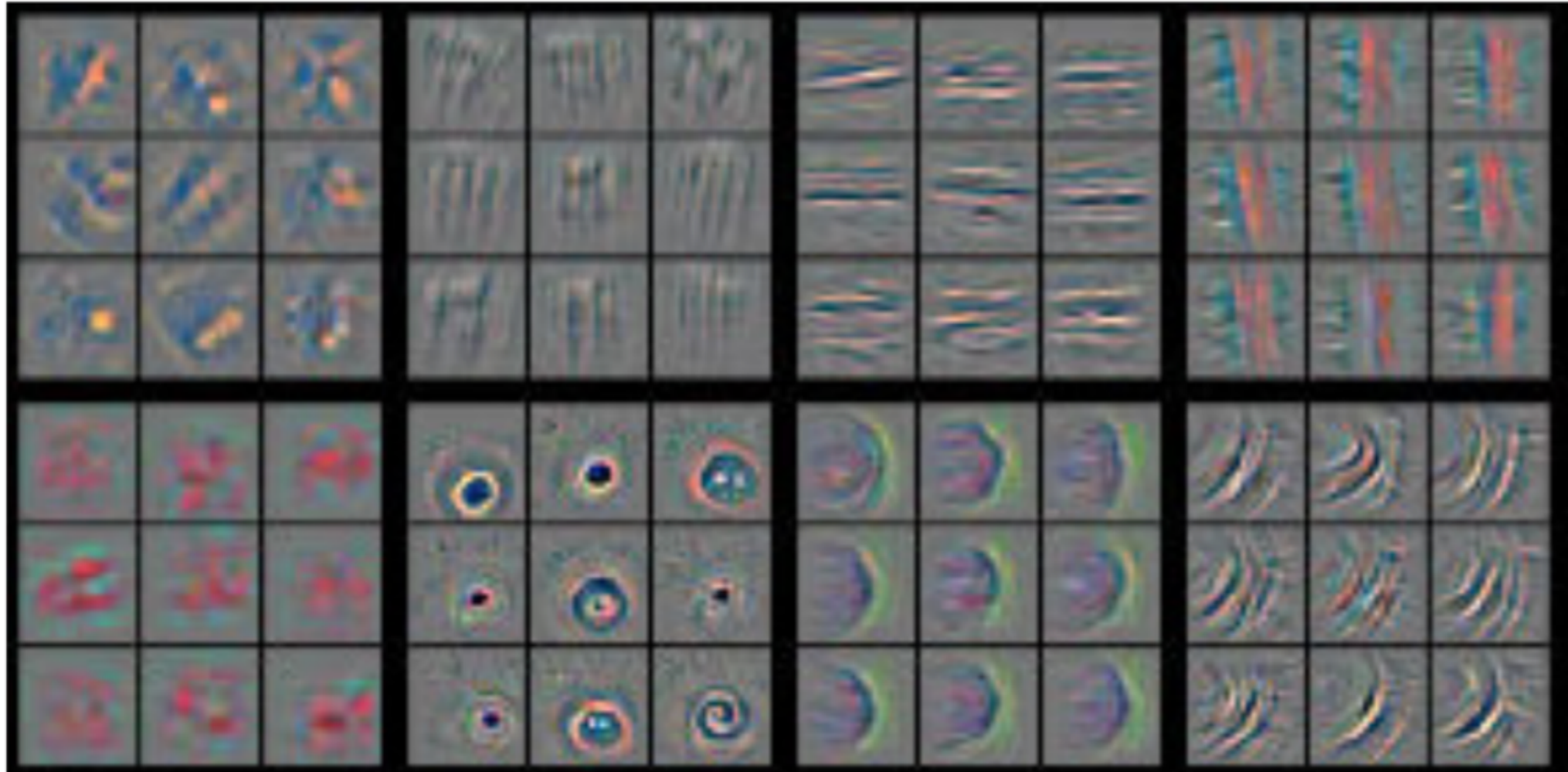


[Zeiler and Fergus, ECCV, 2014]



### 3. Neurons are sensitive to edges and its orientation

Inputs which maximized output of **layer 2**



[Zeiler and Fergus, ECCV, 2014]

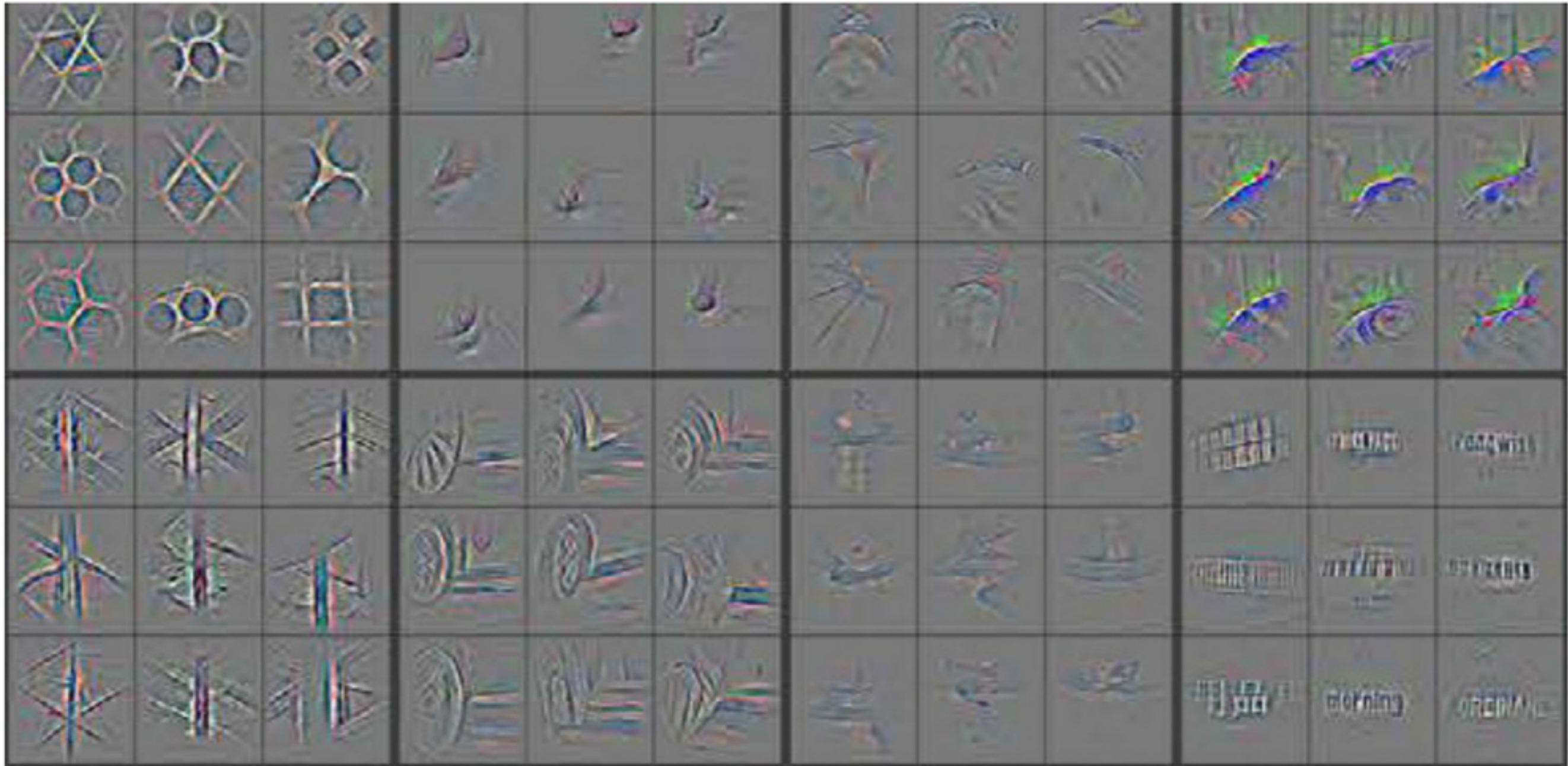
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### 3. Neurons are sensitive to edges and its orientation

Inputs which maximized output of **layer 3**



[Zeiler and Fergus, ECCV, 2014]

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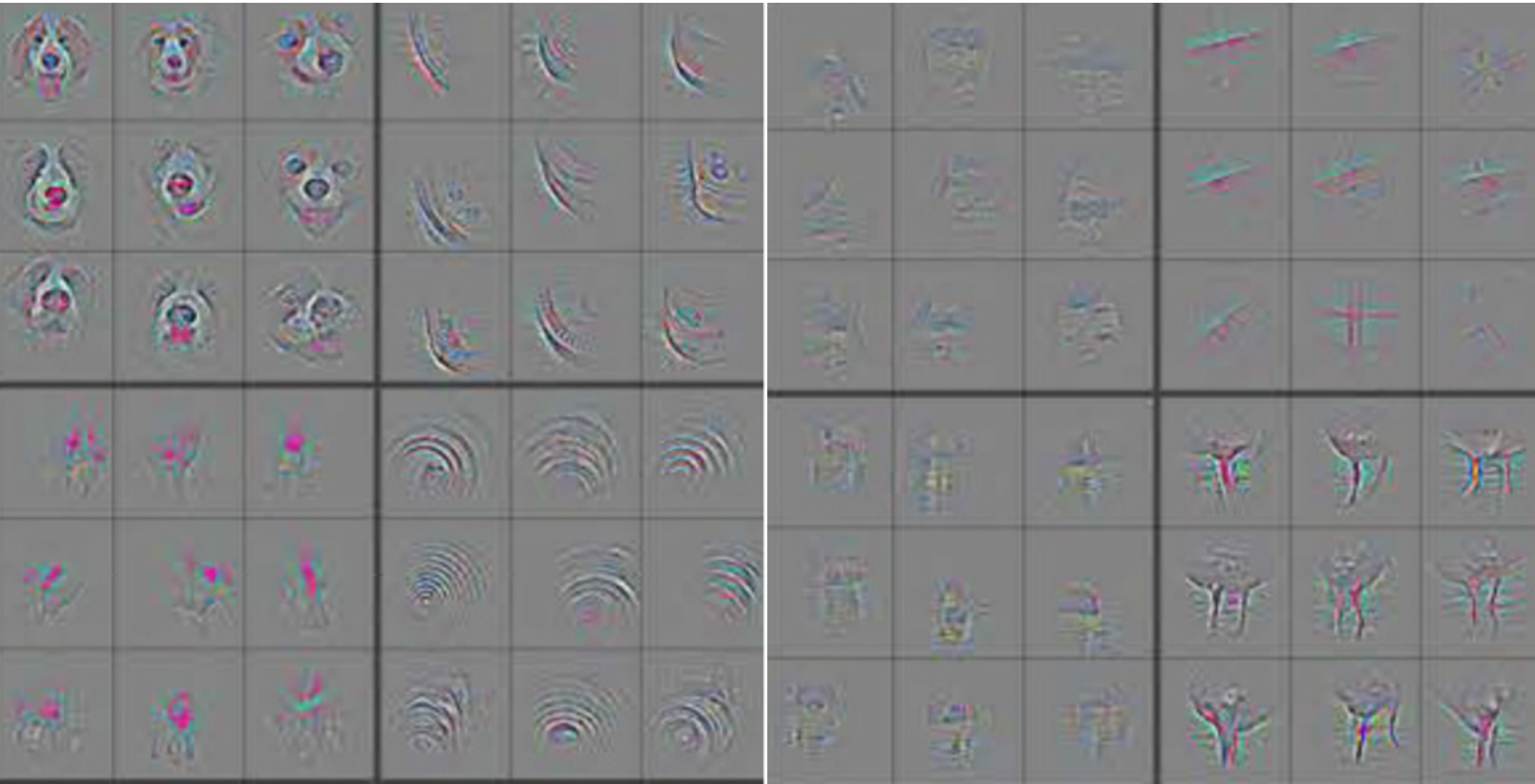
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### 3. Neurons are sensitive to edges and its orientation

Inputs which maximized output of **layer 4**



[Zeiler and Fergus, ECCV, 2014]

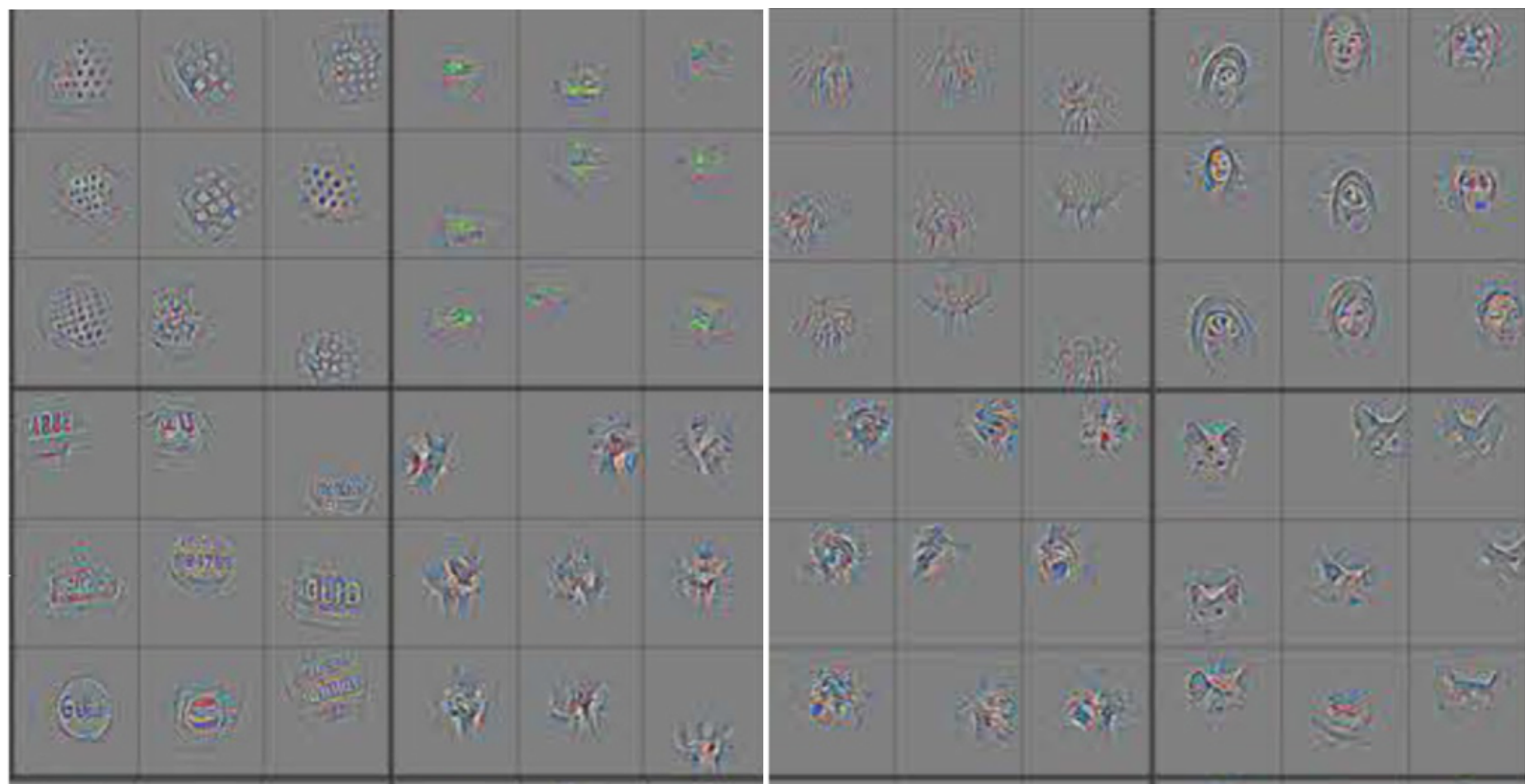
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### 3. Neurons are sensitive to edges and its orientation

Inputs which maximized output of **layer 5**



[Zeiler and Fergus, ECCV, 2014]

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# Hubel and Wiesel experiments in 1950s and 1960s



- Nobel Prize in Physiology and Medicine in 1981
- Dr. Hubel: “There has been a myth that the brain cannot understand itself. It is compared to a man trying to lift himself by his own bootstraps. We feel that is nonsense. The brain can be studied just as the kidney can.”

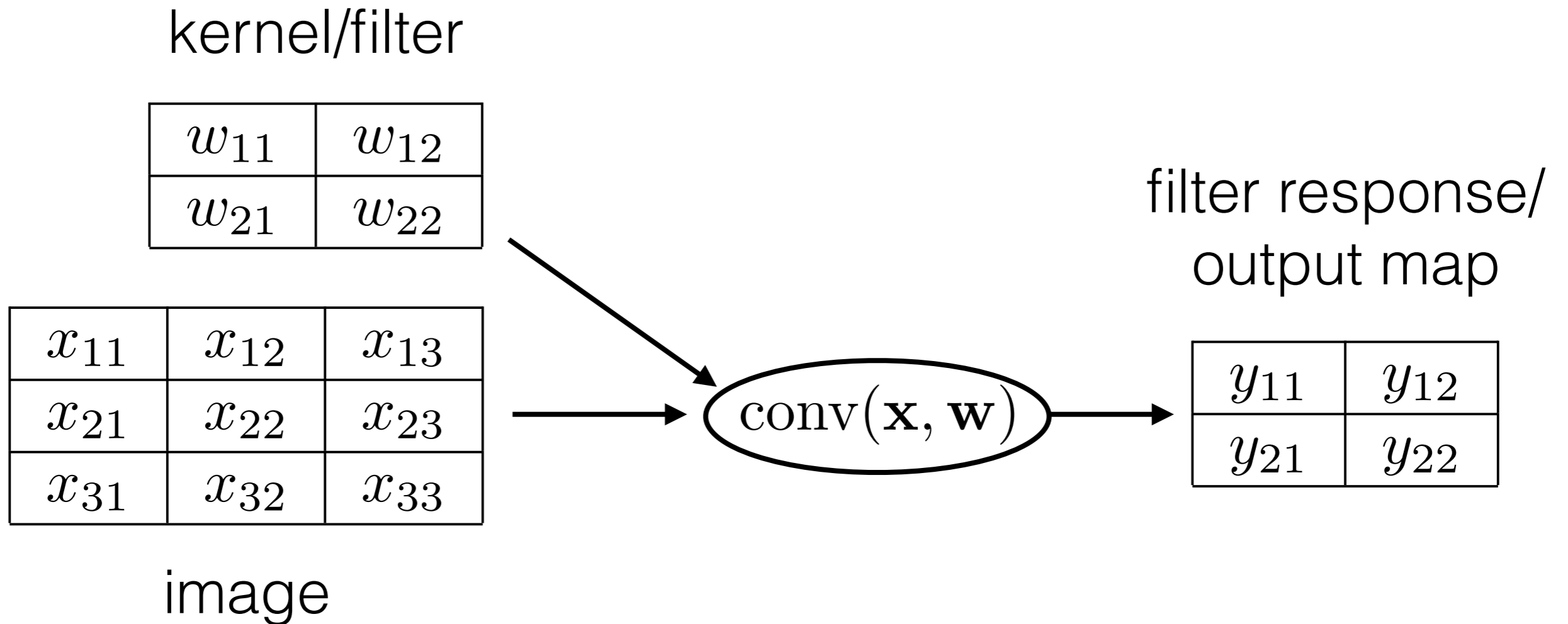
<https://knowingneurons.com/2014/10/29/hubel-and-wiesel-the-neural-basis-of-visual-perception/>

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# Convolution forward pass $\mathbf{y} = \text{conv}(\mathbf{x}, \mathbf{w})$



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$$\begin{array}{|c|c|} \hline y_{11} & y_{12} \\ \hline y_{21} & y_{22} \\ \hline \end{array} = \text{conv} \left( \begin{array}{|c|c|c|} \hline x_{11} & x_{12} & x_{13} \\ \hline x_{21} & x_{22} & x_{23} \\ \hline x_{31} & x_{32} & x_{33} \\ \hline \end{array}, \begin{array}{|c|c|} \hline w_{11} & w_{12} \\ \hline w_{21} & w_{22} \\ \hline \end{array} \right)$$

$$y_{11} = w_{11}x_{11} + w_{12}x_{12} + w_{21}x_{21} + w_{22}x_{22}$$

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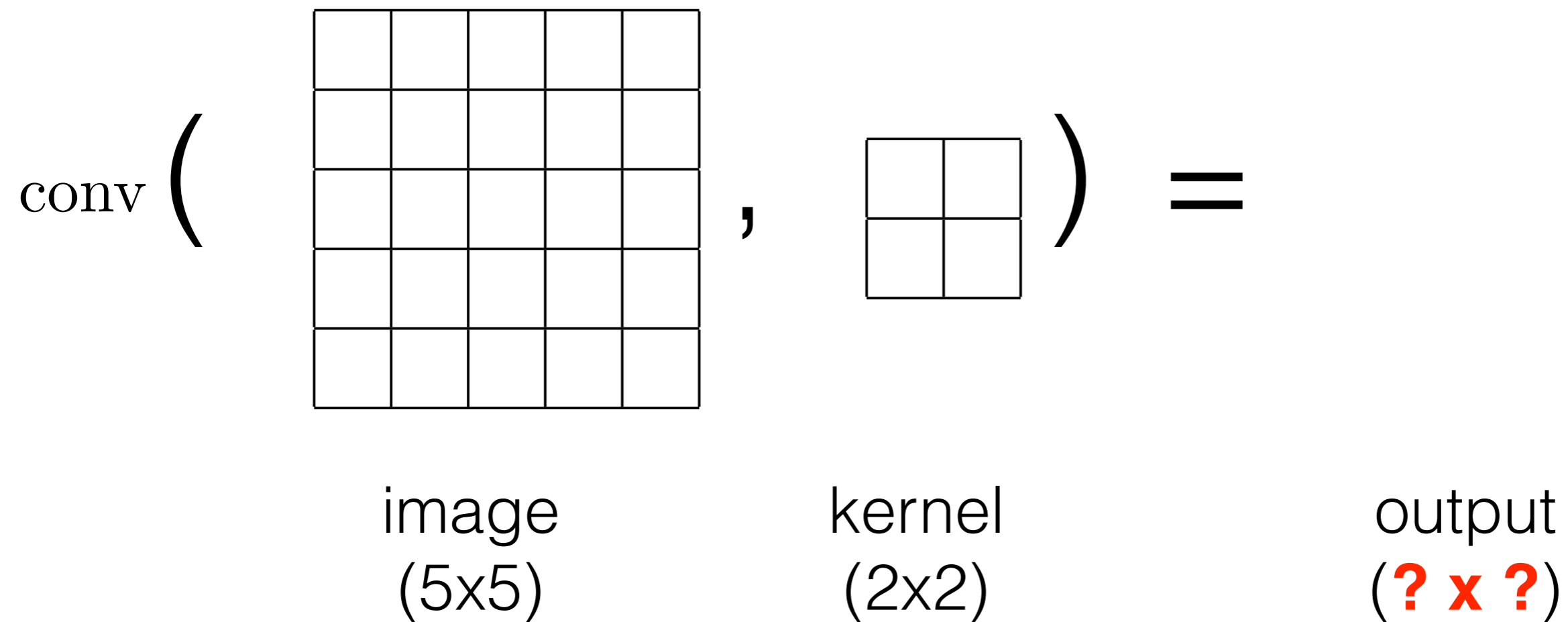
$$y_{12} = w_{11}x_{12} + w_{12}x_{13} + w_{21}x_{22} + w_{22}x_{23}$$

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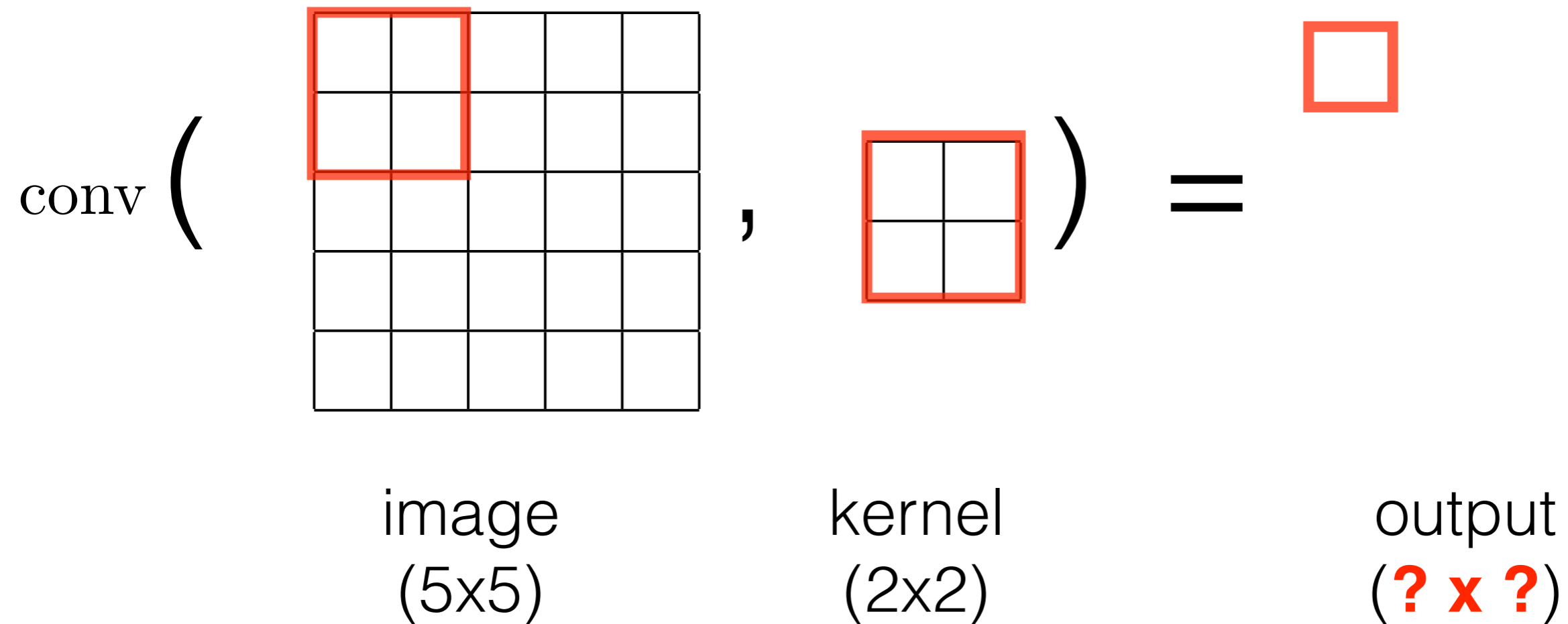
$$y_{22} = w_{11}x_{22} + w_{12}x_{23} + w_{21}x_{32} + w_{22}x_{33}$$



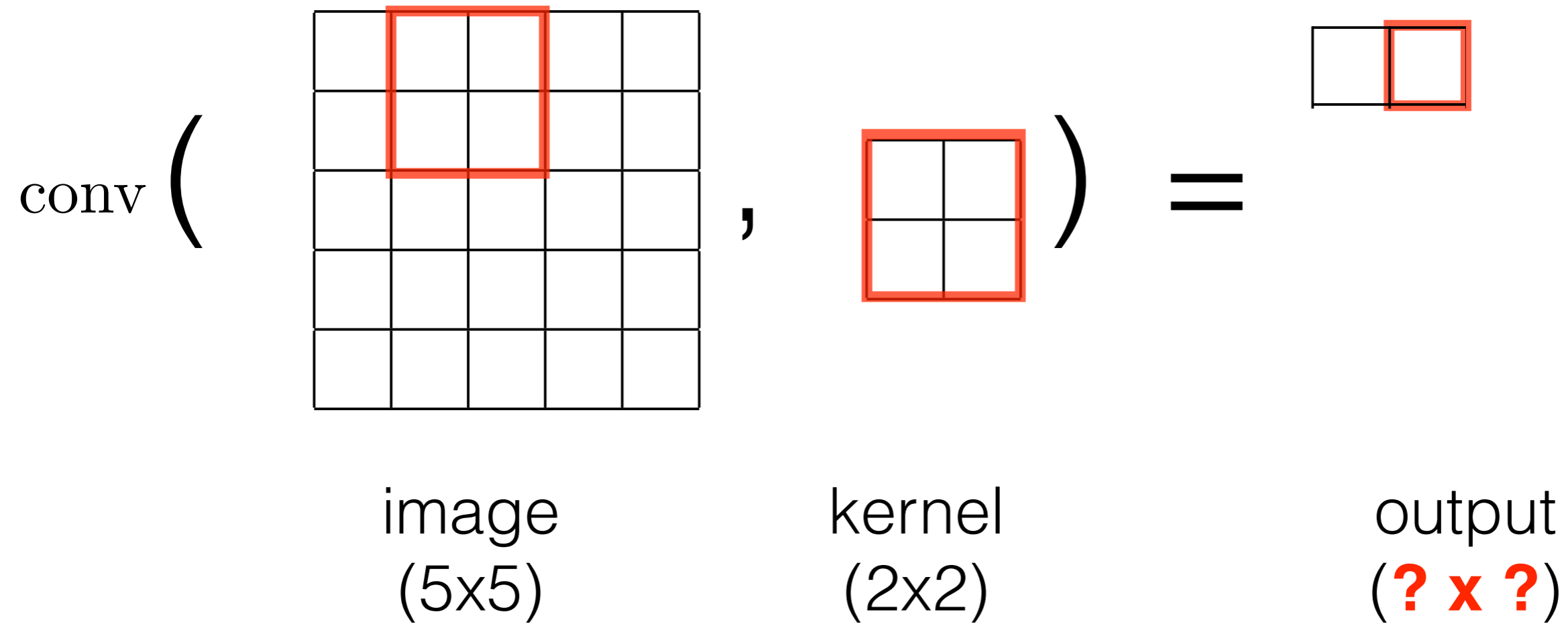
# Convolution layer properties - output size



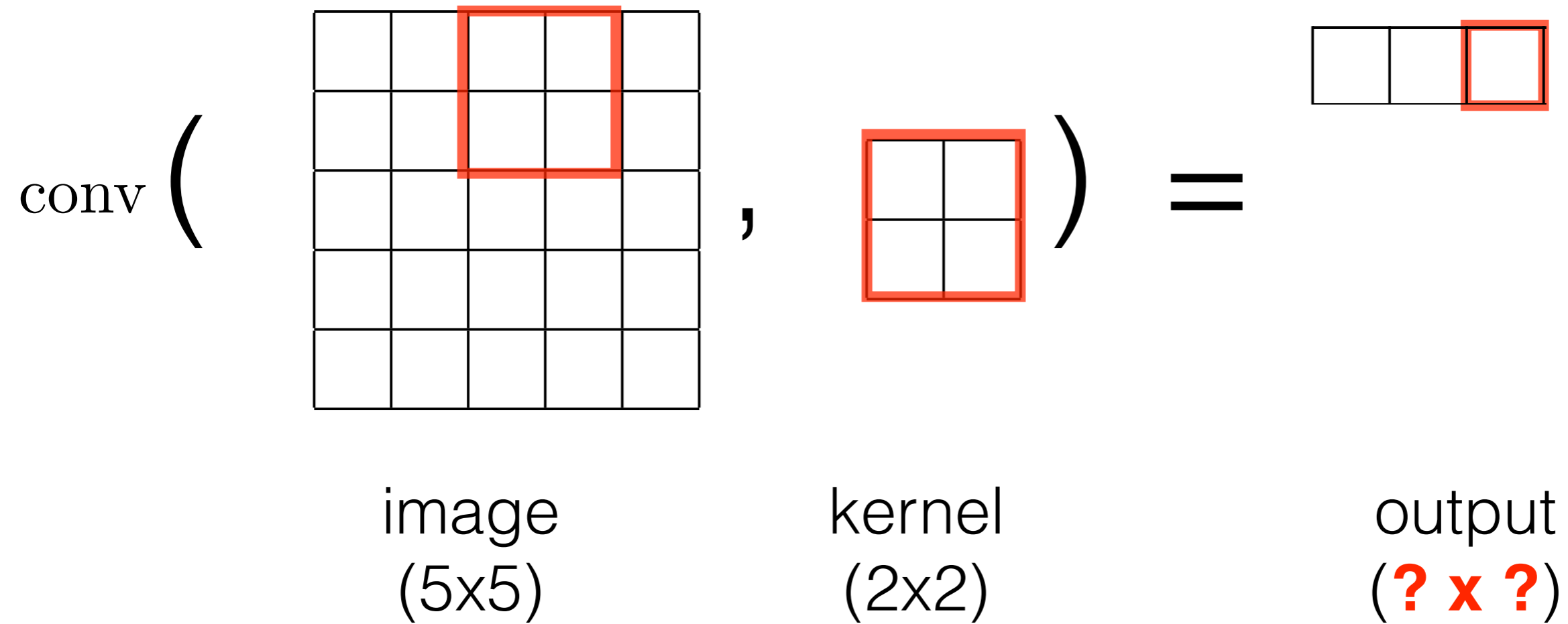
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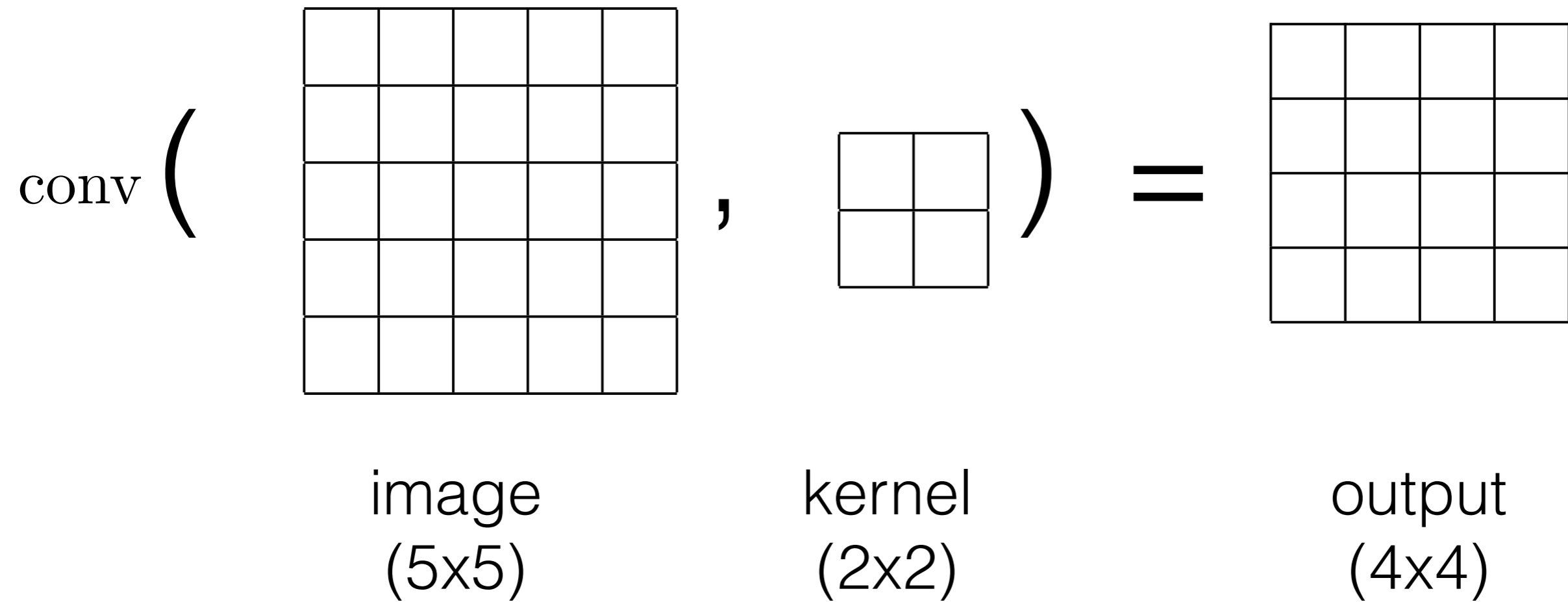
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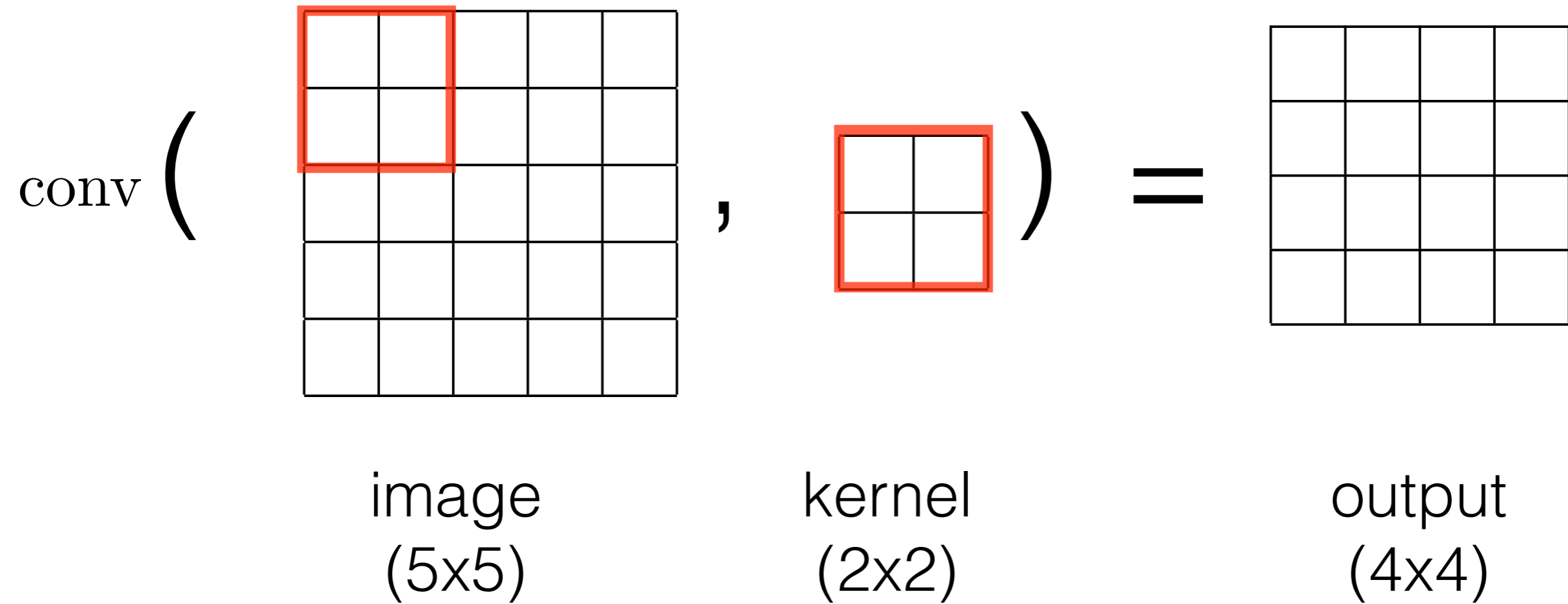
# Convolution layer properties - output size



# Convolution layer properties - stride

stride = 1

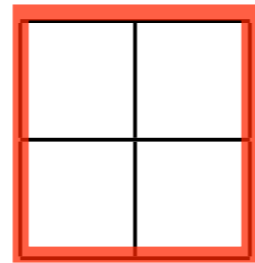
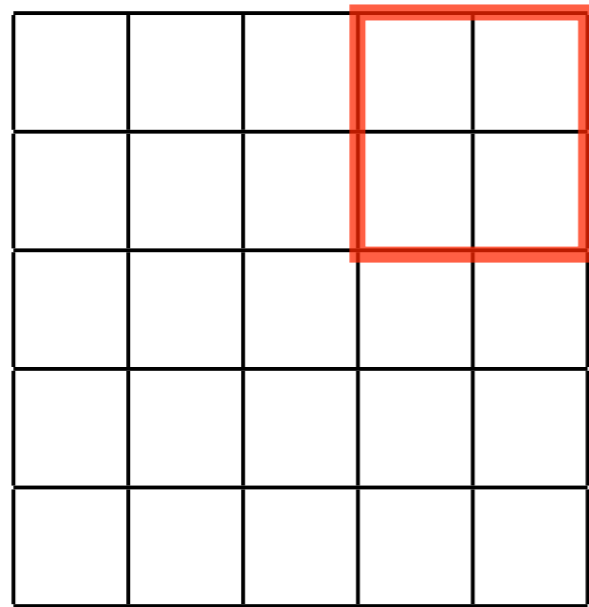
kernel moves by 1 pixel



# Convolution layer properties - stride

stride = 3

kernel moves by 3 pixels



=

conv (

,

)

image  
(5x5)

kernel  
(2x2)

output  
(? x ?)

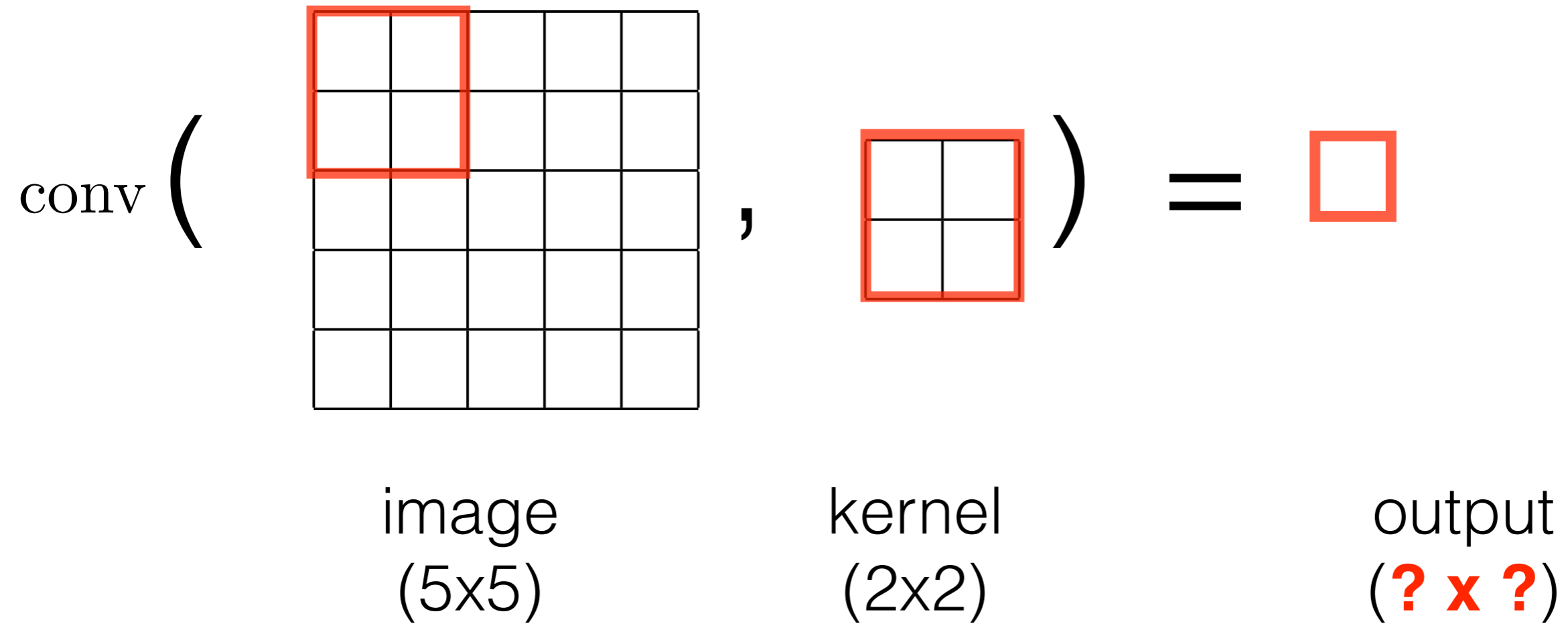




# Convolution layer properties - stride

stride = 3

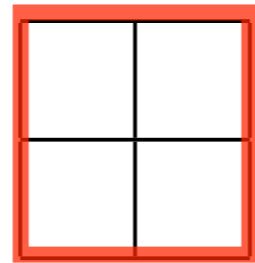
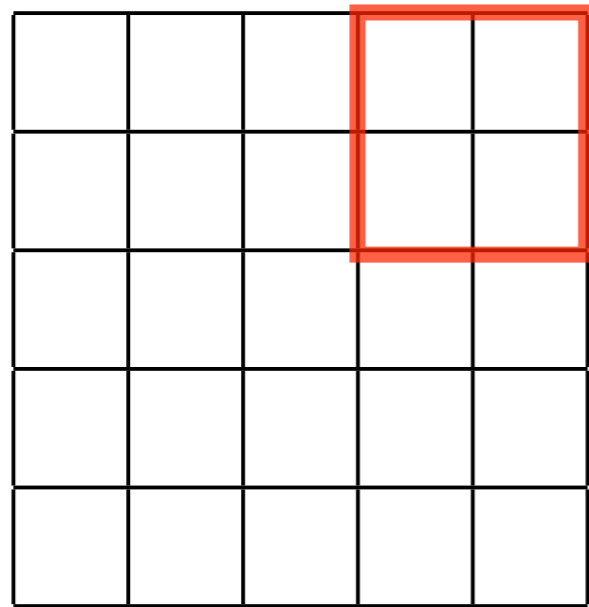
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=



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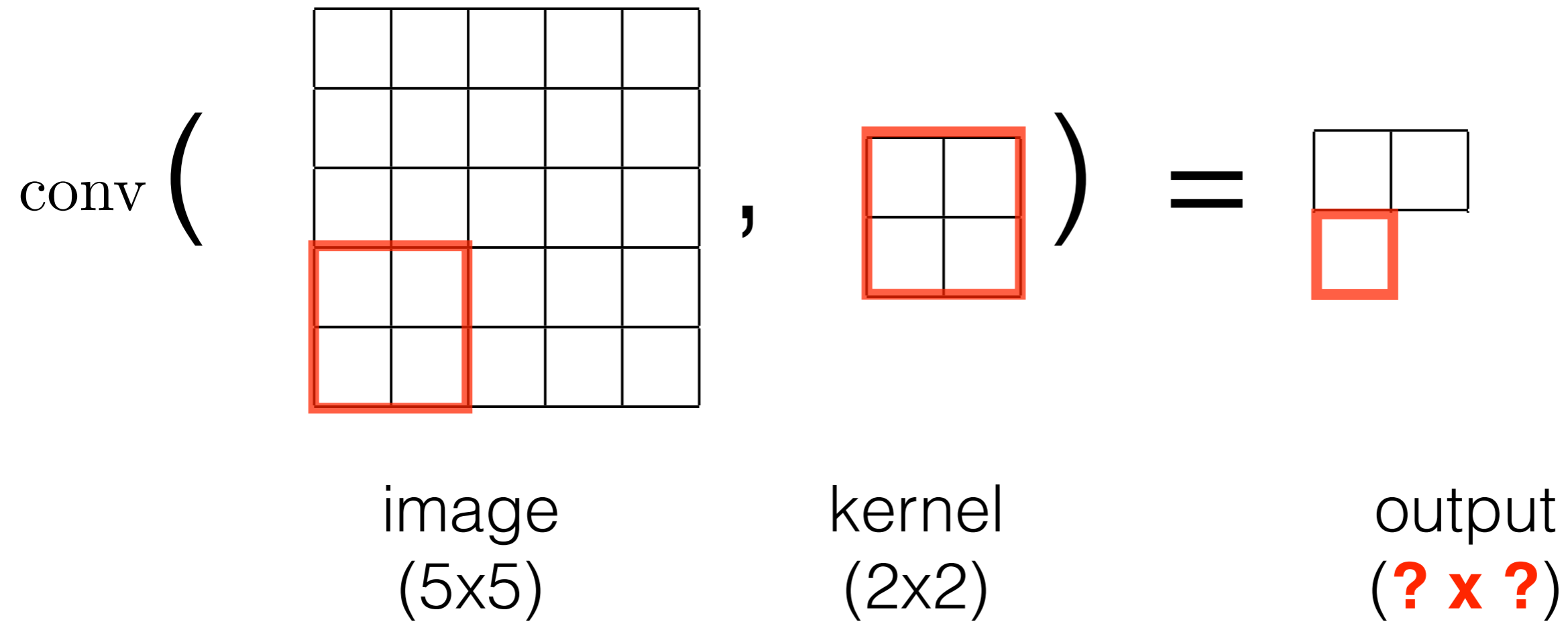
output  
(? x ?)



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stride = 3

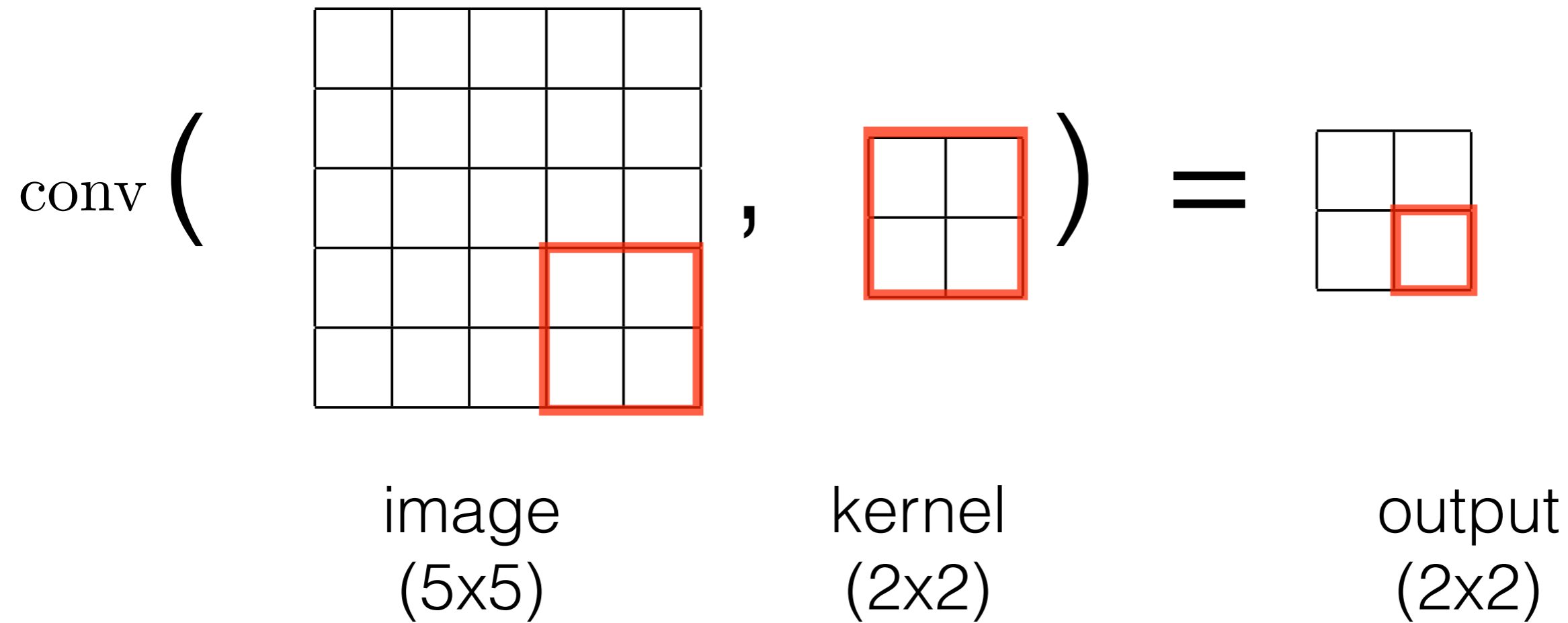
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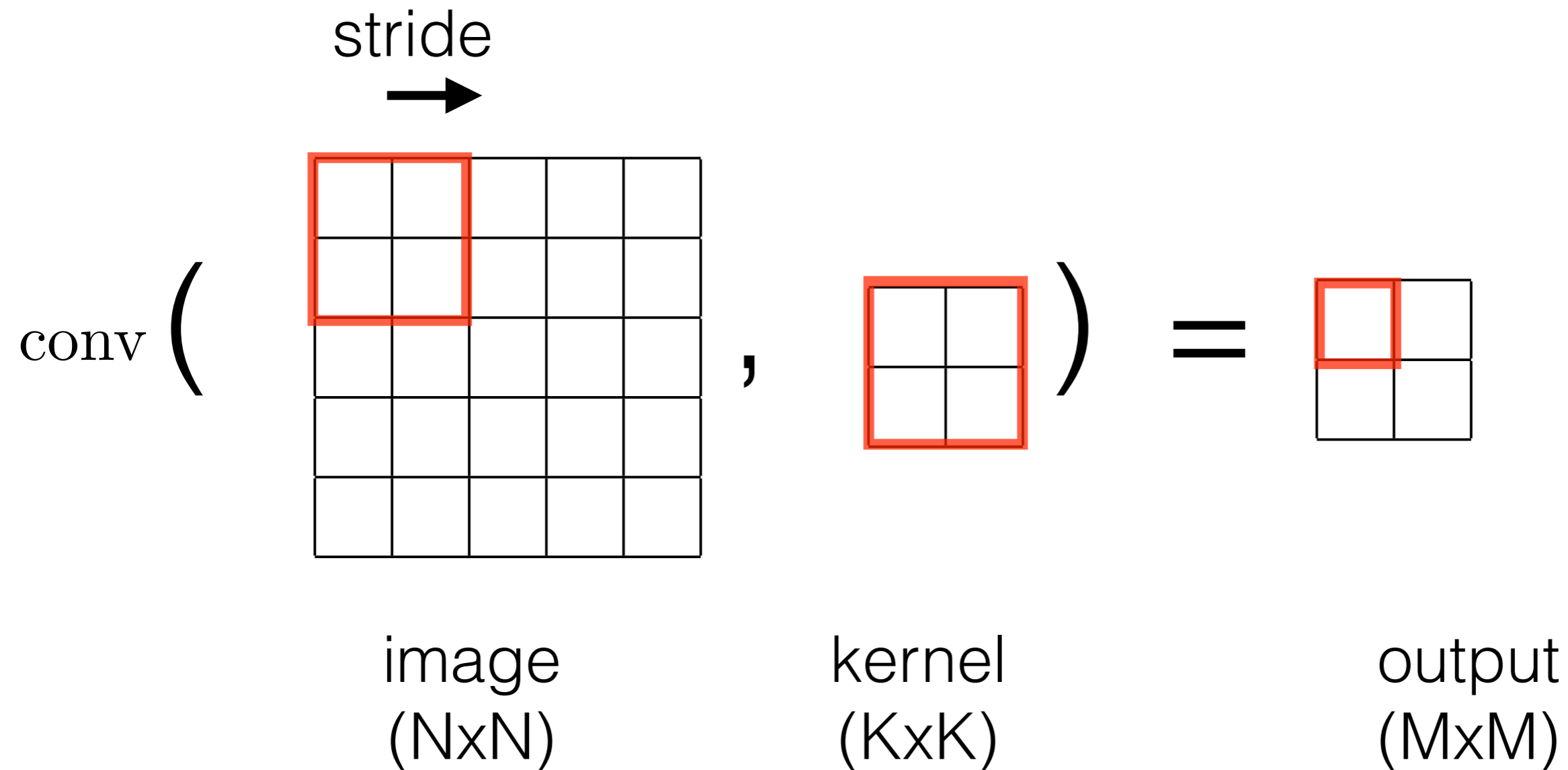
stride = 3

kernel moves by 3 pixels



# Convolution layer properties - stride

$$M = (N - K) / \text{stride} + 1$$

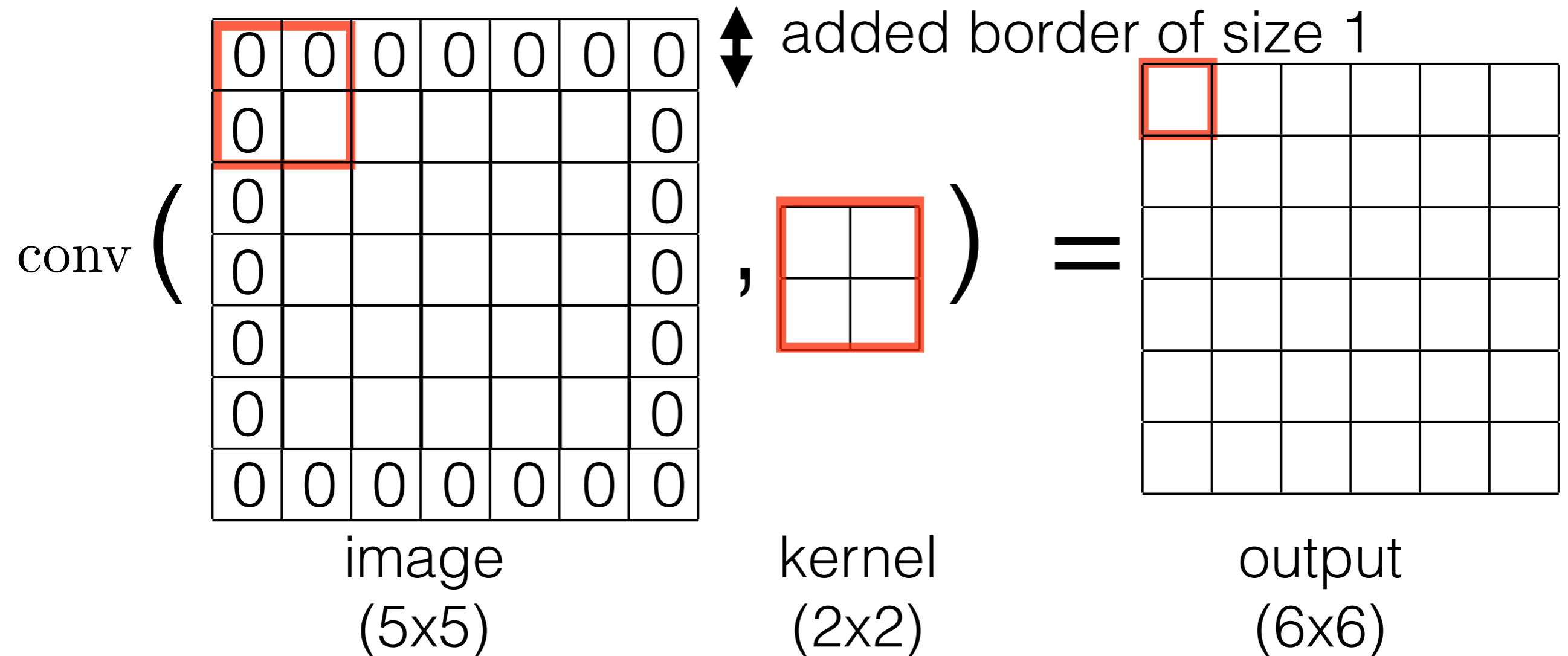


e.g.  $M = (5 - 2) / 3 + 1 = 2$



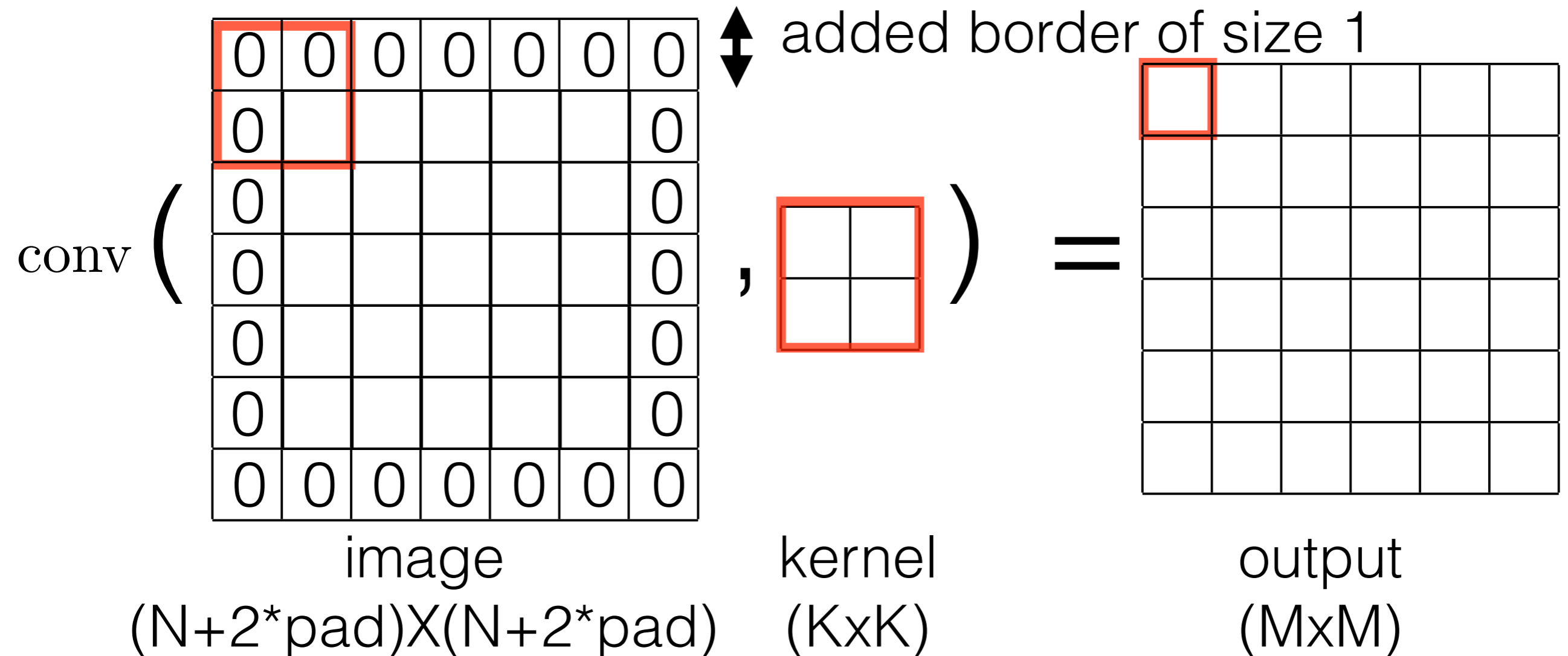
# Convolution layer properties - pad

pad = 1

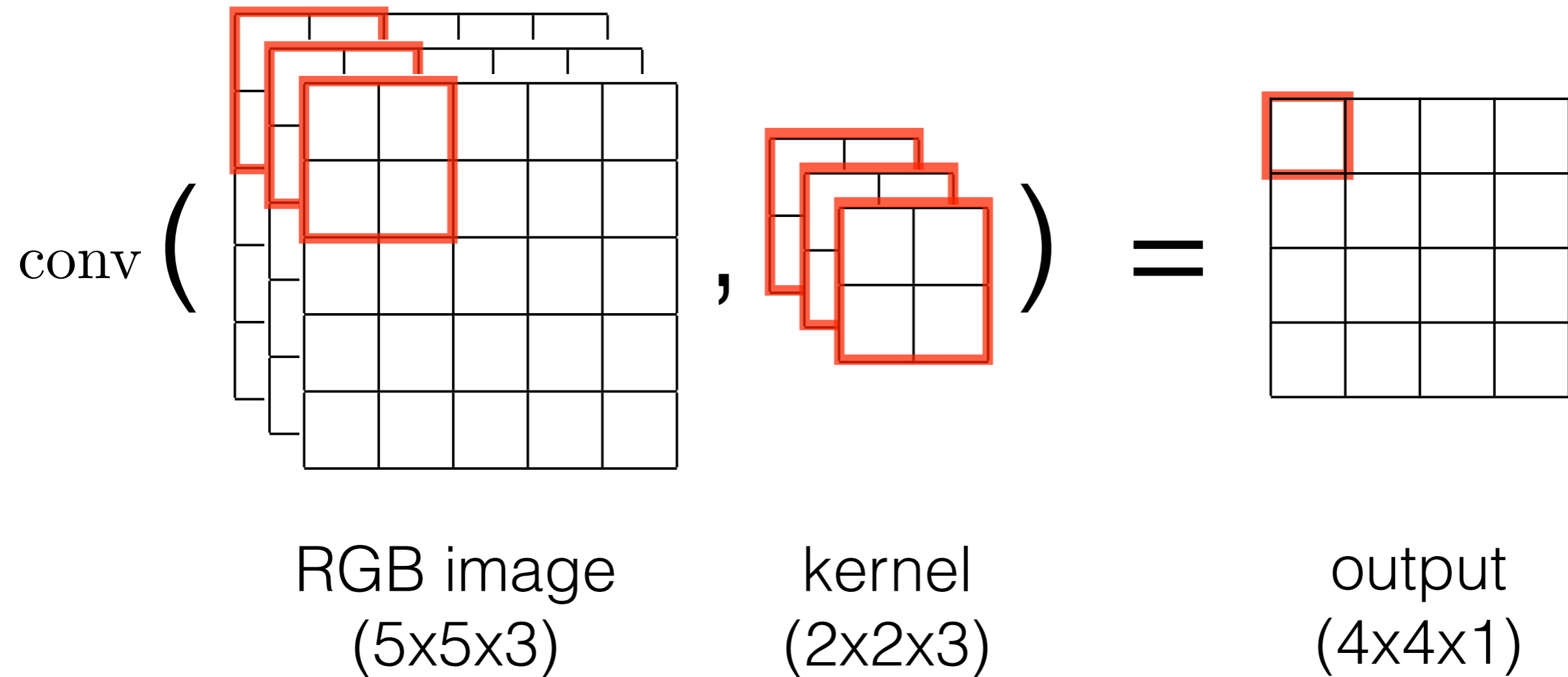


# Convolution layer properties - pad

$$M = (N + 2 * \text{pad} - K) / \text{stride} + 1$$

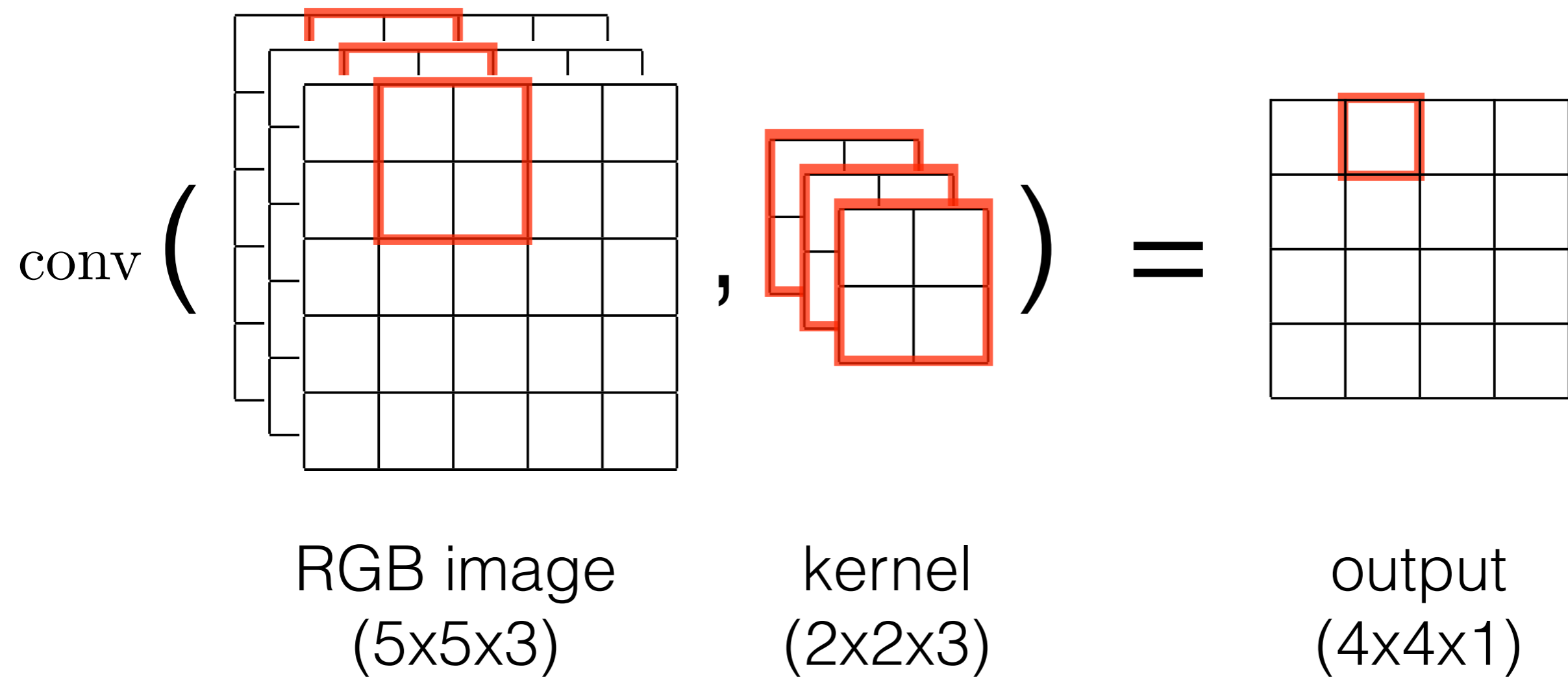


# Multi-channel convolution

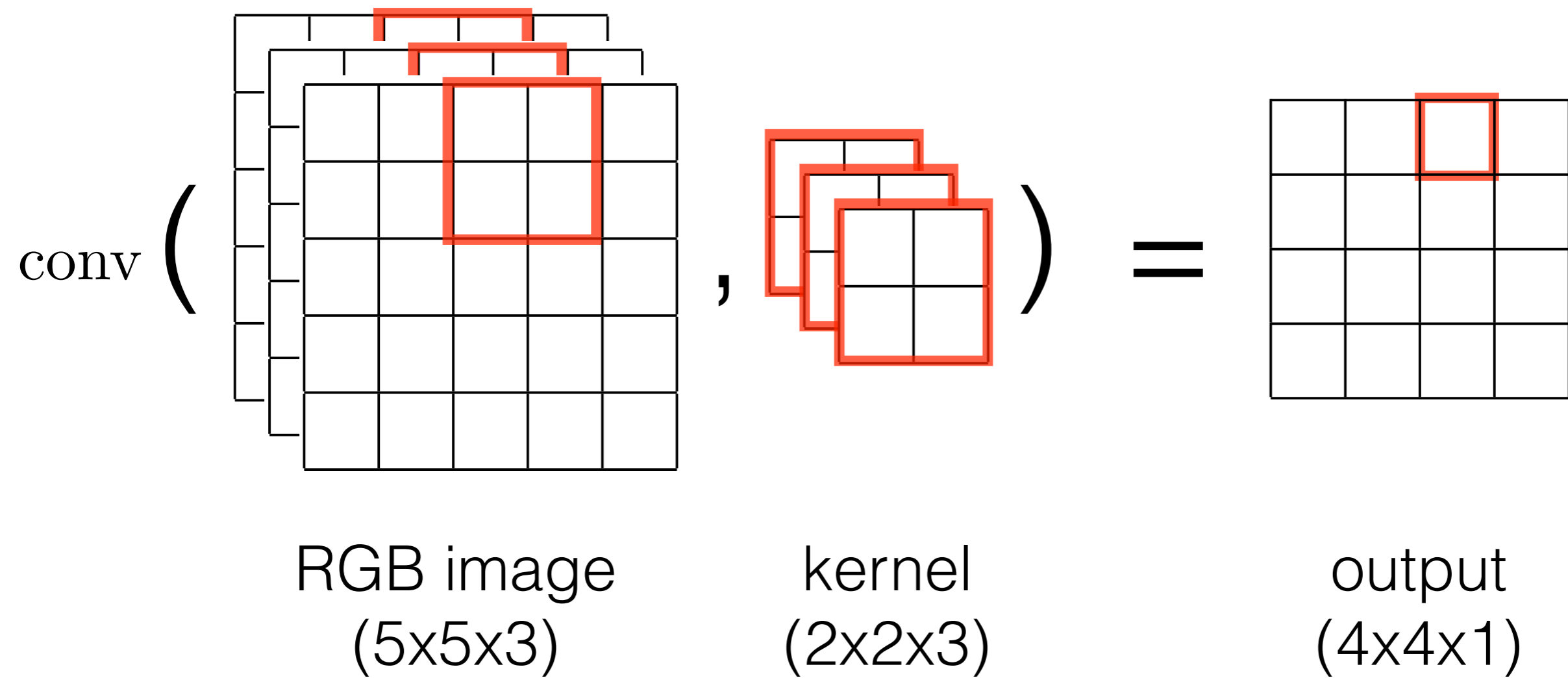




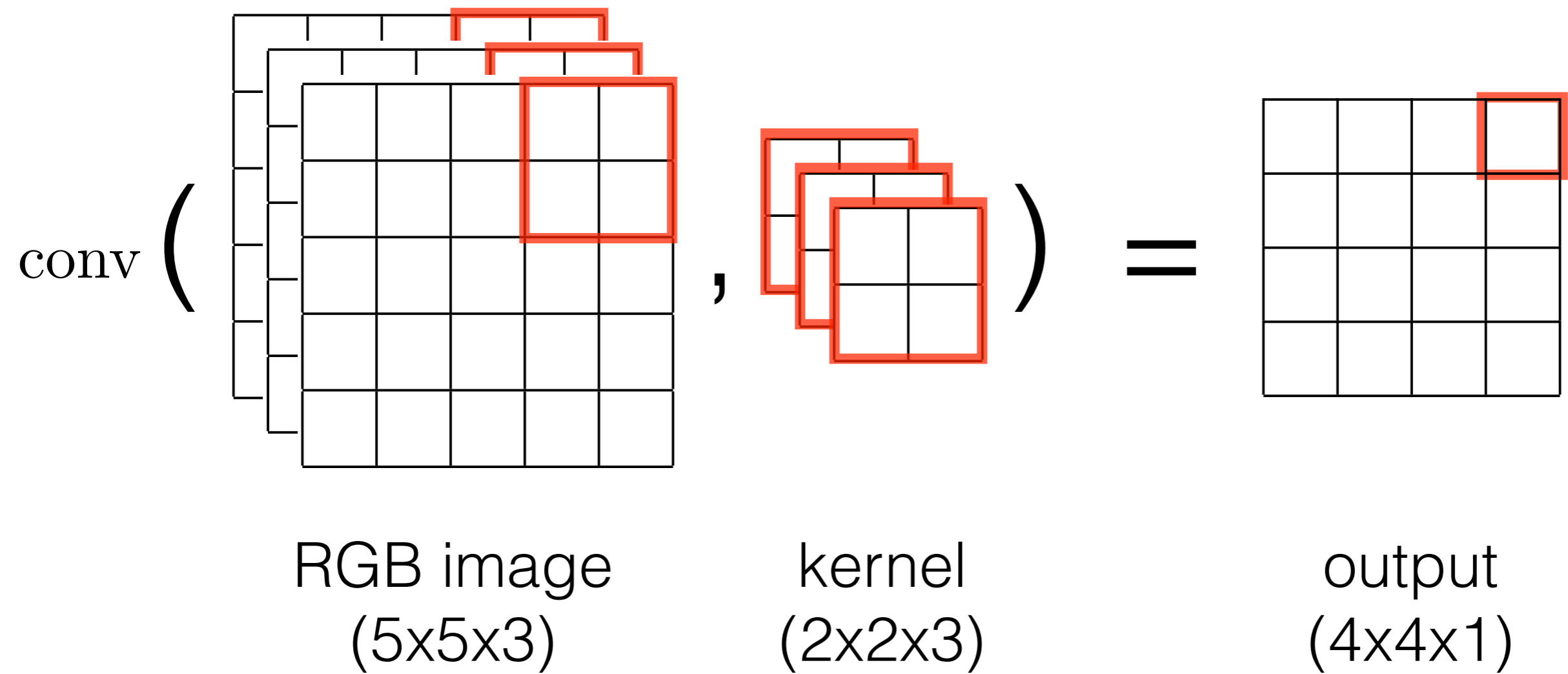
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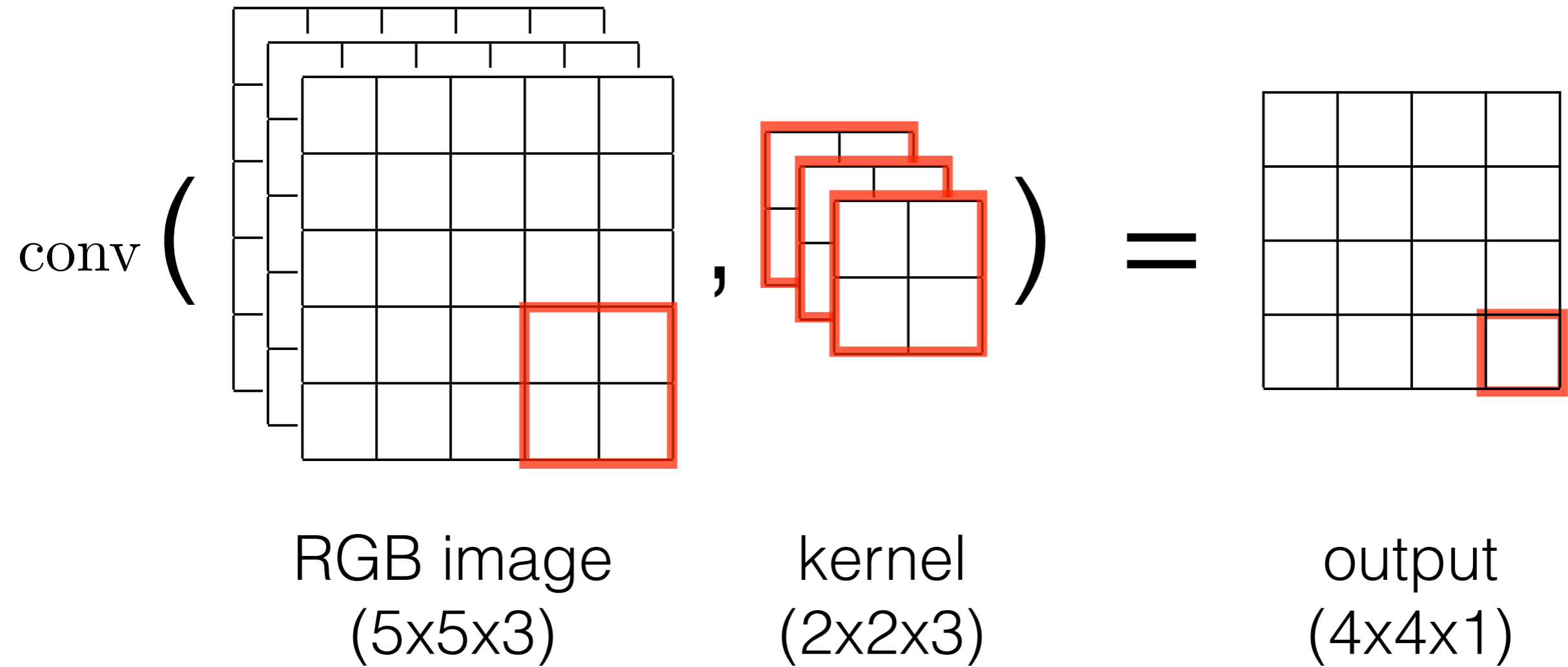
# Multi-channel convolution

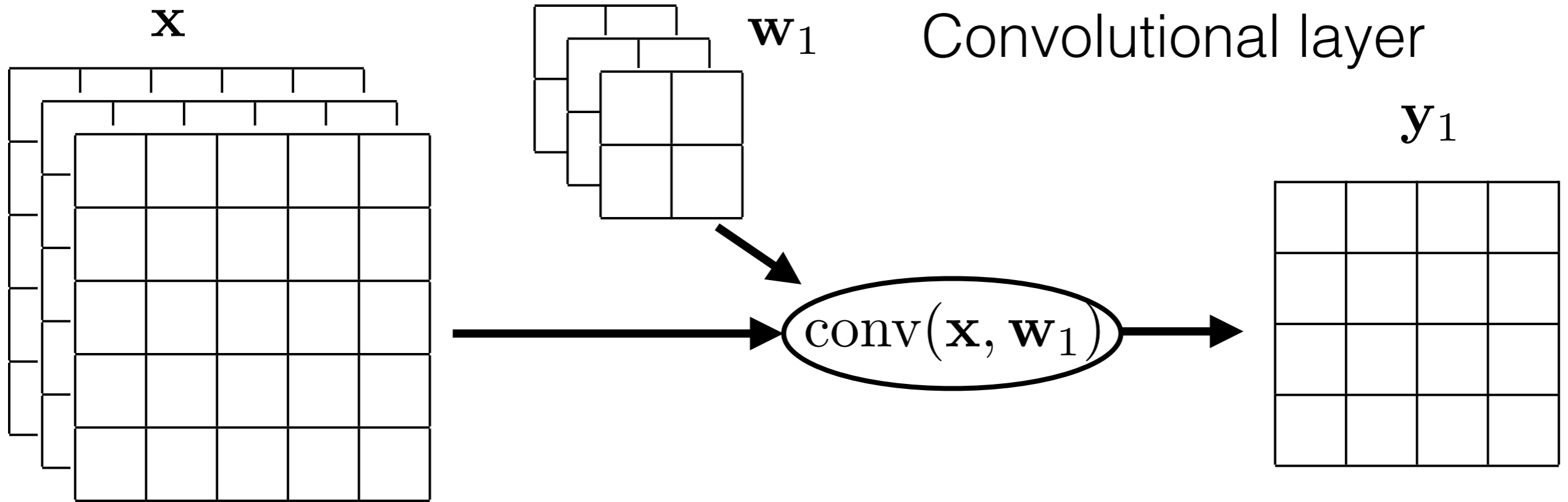


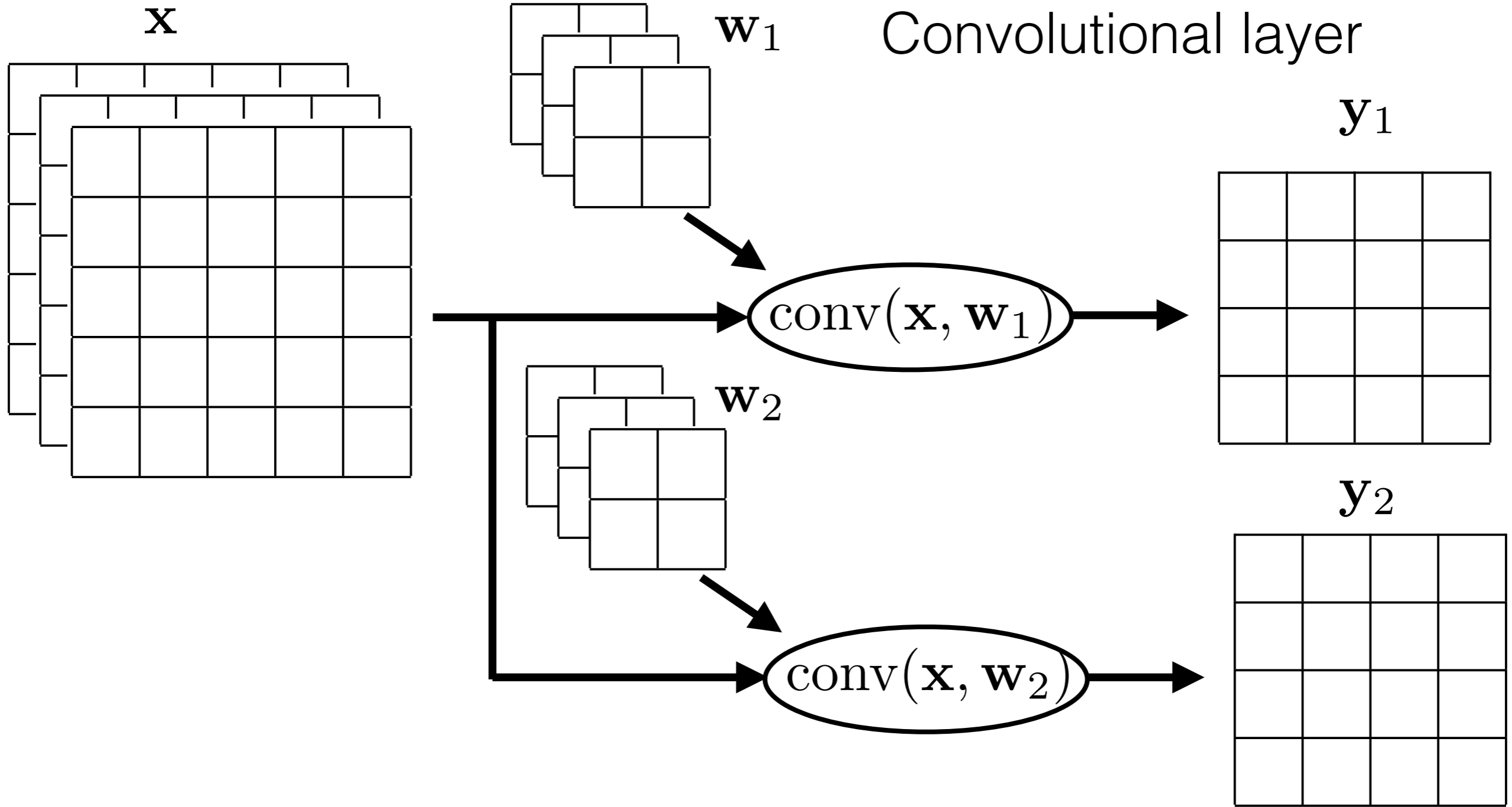
# Multi-channel convolution

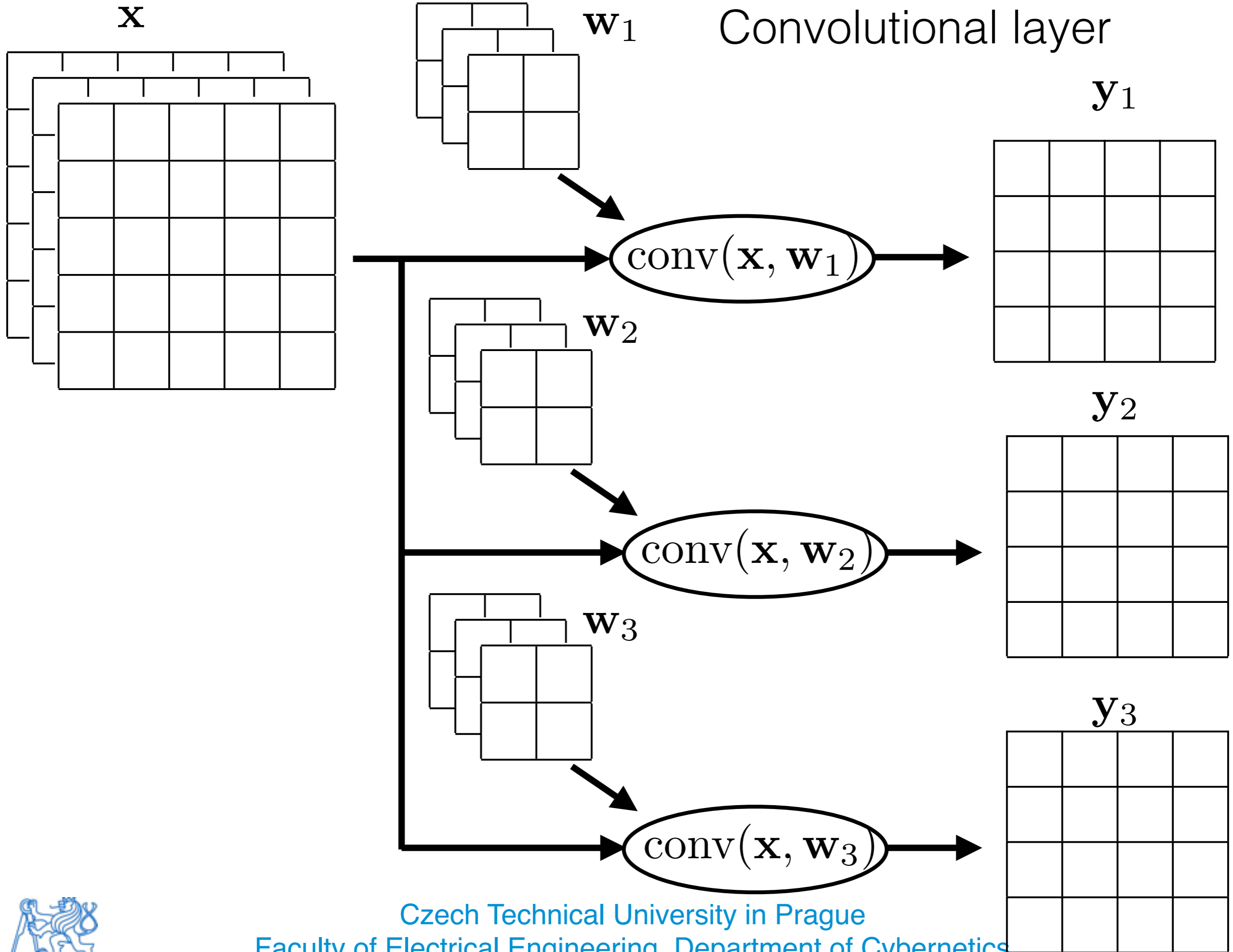


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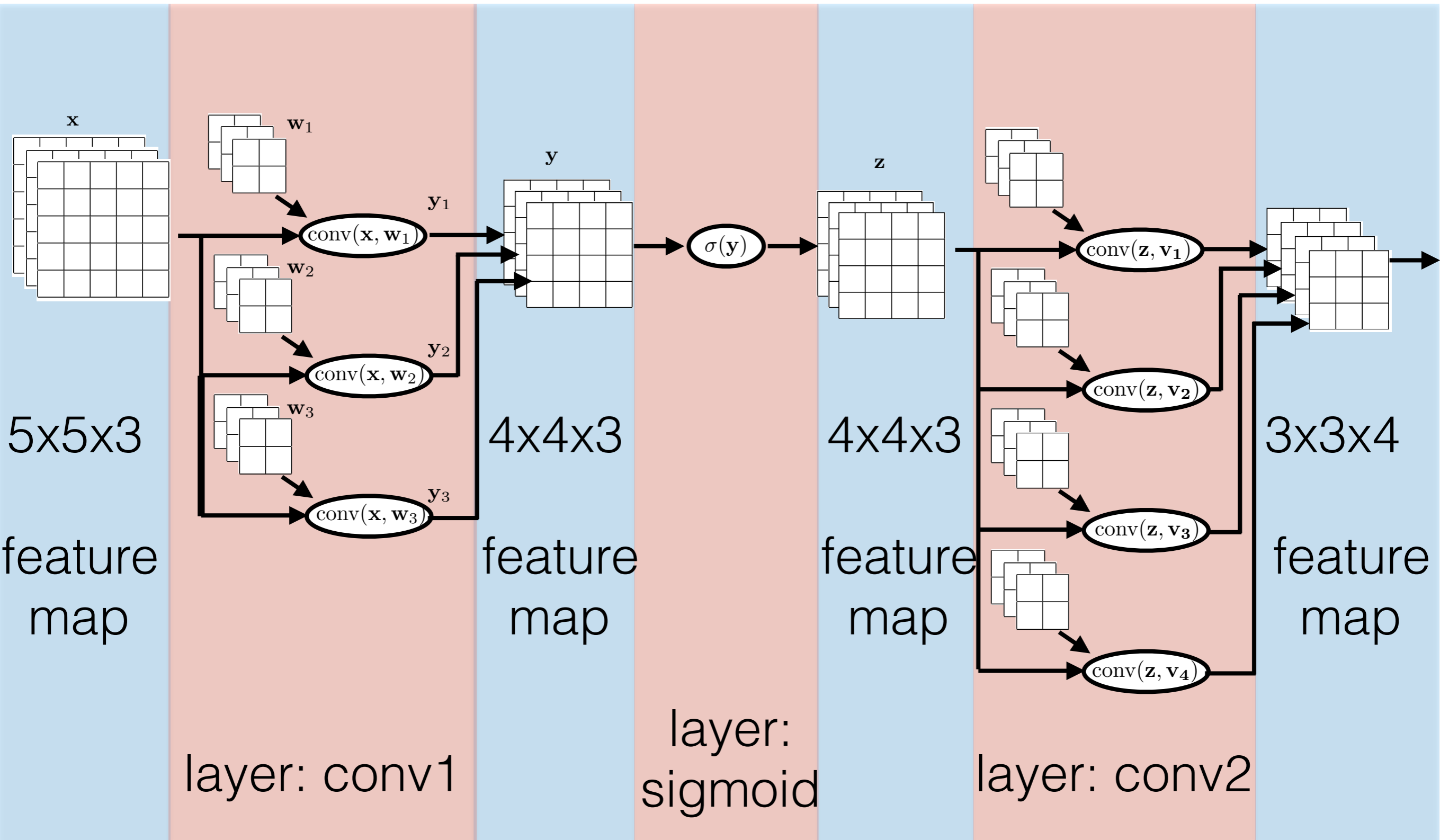








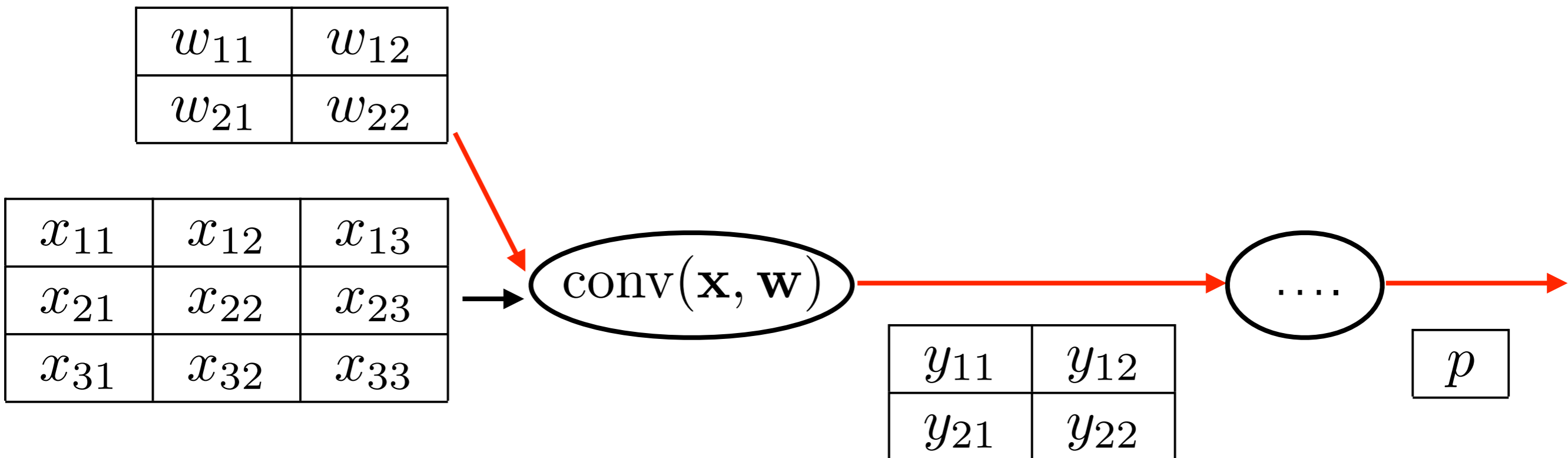
# Convolutional network (ConvNet)





# Convolution backward pass

Learning of convolutional neuron => backpropagation



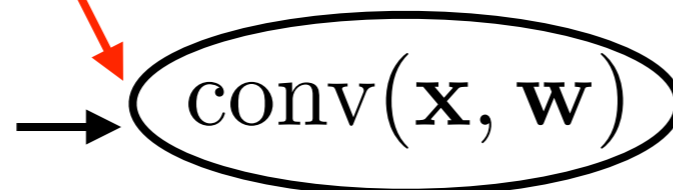
# Convolution backward pass

$\frac{\partial p}{\partial w_{11}}$	$\frac{\partial p}{\partial w_{12}}$
$\frac{\partial p}{\partial w_{21}}$	$\frac{\partial p}{\partial w_{22}}$

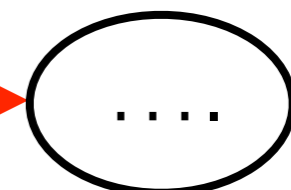
 = ?

$w_{11}$	$w_{12}$
$w_{21}$	$w_{22}$

$x_{11}$	$x_{12}$	$x_{13}$
$x_{21}$	$x_{22}$	$x_{23}$
$x_{31}$	$x_{32}$	$x_{33}$



$y_{11}$	$y_{12}$
$y_{21}$	$y_{22}$

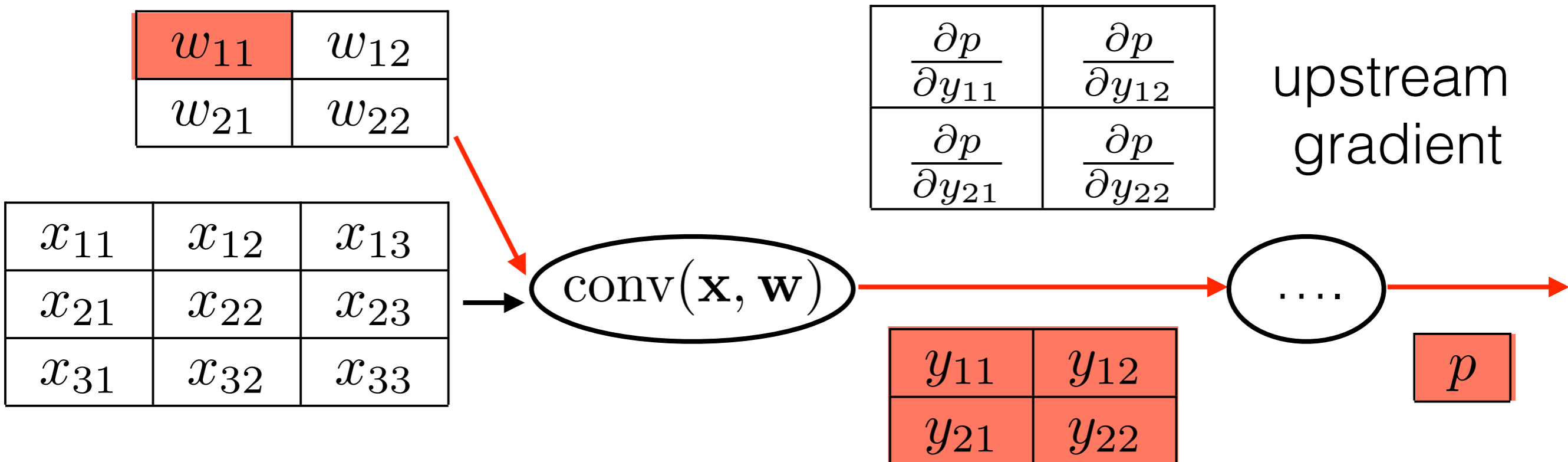


$p$
-----



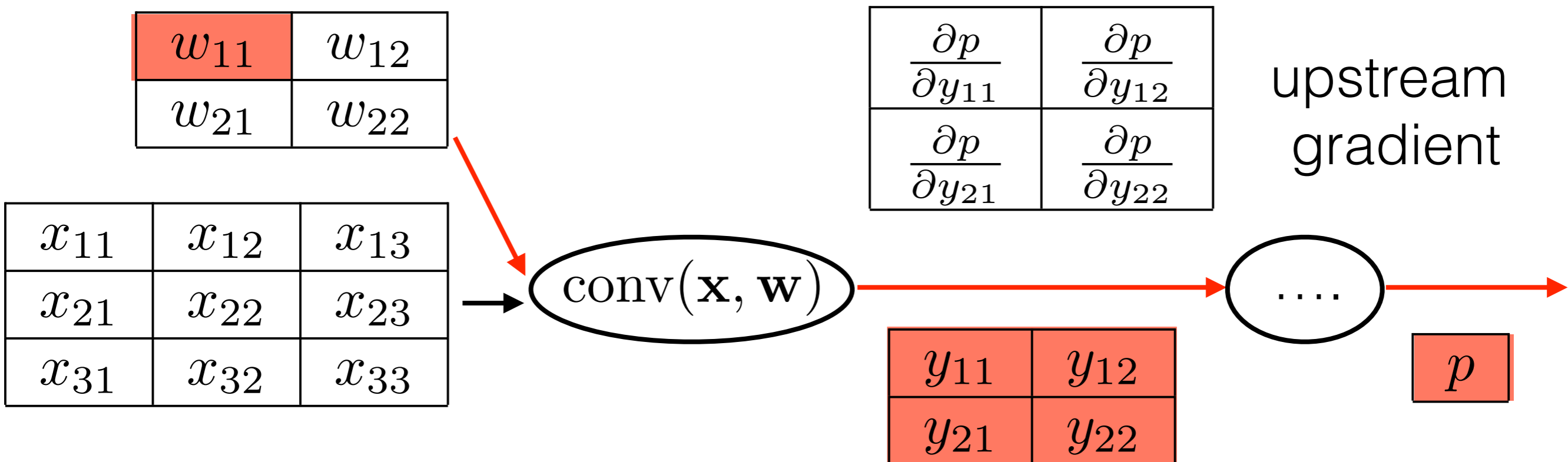
# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = ?$$



# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} \frac{\partial y_{11}}{\partial w_{11}} + \frac{\partial p}{\partial y_{12}} \frac{\partial y_{12}}{\partial w_{11}} + \frac{\partial p}{\partial y_{21}} \frac{\partial y_{21}}{\partial w_{11}} + \frac{\partial p}{\partial y_{22}} \frac{\partial y_{22}}{\partial w_{11}}$$



# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} \frac{\partial y_{11}}{\partial w_{11}} + \frac{\partial p}{\partial y_{12}} \frac{\partial y_{12}}{\partial w_{11}} + \frac{\partial p}{\partial y_{21}} \frac{\partial y_{21}}{\partial w_{11}} + \frac{\partial p}{\partial y_{22}} \frac{\partial y_{22}}{\partial w_{11}}$$

$$\frac{\partial y_{11}}{\partial w_{11}} = \frac{\partial (w_{11}x_{11} + w_{12}x_{12} + w_{21}x_{21} + w_{22}x_{22})}{\partial w_{11}} = x_{11}$$

$w_{11}$	$w_{12}$
$w_{21}$	$w_{22}$

$\frac{\partial p}{\partial y_{11}}$	$\frac{\partial p}{\partial y_{12}}$
$\frac{\partial p}{\partial y_{21}}$	$\frac{\partial p}{\partial y_{22}}$

upstream gradient

$x_{11}$	$x_{12}$	$x_{13}$
$x_{21}$	$x_{22}$	$x_{23}$
$x_{31}$	$x_{32}$	$x_{33}$

conv( $\mathbf{x}, \mathbf{w}$ )

$y_{11}$	$y_{12}$
$y_{21}$	$y_{22}$

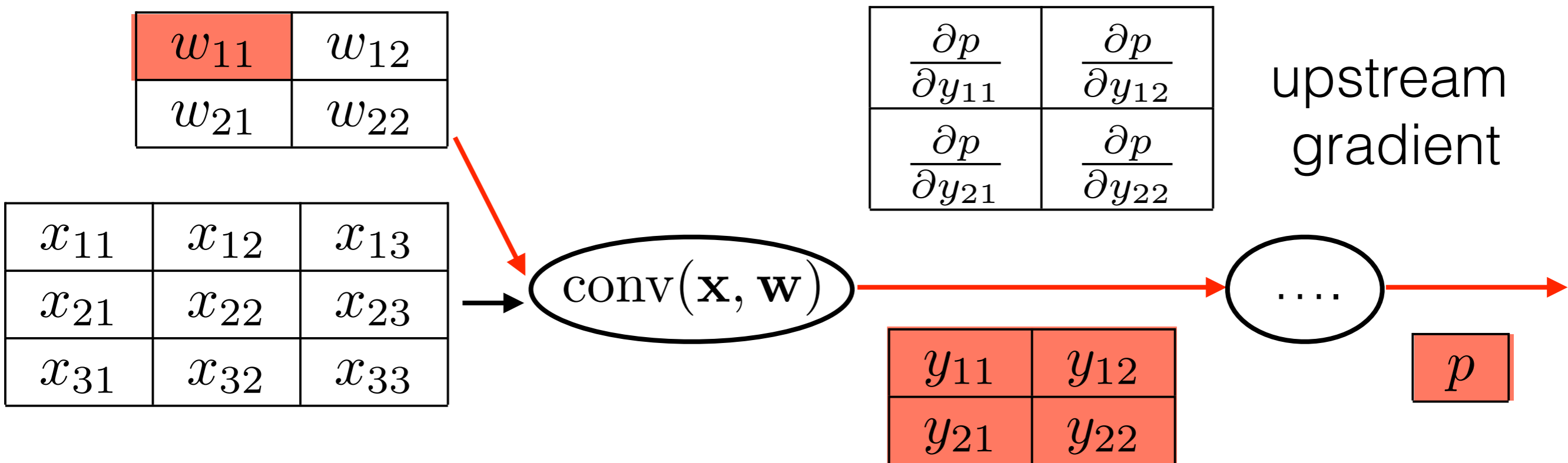
...

$p$



# Convolution backward pass

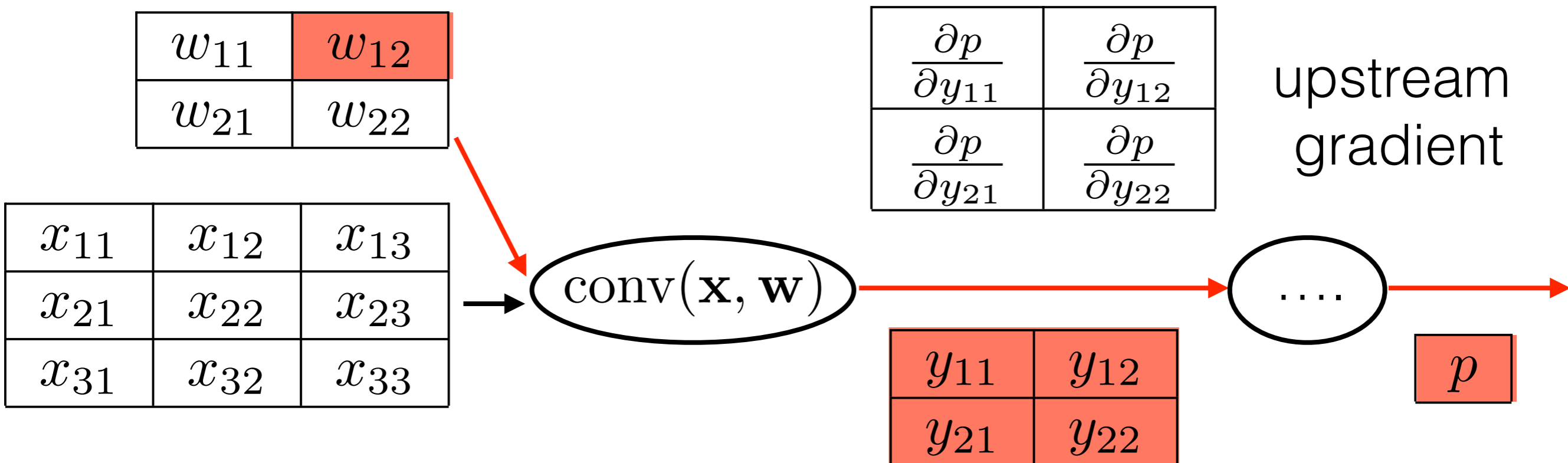
$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22}$$



# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22}$$

$$\frac{\partial p}{\partial w_{12}} = \frac{\partial p}{\partial y_{11}} x_{12} + \frac{\partial p}{\partial y_{12}} x_{13} + \frac{\partial p}{\partial y_{21}} x_{22} + \frac{\partial p}{\partial y_{22}} x_{23}$$

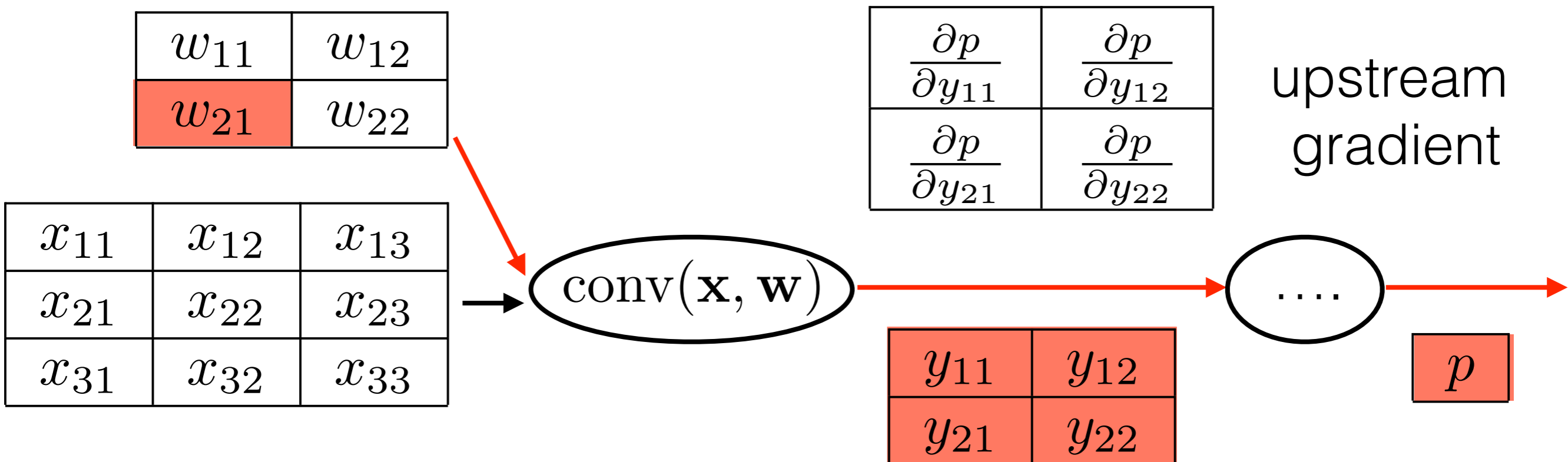


# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22}$$

$$\frac{\partial p}{\partial w_{12}} = \frac{\partial p}{\partial y_{11}} x_{12} + \frac{\partial p}{\partial y_{12}} x_{13} + \frac{\partial p}{\partial y_{21}} x_{22} + \frac{\partial p}{\partial y_{22}} x_{23}$$

$$\frac{\partial p}{\partial w_{21}} = \frac{\partial p}{\partial y_{11}} x_{21} + \frac{\partial p}{\partial y_{12}} x_{22} + \frac{\partial p}{\partial y_{21}} x_{31} + \frac{\partial p}{\partial y_{22}} x_{32}$$





# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22}$$

$$\frac{\partial p}{\partial w_{12}} = \frac{\partial p}{\partial y_{11}} x_{12} + \frac{\partial p}{\partial y_{12}} x_{13} + \frac{\partial p}{\partial y_{21}} x_{22} + \frac{\partial p}{\partial y_{22}} x_{23}$$

$$\frac{\partial p}{\partial w_{21}} = \frac{\partial p}{\partial y_{11}} x_{21} + \frac{\partial p}{\partial y_{12}} x_{22} + \frac{\partial p}{\partial y_{21}} x_{31} + \frac{\partial p}{\partial y_{22}} x_{32}$$

$$\frac{\partial p}{\partial w_{22}} = \frac{\partial p}{\partial y_{11}} x_{22} + \frac{\partial p}{\partial y_{12}} x_{23} + \frac{\partial p}{\partial y_{21}} x_{32} + \frac{\partial p}{\partial y_{22}} x_{33}$$

$w_{11}$	$w_{12}$
$w_{21}$	$w_{22}$

$\frac{\partial p}{\partial y_{11}}$	$\frac{\partial p}{\partial y_{12}}$
$\frac{\partial p}{\partial y_{21}}$	$\frac{\partial p}{\partial y_{22}}$

upstream gradient

$x_{11}$	$x_{12}$	$x_{13}$
$x_{21}$	$x_{22}$	$x_{23}$
$x_{31}$	$x_{32}$	$x_{33}$

conv( $\mathbf{x}, \mathbf{w}$ )

$y_{11}$	$y_{12}$
$y_{21}$	$y_{22}$

...

$p$



# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22}$$

$$\frac{\partial p}{\partial w_{12}} = \frac{\partial p}{\partial y_{11}} x_{12} + \frac{\partial p}{\partial y_{12}} x_{13} + \frac{\partial p}{\partial y_{21}} x_{22} + \frac{\partial p}{\partial y_{22}} x_{23}$$

$$\frac{\partial p}{\partial w_{21}} = \frac{\partial p}{\partial y_{11}} x_{21} + \frac{\partial p}{\partial y_{12}} x_{22} + \frac{\partial p}{\partial y_{21}} x_{31} + \frac{\partial p}{\partial y_{22}} x_{32}$$

$$\frac{\partial p}{\partial w_{22}} = \frac{\partial p}{\partial y_{11}} x_{22} + \frac{\partial p}{\partial y_{12}} x_{23} + \frac{\partial p}{\partial y_{21}} x_{32} + \frac{\partial p}{\partial y_{22}} x_{33}$$

$w_{11}$	$w_{12}$
$w_{21}$	$w_{22}$

$\frac{\partial p}{\partial y_{11}}$	$\frac{\partial p}{\partial y_{12}}$
$\frac{\partial p}{\partial y_{21}}$	$\frac{\partial p}{\partial y_{22}}$

upstream gradient

$x_{11}$	$x_{12}$	$x_{13}$
$x_{21}$	$x_{22}$	$x_{23}$
$x_{31}$	$x_{32}$	$x_{33}$

conv( $\mathbf{x}, \mathbf{w}$ )

$y_{11}$	$y_{12}$
$y_{21}$	$y_{22}$

...

$p$



# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22}$$

$$\frac{\partial p}{\partial w_{12}} = \frac{\partial p}{\partial y_{11}} x_{12} + \frac{\partial p}{\partial y_{12}} x_{13} + \frac{\partial p}{\partial y_{21}} x_{22} + \frac{\partial p}{\partial y_{22}} x_{23}$$

$$\frac{\partial p}{\partial w_{21}} = \frac{\partial p}{\partial y_{11}} x_{21} + \frac{\partial p}{\partial y_{12}} x_{22} + \frac{\partial p}{\partial y_{21}} x_{31} + \frac{\partial p}{\partial y_{22}} x_{32}$$

$$\frac{\partial p}{\partial w_{22}} = \frac{\partial p}{\partial y_{11}} x_{22} + \frac{\partial p}{\partial y_{12}} x_{23} + \frac{\partial p}{\partial y_{21}} x_{32} + \frac{\partial p}{\partial y_{22}} x_{33}$$

$\frac{\partial p}{\partial w_{11}}$	$\frac{\partial p}{\partial w_{12}}$
$\frac{\partial p}{\partial w_{21}}$	$\frac{\partial p}{\partial w_{22}}$

= conv

$x_{11}$	$x_{12}$	$x_{13}$
$x_{21}$	$x_{22}$	$x_{23}$
$x_{31}$	$x_{32}$	$x_{33}$

$\frac{\partial p}{\partial y_{11}}$	$\frac{\partial p}{\partial y_{12}}$
$\frac{\partial p}{\partial y_{21}}$	$\frac{\partial p}{\partial y_{22}}$



# Convolution backward pass

$$\frac{\partial p}{\partial w_{11}} = \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22}$$

$$\frac{\partial p}{\partial w_{12}} = \frac{\partial p}{\partial y_{11}} x_{12} + \frac{\partial p}{\partial y_{12}} x_{13} + \frac{\partial p}{\partial y_{21}} x_{22} + \frac{\partial p}{\partial y_{22}} x_{23}$$

$$\frac{\partial p}{\partial w_{21}} = \frac{\partial p}{\partial y_{11}} x_{21} + \frac{\partial p}{\partial y_{12}} x_{22} + \frac{\partial p}{\partial y_{21}} x_{31} + \frac{\partial p}{\partial y_{22}} x_{32}$$

$$\frac{\partial p}{\partial w_{22}} = \frac{\partial p}{\partial y_{11}} x_{22} + \frac{\partial p}{\partial y_{12}} x_{23} + \frac{\partial p}{\partial y_{21}} x_{32} + \frac{\partial p}{\partial y_{22}} x_{33}$$

$\frac{\partial p}{\partial w_{11}}$	$\frac{\partial p}{\partial w_{12}}$
$\frac{\partial p}{\partial w_{21}}$	$\frac{\partial p}{\partial w_{22}}$

= conv

$x_{11}$	$x_{12}$	$x_{13}$
$x_{21}$	$x_{22}$	$x_{23}$
$x_{31}$	$x_{32}$	$x_{33}$

$\frac{\partial p}{\partial y_{11}}$	$\frac{\partial p}{\partial y_{12}}$
$\frac{\partial p}{\partial y_{21}}$	$\frac{\partial p}{\partial y_{22}}$



# Convolution backward pass

$$\begin{aligned} \frac{\partial p}{\partial w_{11}} &= \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22} \\ \frac{\partial p}{\partial w_{12}} &= \frac{\partial p}{\partial y_{11}} x_{12} + \frac{\partial p}{\partial y_{12}} x_{13} + \frac{\partial p}{\partial y_{21}} x_{22} + \frac{\partial p}{\partial y_{22}} x_{23} \\ \frac{\partial p}{\partial w_{21}} &= \frac{\partial p}{\partial y_{11}} x_{21} + \frac{\partial p}{\partial y_{12}} x_{22} + \frac{\partial p}{\partial y_{21}} x_{31} + \frac{\partial p}{\partial y_{22}} x_{32} \\ \frac{\partial p}{\partial w_{22}} &= \frac{\partial p}{\partial y_{11}} x_{22} + \frac{\partial p}{\partial y_{12}} x_{23} + \frac{\partial p}{\partial y_{21}} x_{32} + \frac{\partial p}{\partial y_{22}} x_{33} \end{aligned}$$

$\frac{\partial p}{\partial w_{11}}$	$\frac{\partial p}{\partial w_{12}}$
$\frac{\partial p}{\partial w_{21}}$	$\frac{\partial p}{\partial w_{22}}$

= conv

$x_{11}$	$x_{12}$	$x_{13}$
$x_{21}$	$x_{22}$	$x_{23}$
$x_{31}$	$x_{32}$	$x_{33}$

$\frac{\partial p}{\partial y_{11}}$	$\frac{\partial p}{\partial y_{12}}$
$\frac{\partial p}{\partial y_{21}}$	$\frac{\partial p}{\partial y_{22}}$



# Convolution backward pass

$$\begin{aligned} \frac{\partial p}{\partial w_{11}} &= \frac{\partial p}{\partial y_{11}} x_{11} + \frac{\partial p}{\partial y_{12}} x_{12} + \frac{\partial p}{\partial y_{21}} x_{21} + \frac{\partial p}{\partial y_{22}} x_{22} \\ \frac{\partial p}{\partial w_{12}} &= \frac{\partial p}{\partial y_{11}} x_{12} + \frac{\partial p}{\partial y_{12}} x_{13} + \frac{\partial p}{\partial y_{21}} x_{22} + \frac{\partial p}{\partial y_{22}} x_{23} \\ \frac{\partial p}{\partial w_{21}} &= \frac{\partial p}{\partial y_{11}} x_{21} + \frac{\partial p}{\partial y_{12}} x_{22} + \frac{\partial p}{\partial y_{21}} x_{31} + \frac{\partial p}{\partial y_{22}} x_{32} \\ \frac{\partial p}{\partial w_{22}} &= \frac{\partial p}{\partial y_{11}} x_{22} + \frac{\partial p}{\partial y_{12}} x_{23} + \frac{\partial p}{\partial y_{21}} x_{32} + \frac{\partial p}{\partial y_{22}} x_{33} \end{aligned}$$

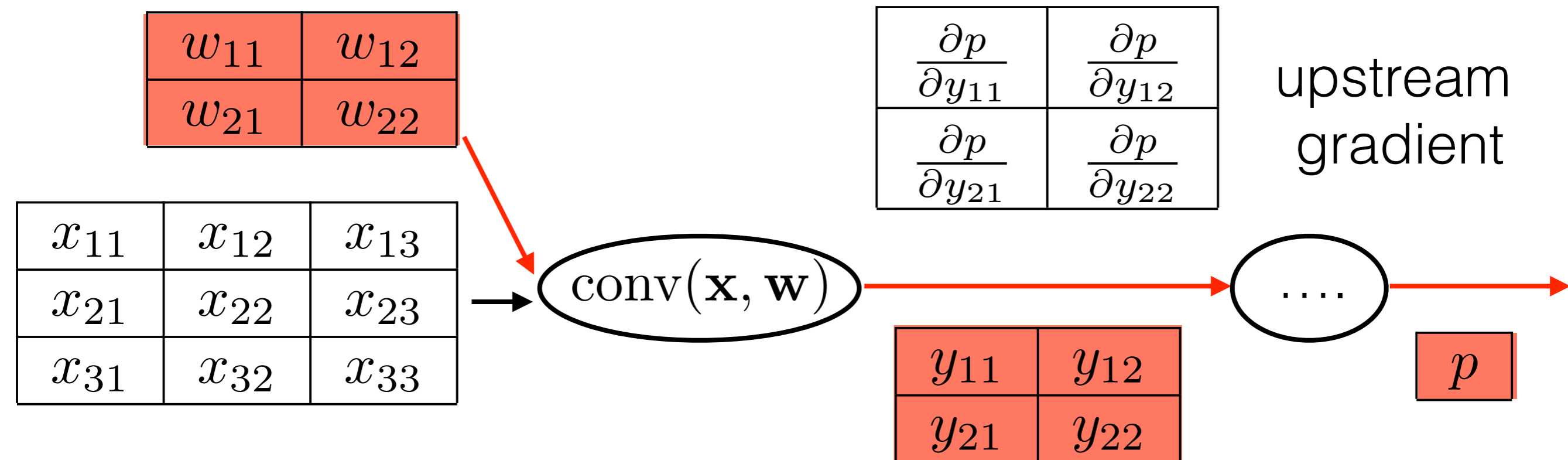
$$\begin{pmatrix} \frac{\partial p}{\partial w_{11}} & \frac{\partial p}{\partial w_{12}} \\ \frac{\partial p}{\partial w_{21}} & \frac{\partial p}{\partial w_{22}} \end{pmatrix} = \text{conv} \left( \begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{pmatrix}, \begin{pmatrix} \frac{\partial p}{\partial y_{11}} & \frac{\partial p}{\partial y_{12}} \\ \frac{\partial p}{\partial y_{21}} & \frac{\partial p}{\partial y_{22}} \end{pmatrix} \right)$$



# Convolution backward pass wrt weights

- Backpropagation in convolutional layer wrt weights is:  
**“convolution of input feature map with upstream gradient”**

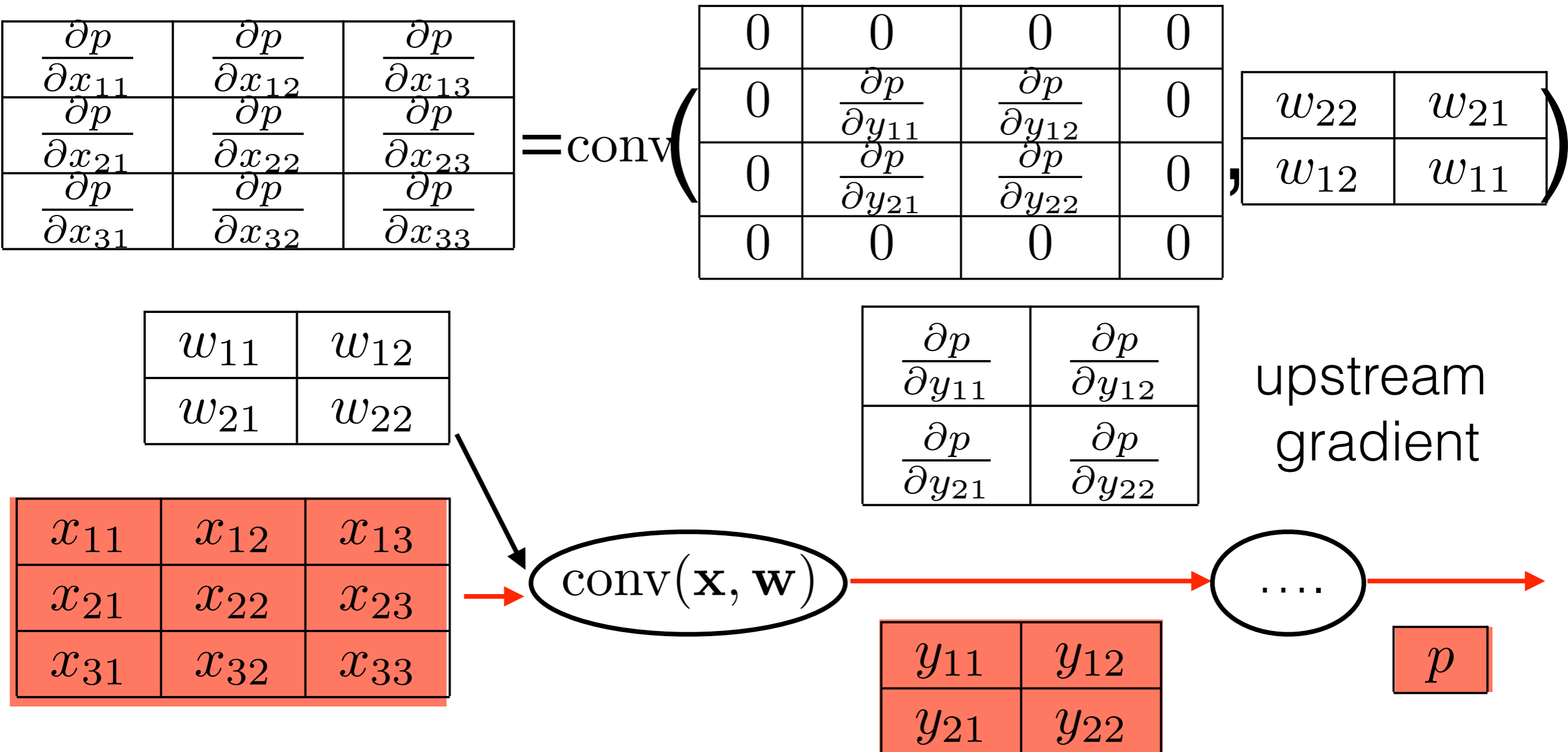
$$\begin{array}{|c|c|} \hline \frac{\partial p}{\partial w_{11}} & \frac{\partial p}{\partial w_{12}} \\ \hline \frac{\partial p}{\partial w_{21}} & \frac{\partial p}{\partial w_{22}} \\ \hline \end{array} = \text{conv} \left( \begin{array}{|c|c|c|} \hline x_{11} & x_{12} & x_{13} \\ \hline x_{21} & x_{22} & x_{23} \\ \hline x_{31} & x_{32} & x_{33} \\ \hline \end{array}, \begin{array}{|c|c|} \hline \frac{\partial p}{\partial y_{11}} & \frac{\partial p}{\partial y_{12}} \\ \hline \frac{\partial p}{\partial y_{21}} & \frac{\partial p}{\partial y_{22}} \\ \hline \end{array} \right)$$



# Convolution backward pass wrt input feature map

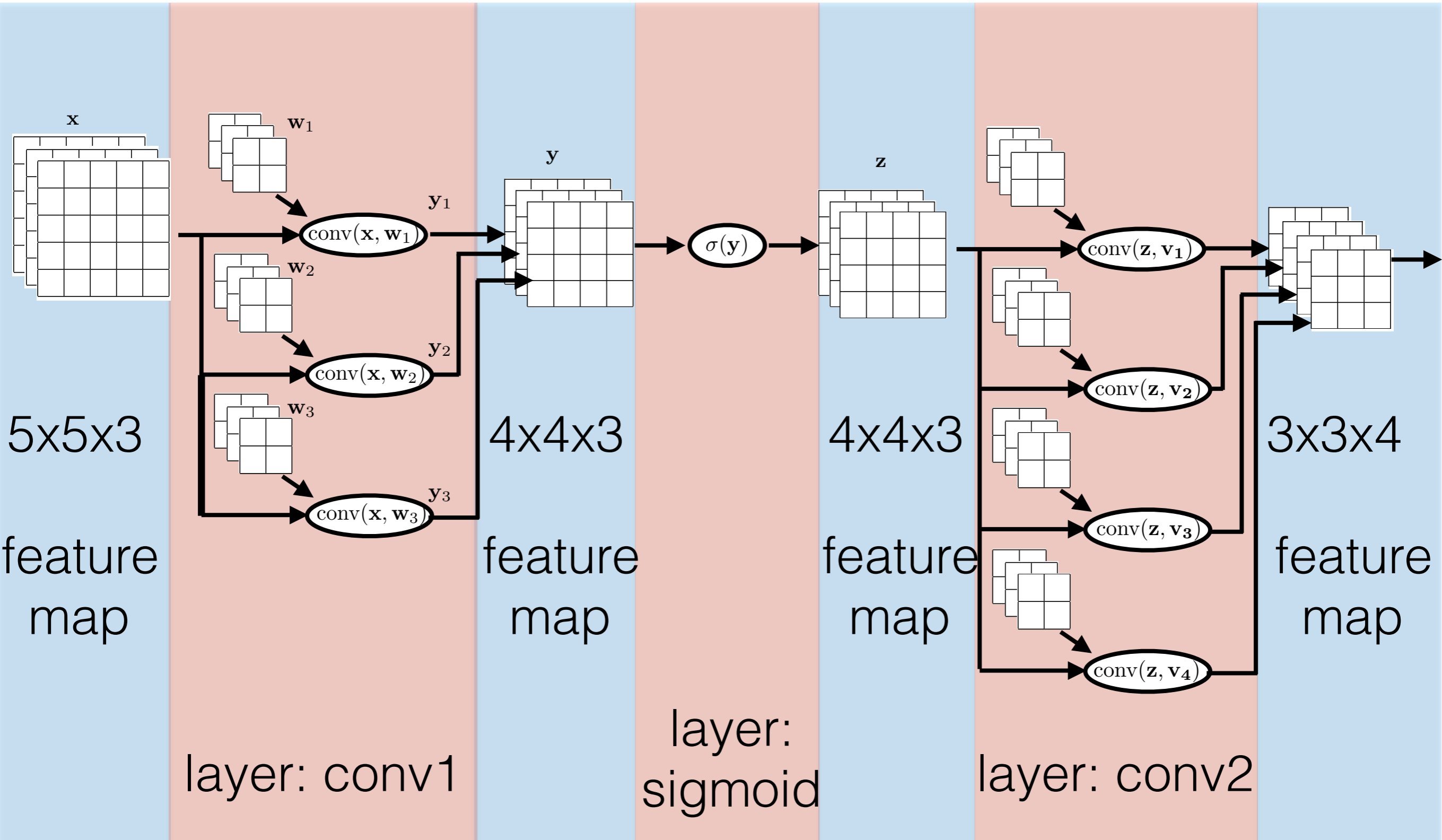
Backpropagation in convolutional layer is:

**“convolution of padded upstream gradient with mirrored weights”**





# ???? Convolutional network backprop ?????

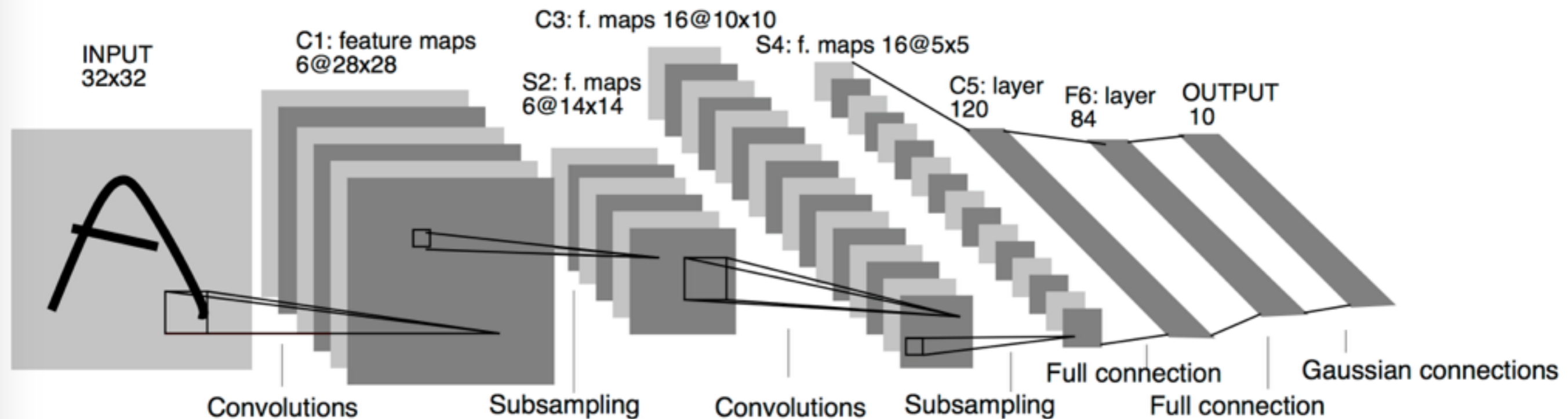


# Convolutional net

- Convolutional network (ConvNet) is concatenation of convolutional layers
- Backprop in ConvNet is convolution of feature maps or kernels with upstream gradient.
- Feed-forward and backprop are convolutions => efficient implementation on GPU



# LeCun's letter recognition 1998 (over 13k citations !!!)

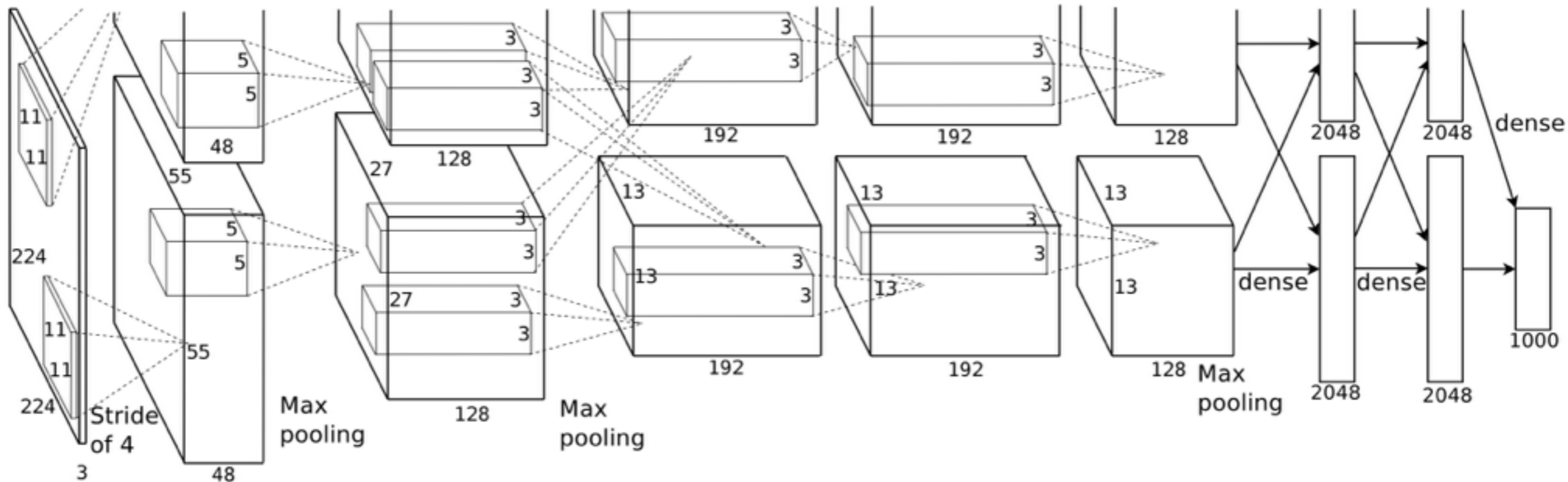


LeCun et al, Gradient based learning applied to document recognition, IEEE, 1998

<http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf>



# AlexNet on ImageNet 2012 (**over 27k citations !!!**)



Alex Krizhevsky et al, Imagenet classification with deep convolutional neural networks, NIPS, 2012

<https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf>



## Classification results

<http://image-net.org/challenges/LSVRC/2017/index>

### Steel drum



**Output:**  
Scale  
T-shirt  
Steel drum  
Drumstick  
Mud turtle



**Output:**  
Scale  
T-shirt  
Giant panda  
Drumstick  
Mud turtle

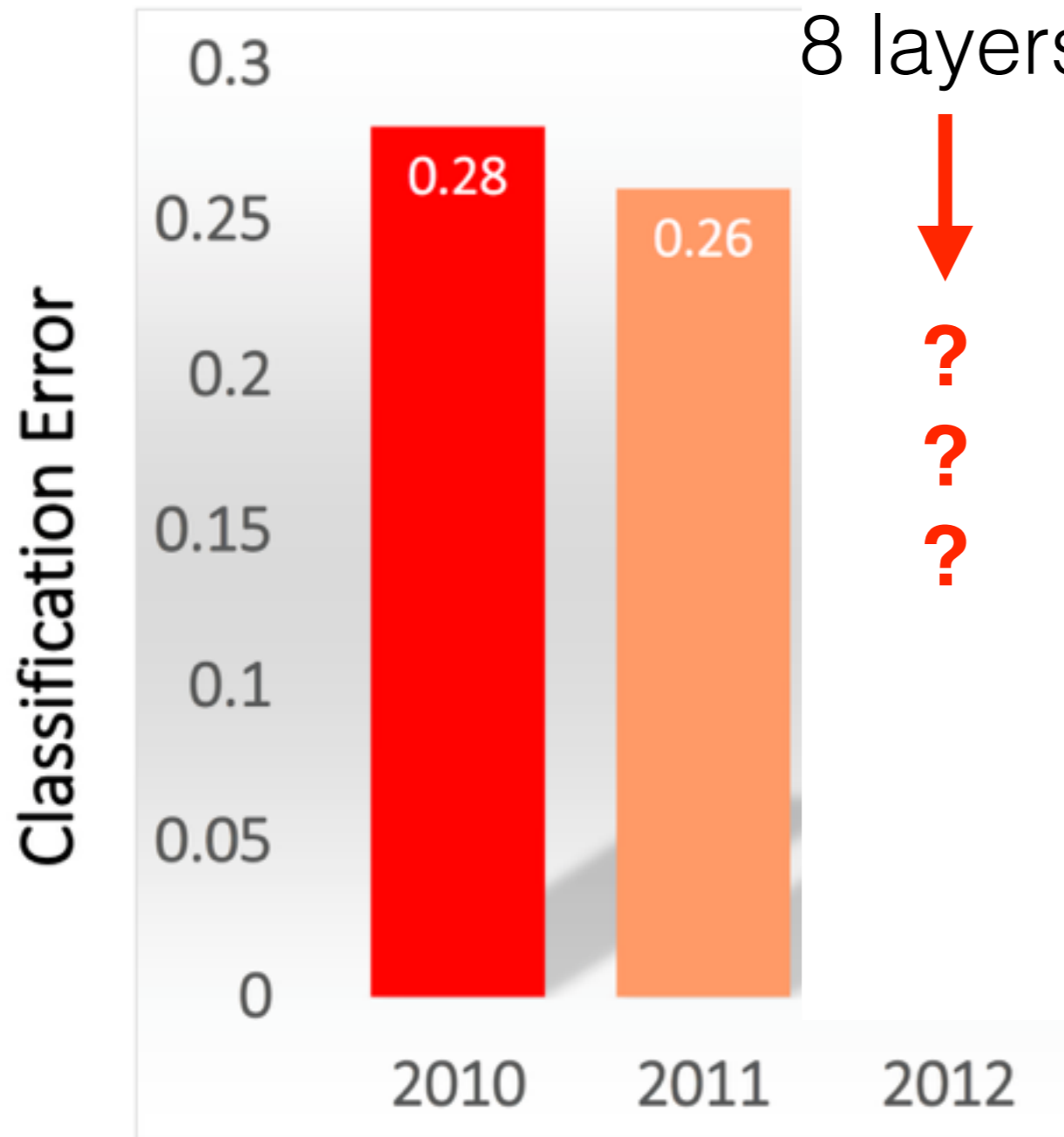


$$\text{Error} = \frac{1}{100,000} \sum_{100,000 \text{ images}} 1[\text{incorrect on image } i]$$

## Classification results

AlexNet

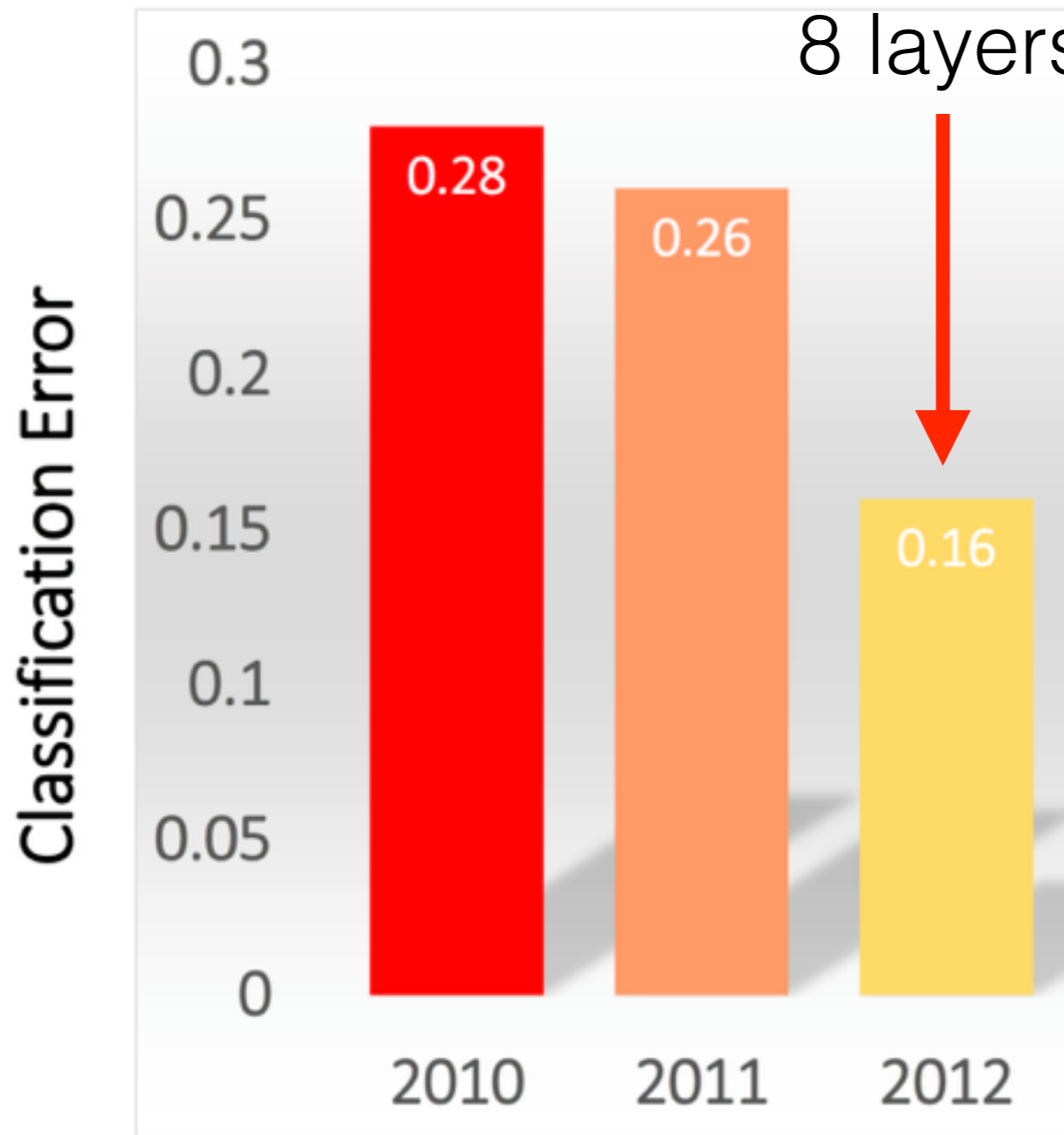
8 layers



## Classification results

AlexNet

8 layers



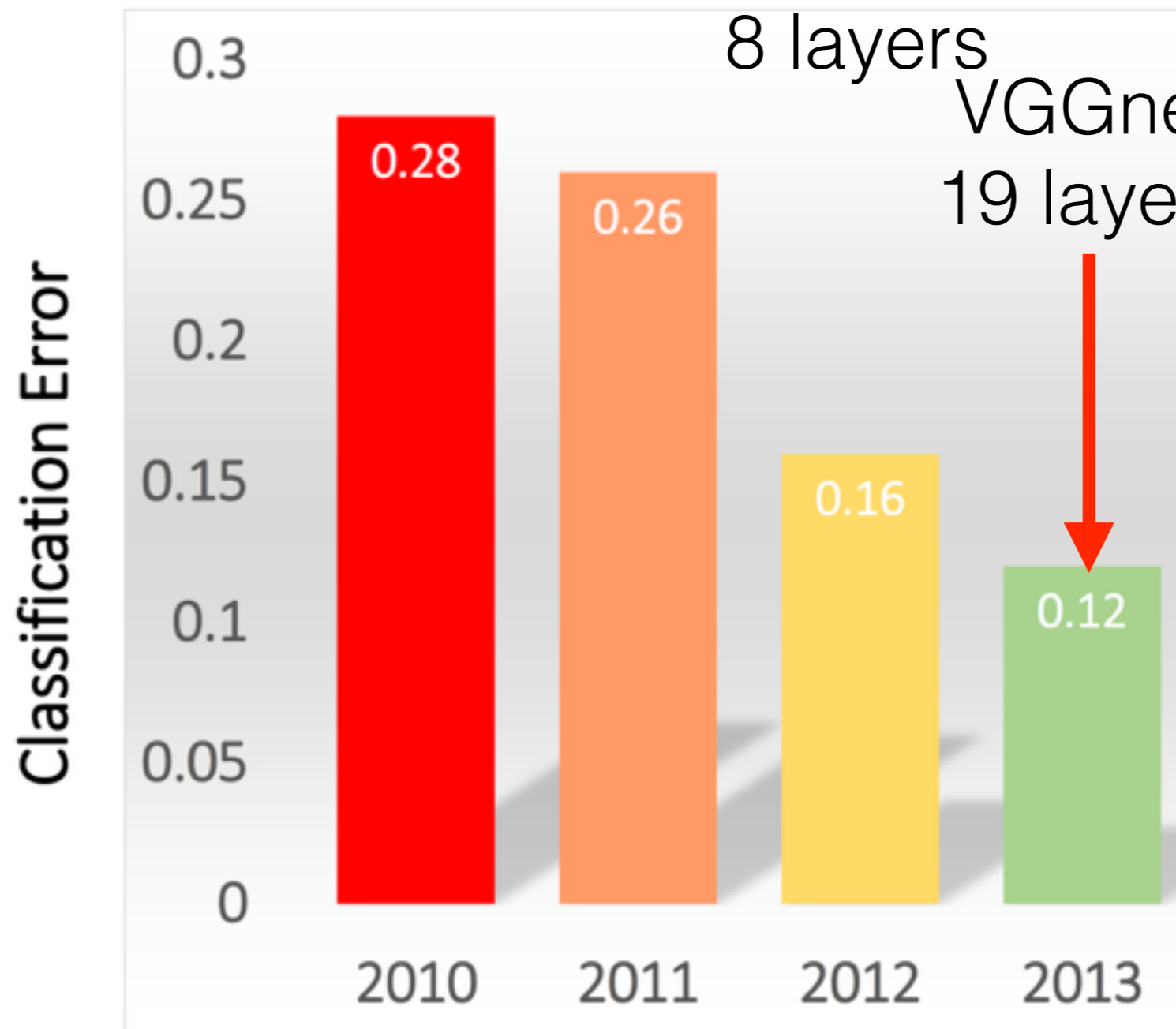
## Classification results

AlexNet

8 layers

VGGnet

19 layers





# IMAGENET

Classification results

AlexNet

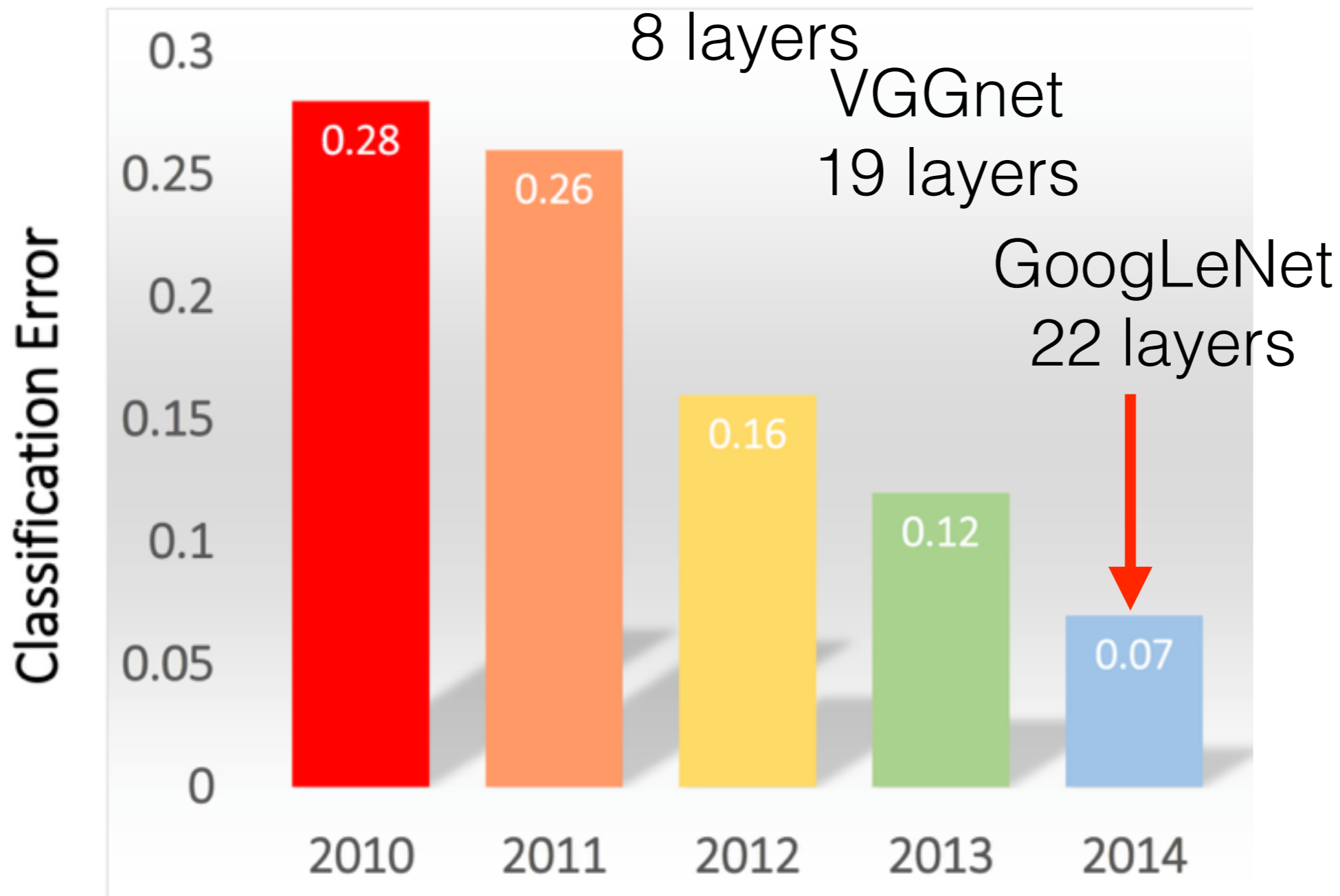
8 layers

VGGnet

19 layers

GoogLeNet

22 layers



# IMAGENET

## Classification results

AlexNet

8 layers

VGGnet

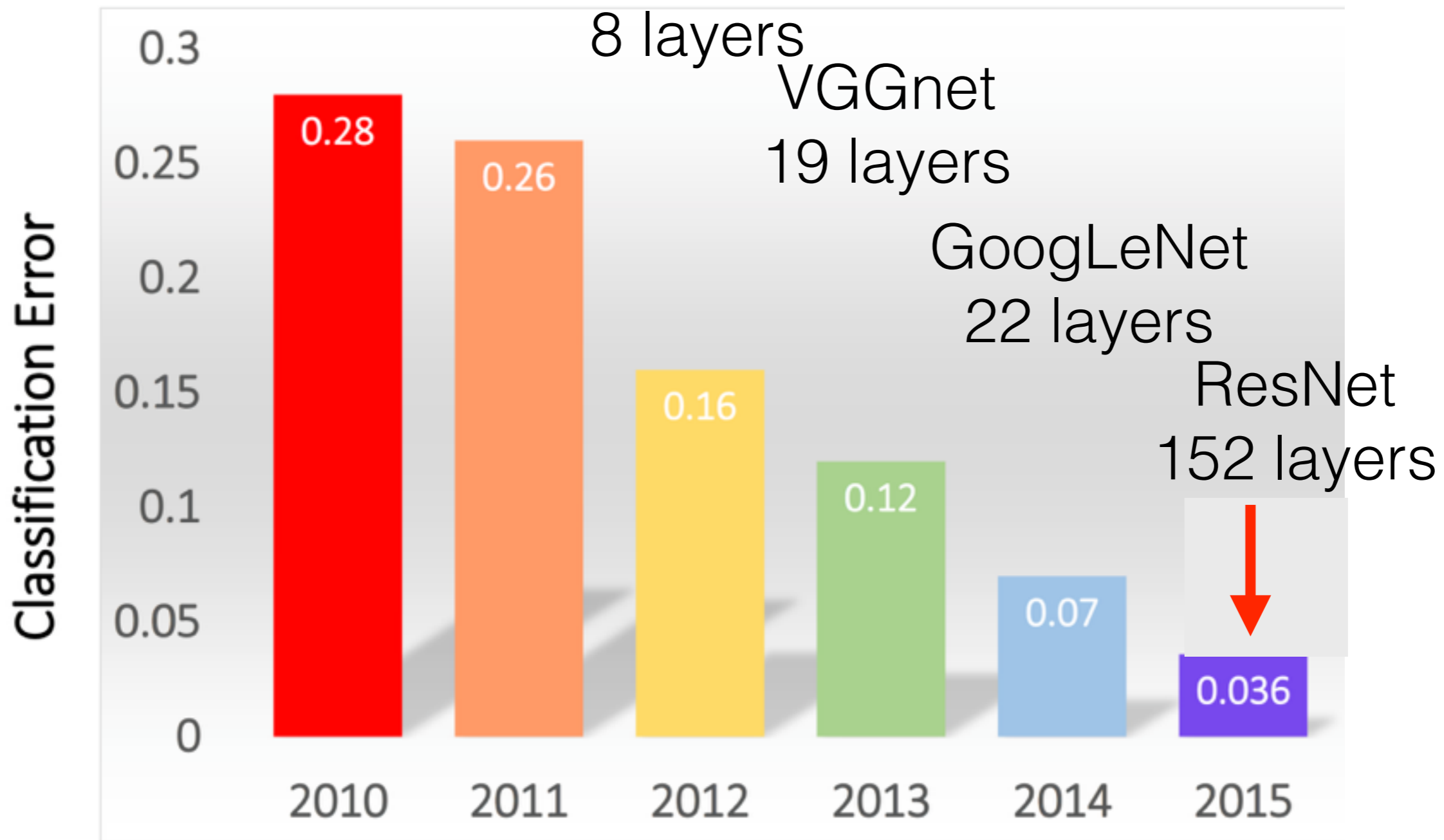
19 layers

GoogLeNet

22 layers

ResNet

152 layers



# IMAGENET

## Classification results

AlexNet

8 layers

VGGnet

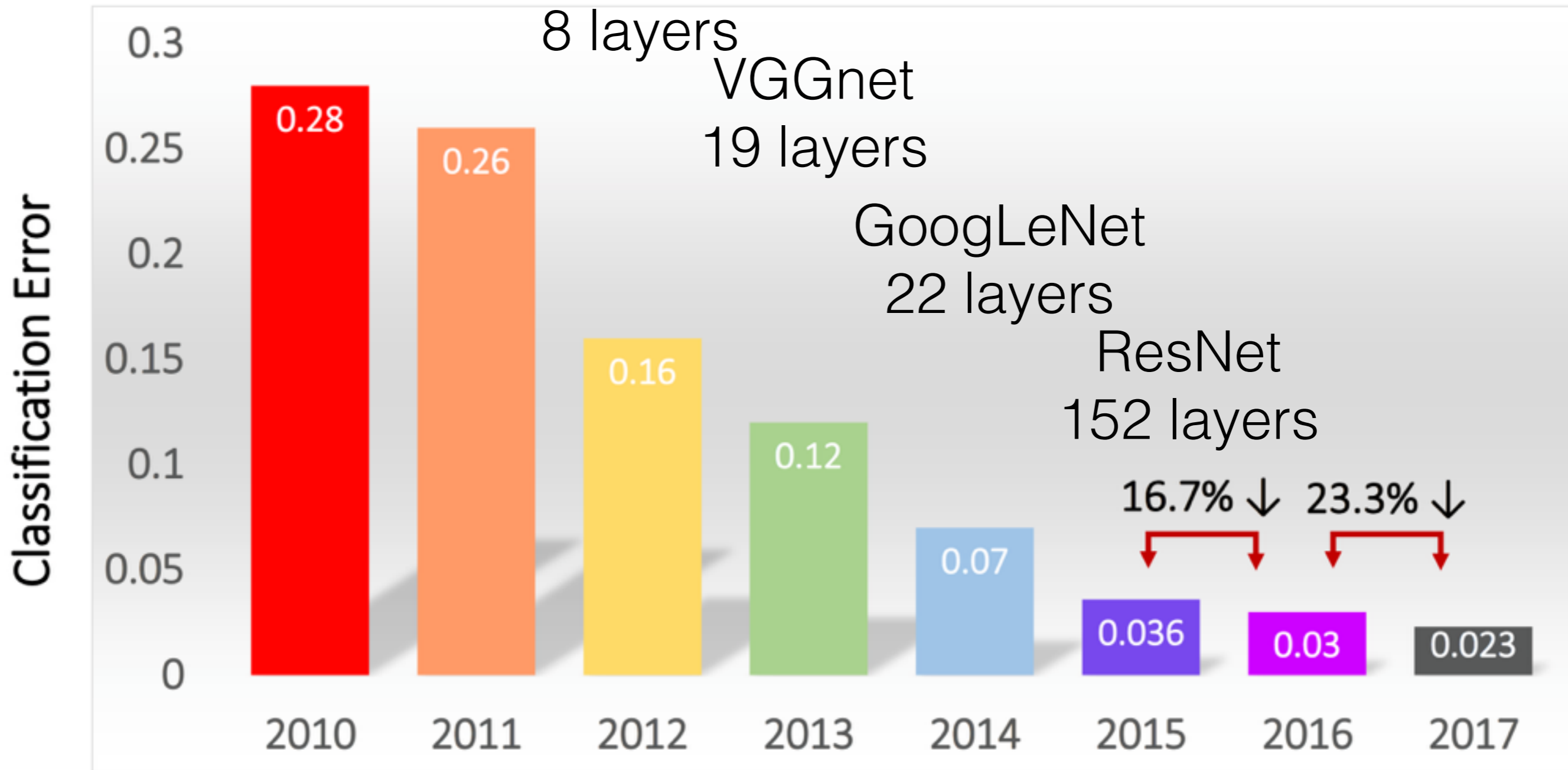
19 layers

GoogLeNet

22 layers

ResNet

152 layers



# Demo

- convnet demo from Karpathy:  
<https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html>



# Next lecture

- gradient learning (what make it tough)
- other layers:
  - activation function,
  - batch normalization,
  - drop out,
  - loss layers

