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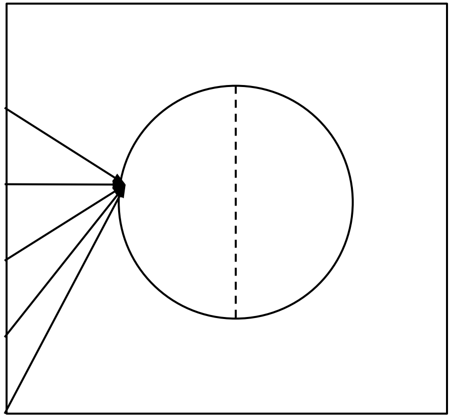
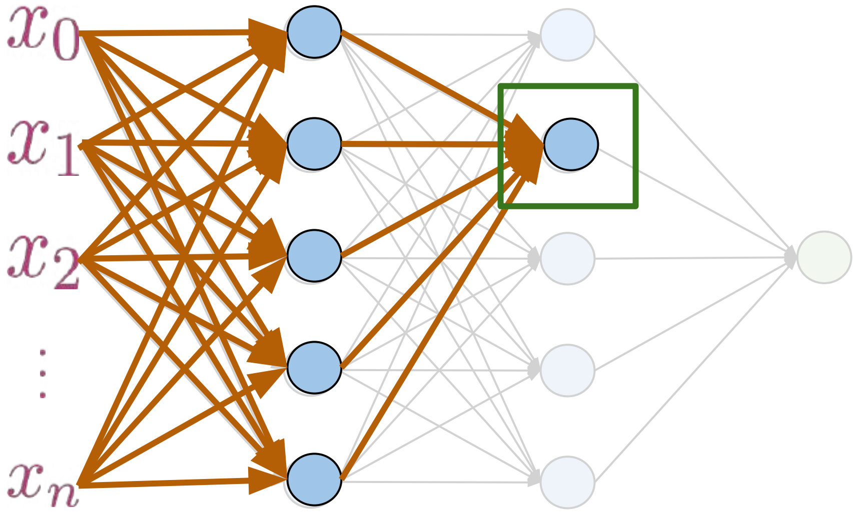
Activations (Basic Properties)

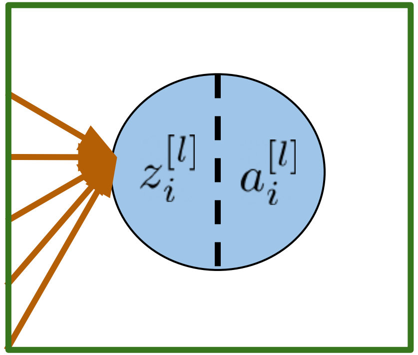
Outline

- What are activations
- Reasoning behind non-linear differential activations



Activations





$$z_i^{[l]} = \sum_{i=0} W_i^{[l]} a_i^{[l-1]}$$

$$a_i^{[l]} = \boxed{g^{[l]}}(z_i^{[l]})$$

Differentiable non-linear function

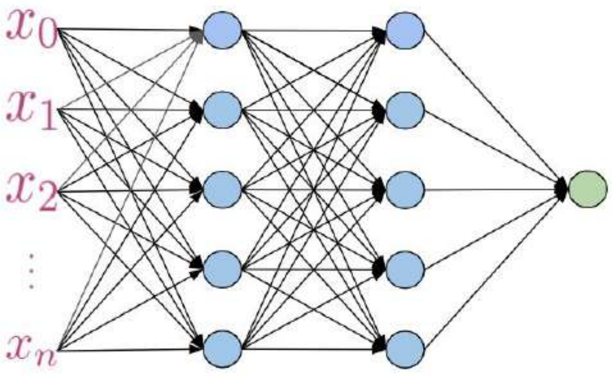
Activations

$$a_i^{[l]} = \boxed{g^{[l]}}(z_i^{[l]})$$

Differentiable non-linear function

1. Differentiable for backpropagation

2. Non-linear to compute complex features, **if not**:



$$\equiv \quad WX + b$$

Linear regression

Summary

- Activation functions are non-linear and differentiable
- Differentiable for backpropagation
- Non-linear to approximate complex functions

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Common Activation Functions

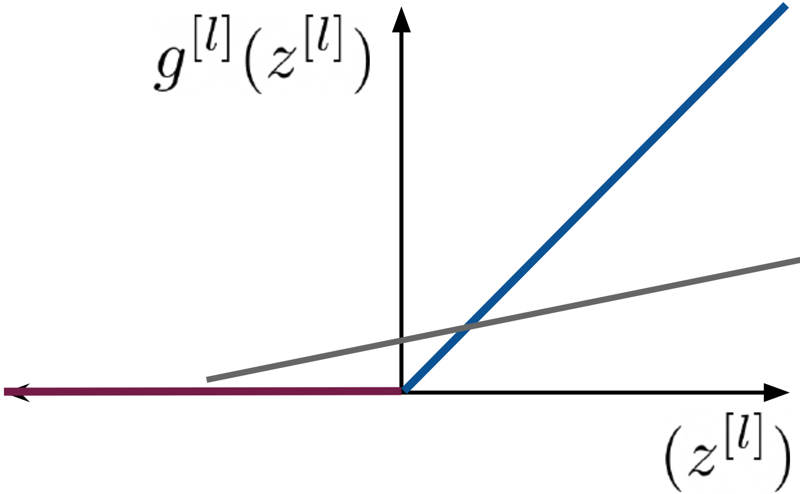
Outline

- Common activations and their structure
    - ReLU
    - Leaky ReLU
    - Sigmoid
    - Tanh

Activations: ReLU

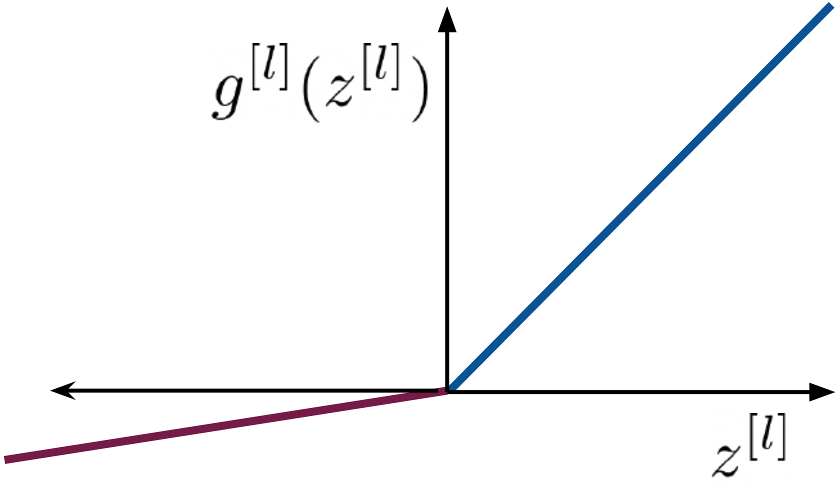
ReLU = Rectified Linear Unit

$$g^{[l]}(z^{[l]}) = \max(\underline{0}, \underline{z^{[l]}})$$



Dying ReLU problem

Activations: Leaky ReLU

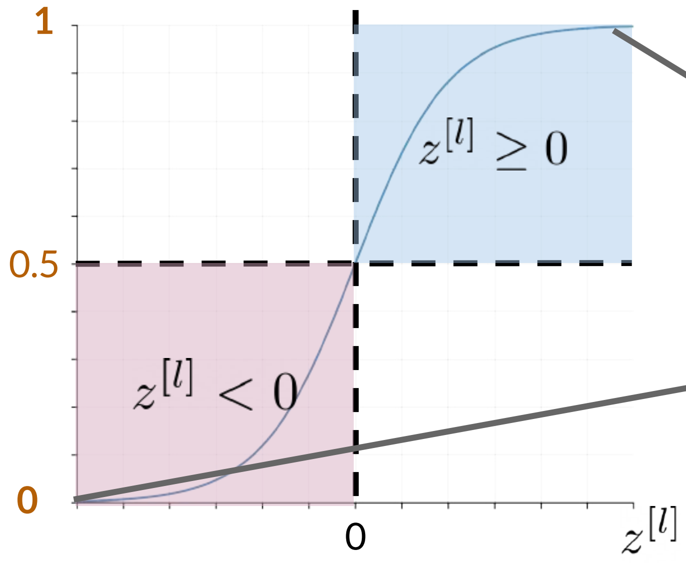


$$g^{[l]}(z^{[l]}) = max(\underline{az^{[l]}}, \underline{z^{[l]}})$$

Solves the dying ReLU problem

Activations: Sigmoid

$$g^{[l]}(z^{[l]}) = \frac{1}{1+e^{-z^{[l]}}}$$

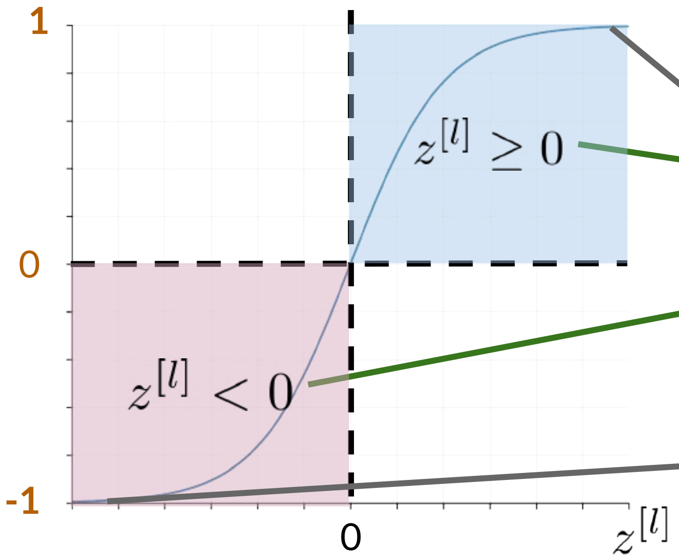


Values between 0 and 1

Vanishing gradient and saturation problems

Activations: Tanh

$$g^{[l]}(z^{[l]}) = tanh(z^{[l]})$$



Values between -1 and 1

Keeps the sign of the input

Same issues as Sigmoid

Summary

- ReLU activations suffer from dying ReLU
- Leaky ReLU solve the dying ReLu problem
- Sigmoid and Tanh have vanishing gradient and saturation problems

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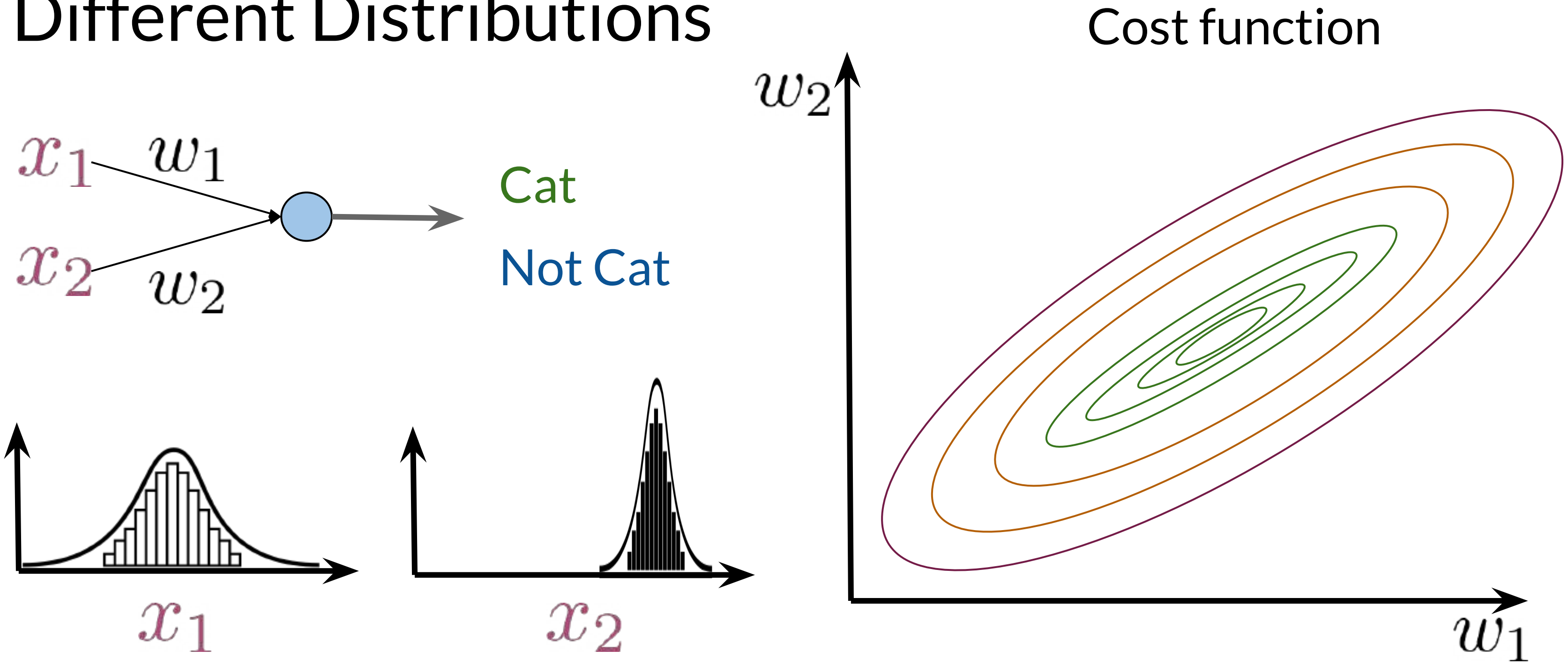
Batch Normalization (Explained)

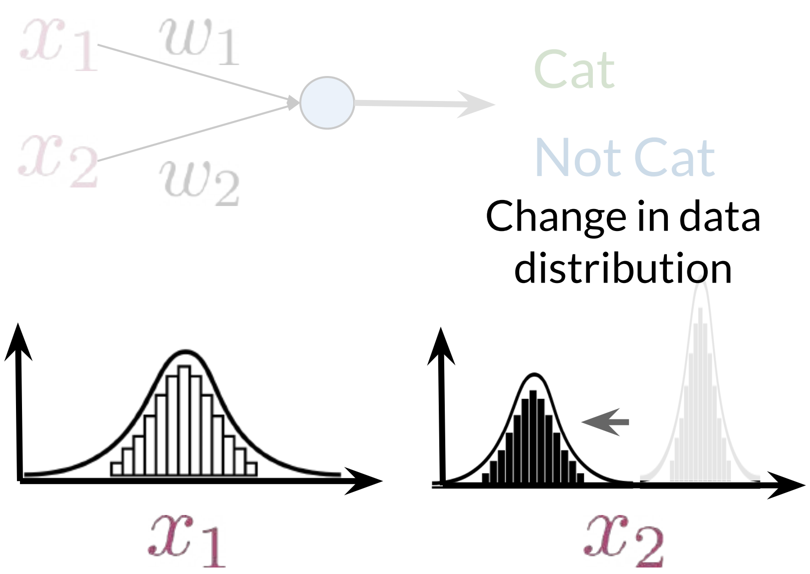
Outline

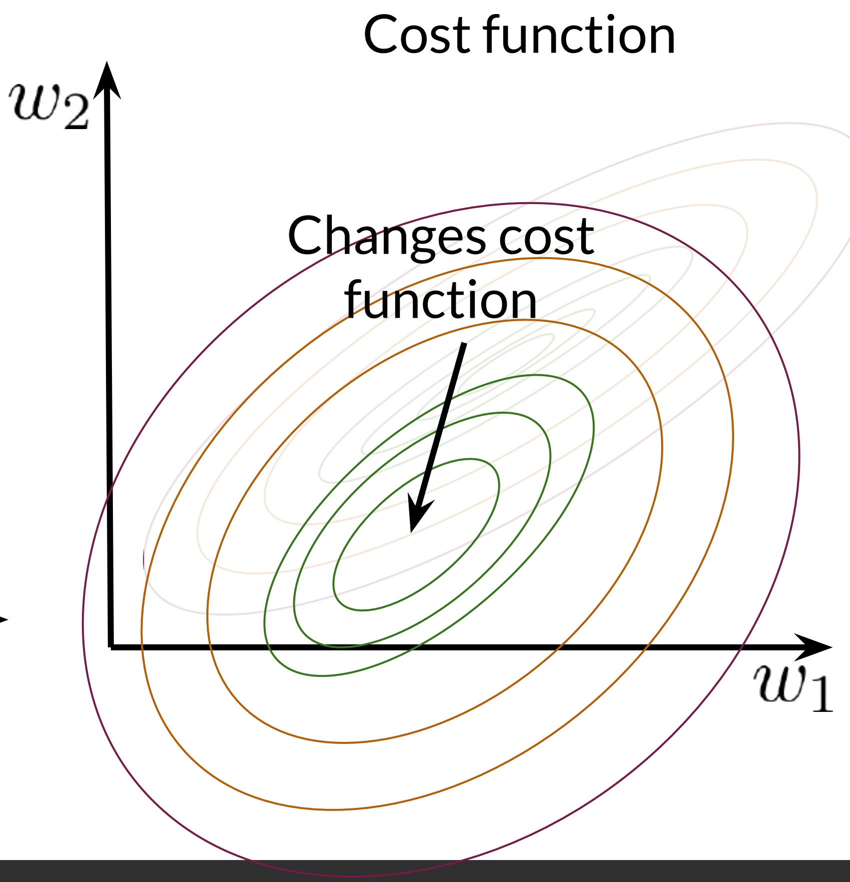
- How normalization helps models
- Internal covariate shift
- Batch normalization

Different Distributions

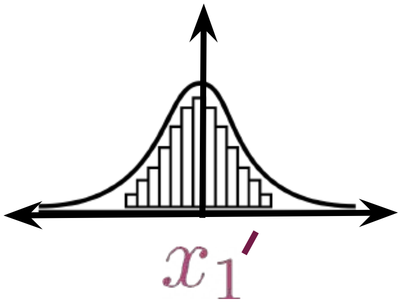


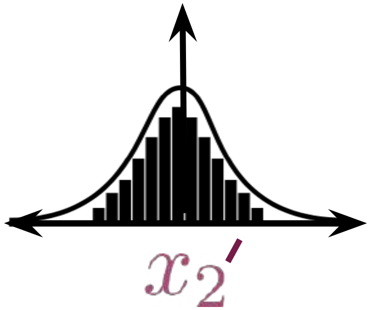
Covariate Shift



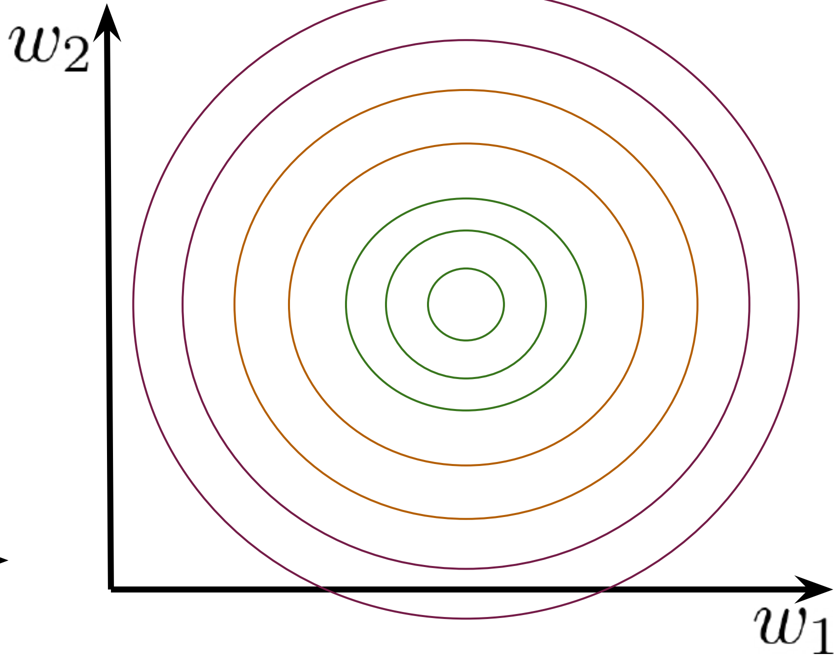


Normalization and Its Effects

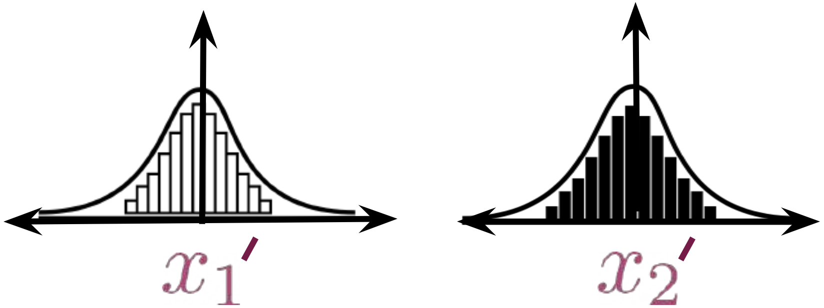


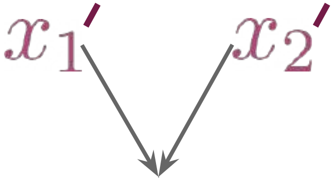


Cost function



Normalization and Its Effects



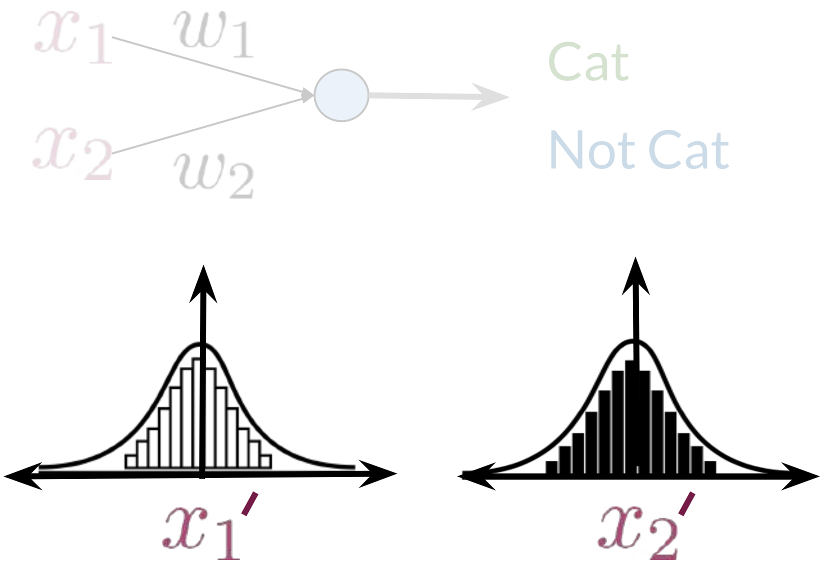


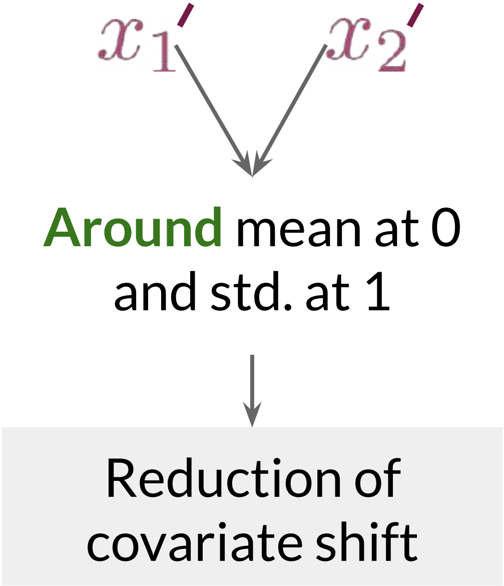
Around mean at 0
and std. at 1

Training data uses
batch stats

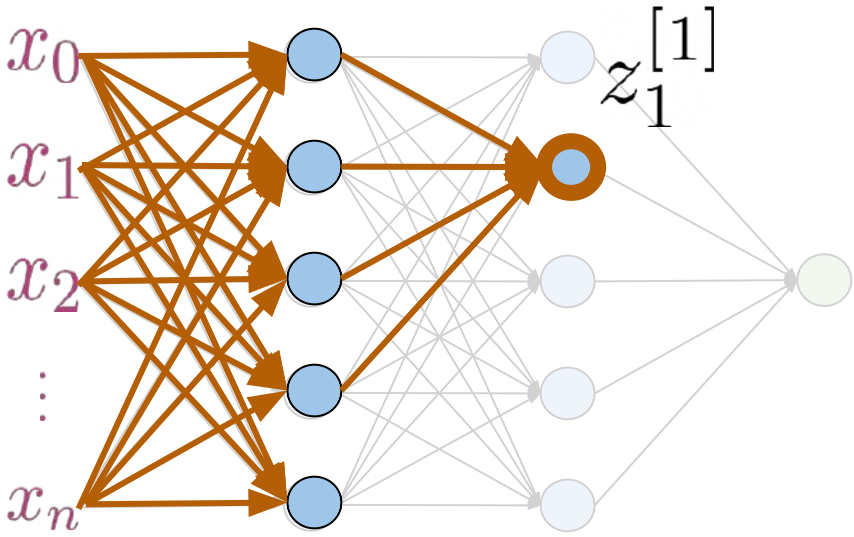
Test data uses
training stats

Normalization and Its Effects





Internal Covariate Shift

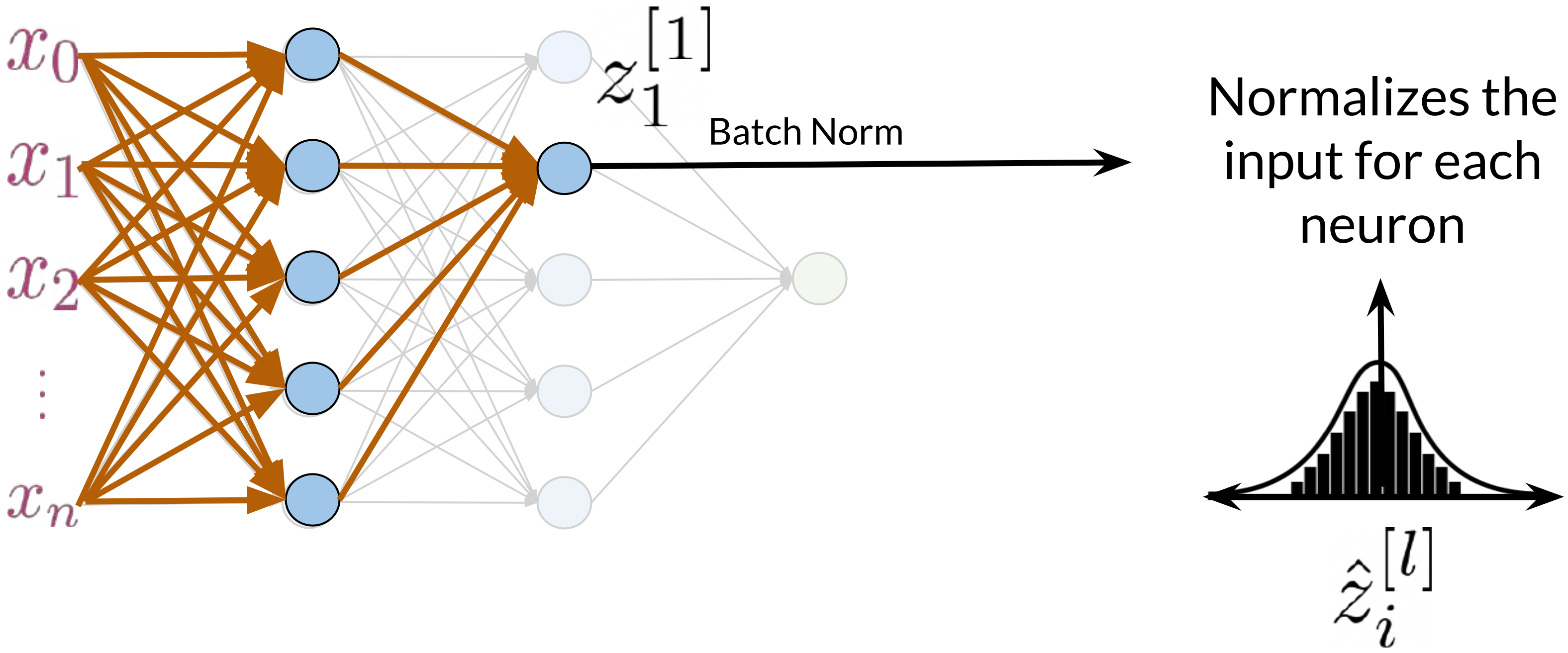


Changes in weights

↓

Changes in activation distribution

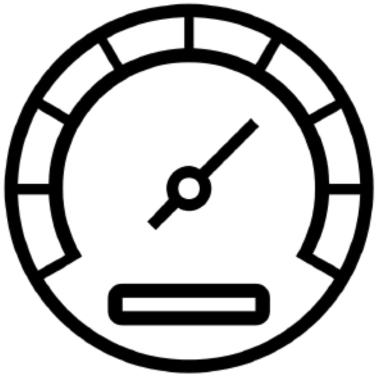
Batch Normalization



Normalizes the input for each neuron

Summary

- Batch normalization smooths the cost function
- Batch normalization reduces the internal covariate shift
- Batch normalization speeds up learning!



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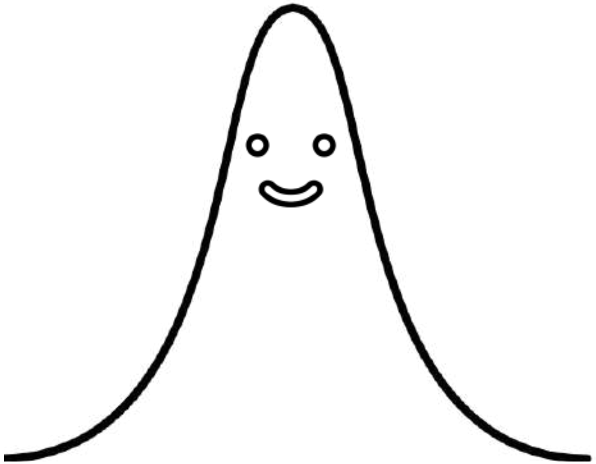
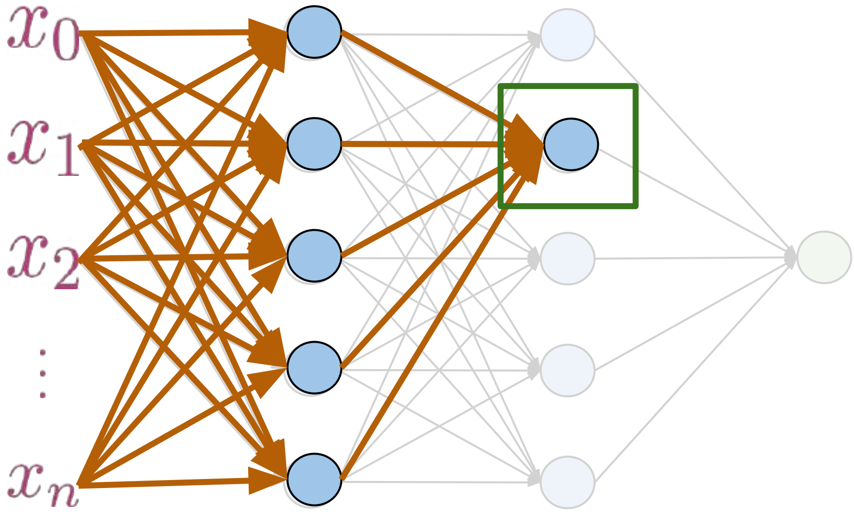
Batch Normalization (Procedure)

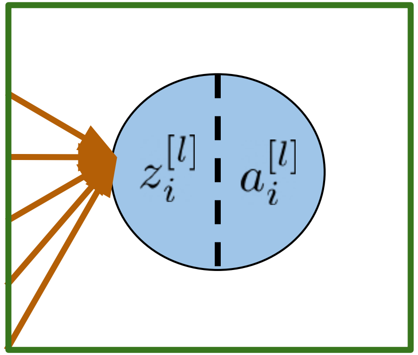
Outline

- Batch norm for training
- Batch norm for testing



Batch Normalization: Training





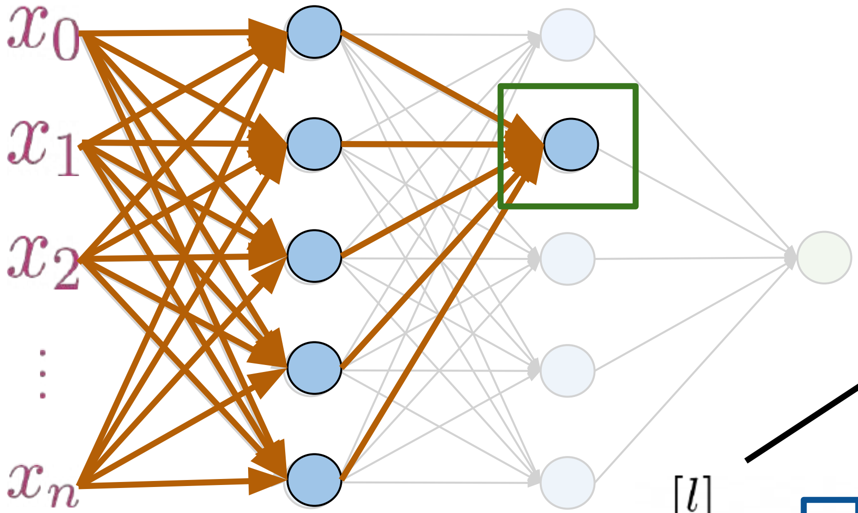
$$z_i^{[l]} = \sum_{i=0} W_i^{[l]} a_i^{[l-1]} \longrightarrow$$ For every example in the batch

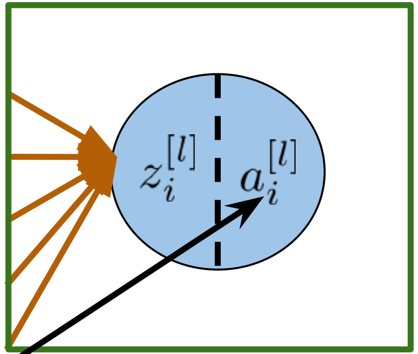
$$\hat{z}_i^{[l]} = \frac{z_i^{[l]} - \boxed{\mu_{z_i^{[l]}}}}{\boxed{\sqrt{\sigma^2_{z_i^{[l]}} + \epsilon}}}$$

Batch mean of $z_i^{[l]}$

Batch std of $z_i^{[l]}$

Batch Normalization: Training





$$\hat{z}_i^{[l]} = \frac{z_i^{[l]} - \mu_{z_i^{[l]}}}{\sqrt{\sigma^2_{z_i^{[l]}} + \epsilon}}$$

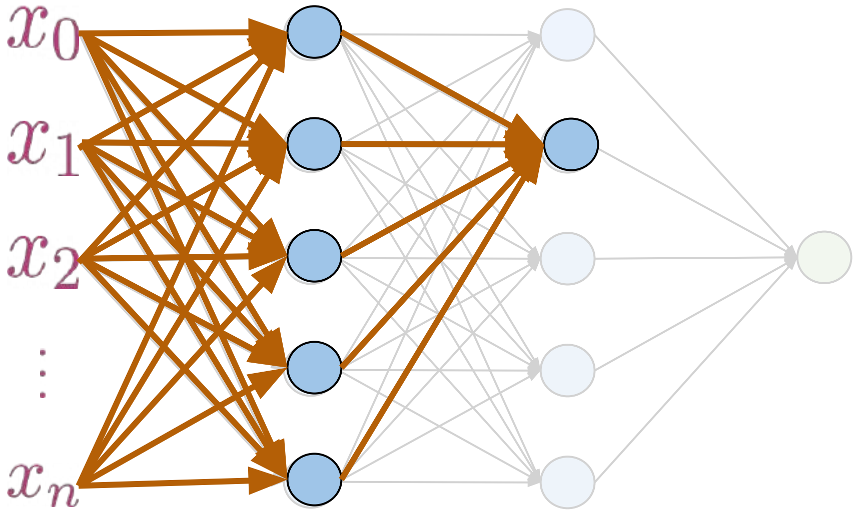
$$y_i^{[l]} = \boxed{\gamma}\hat{z}_i^{[l]} + \boxed{\beta}$$

Shift factor

Scale Factor

Learnable parameters to get the optimal dist.

Batch Normalization: Test



$$\hat{z}_i^{[l]} = \frac{z_i^{[l]} - \boxed{\mathbf{E}(z_i^{[l]})}}{\boxed{\sqrt{\mathrm{Var}(z_i^{[l]}) + \epsilon}}}$$

Running mean and running std from training

Frameworks like Tensorflow and Pytorch keep track of them

Summary

- Batch norm introduces learnable shift and scale factors
- During test, the running statistics from training are used
- Frameworks take care of the whole process

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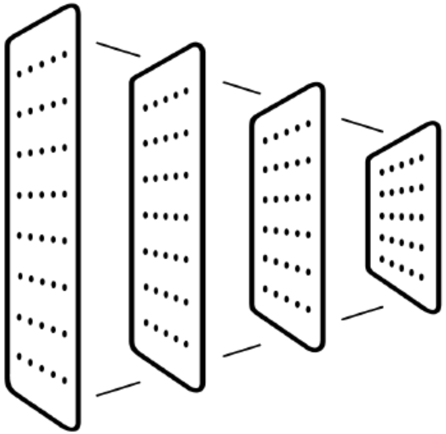
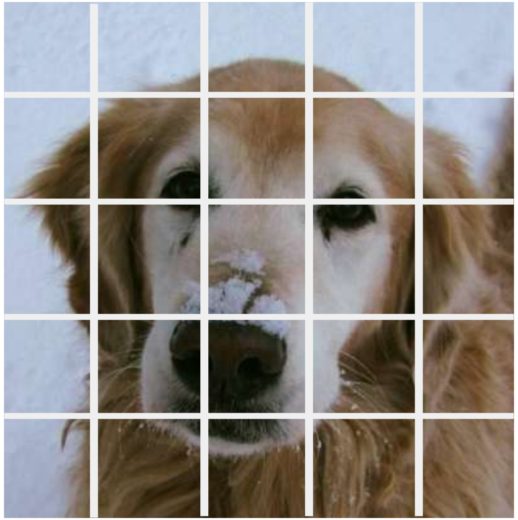
Review of Convolutions

Outline

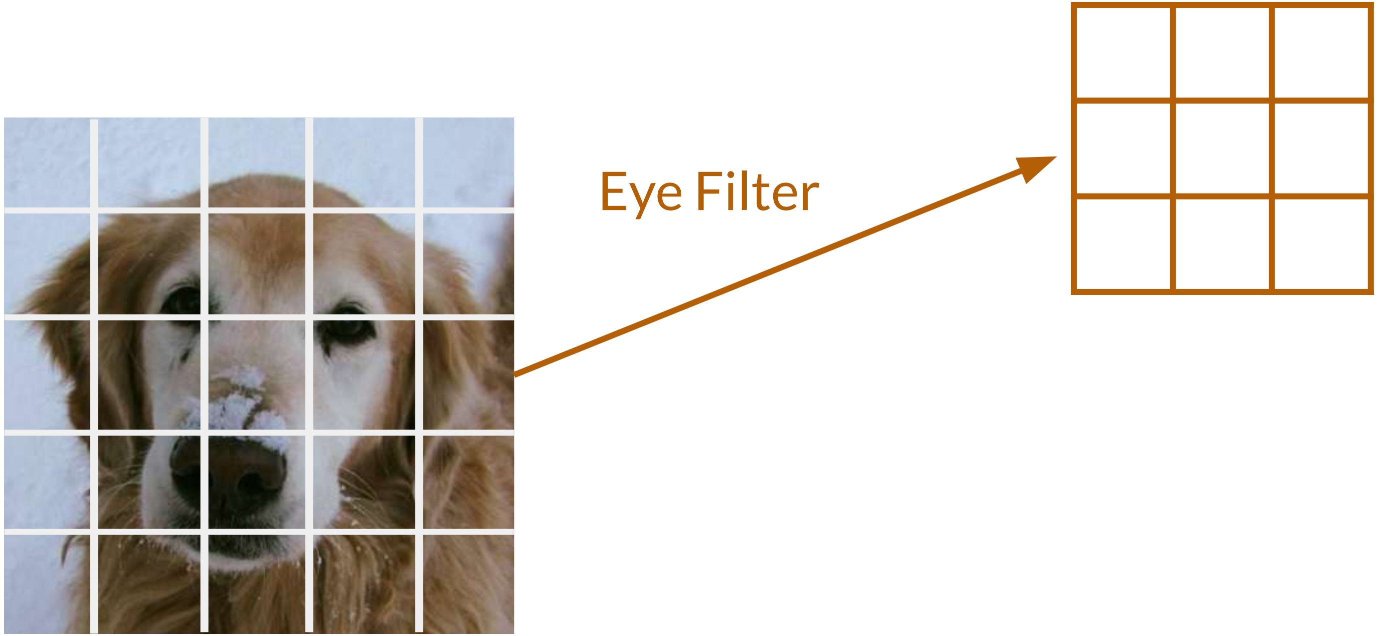
- What convolutions are
- How they work



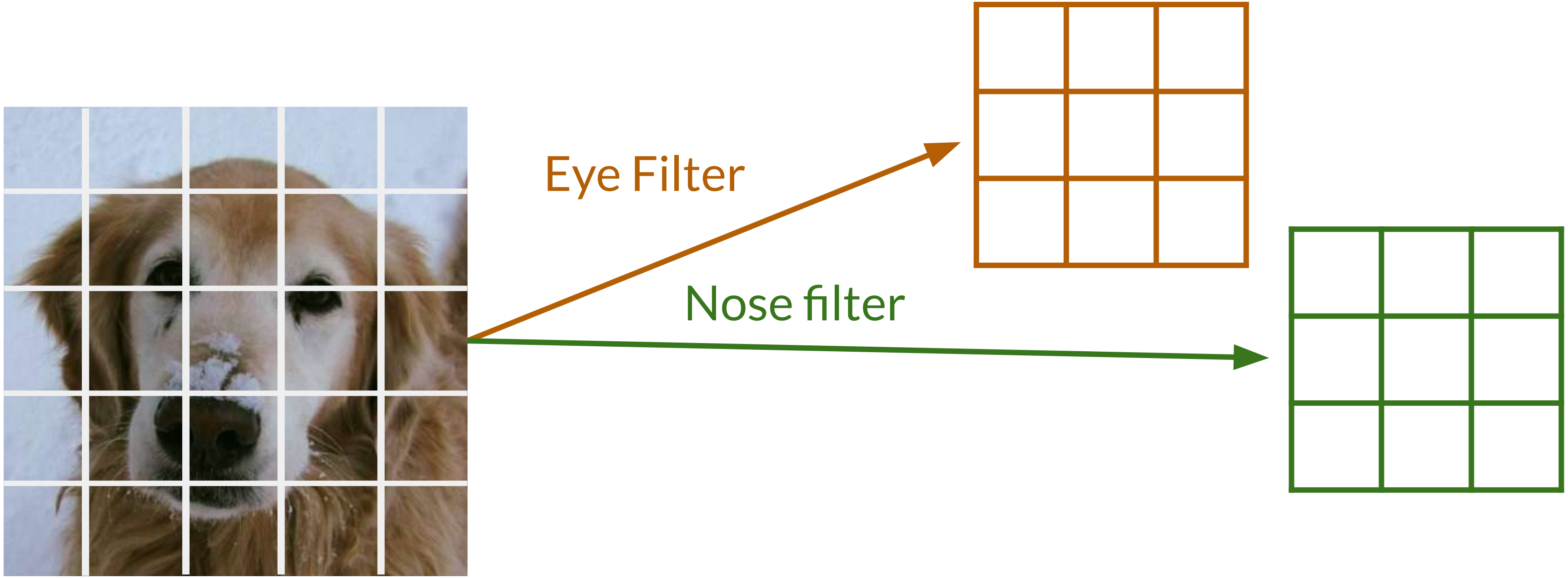
What is a convolution?



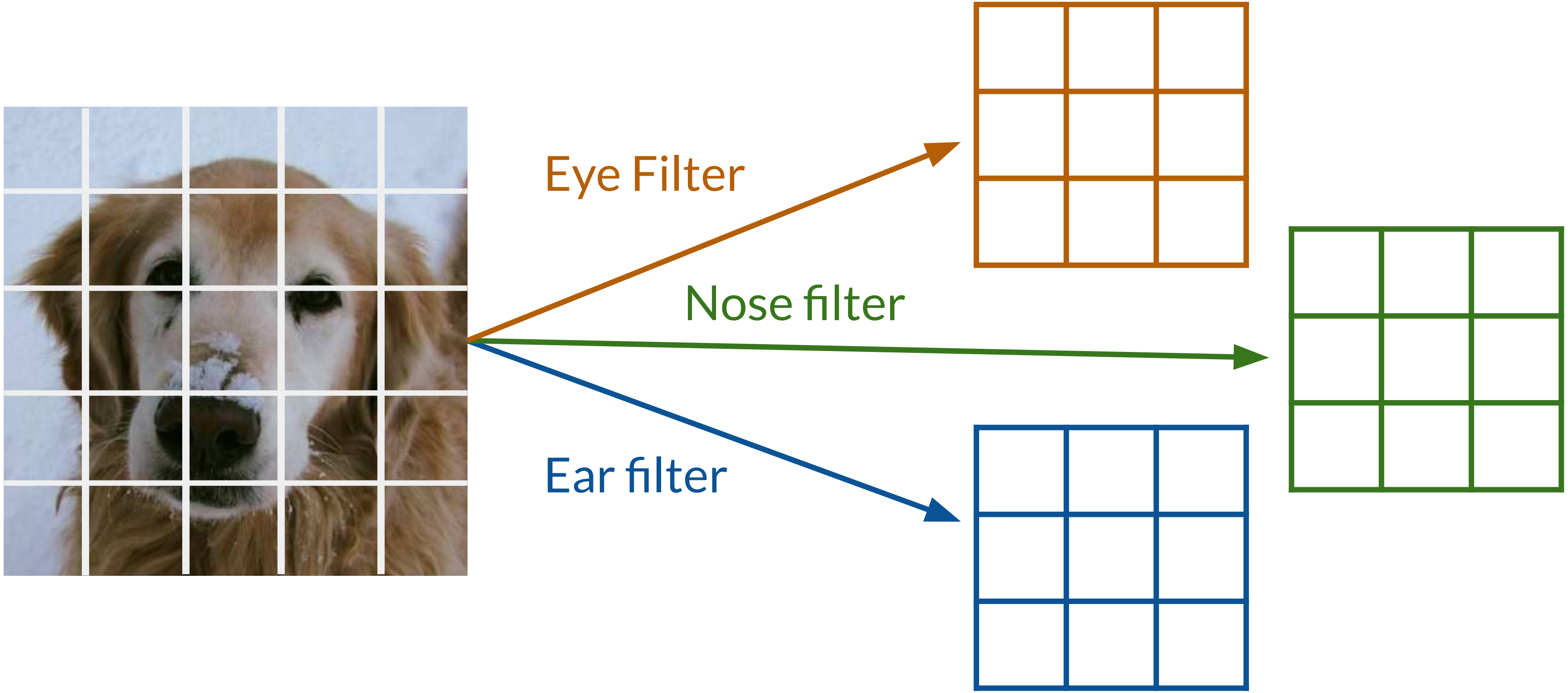
What is a convolution?



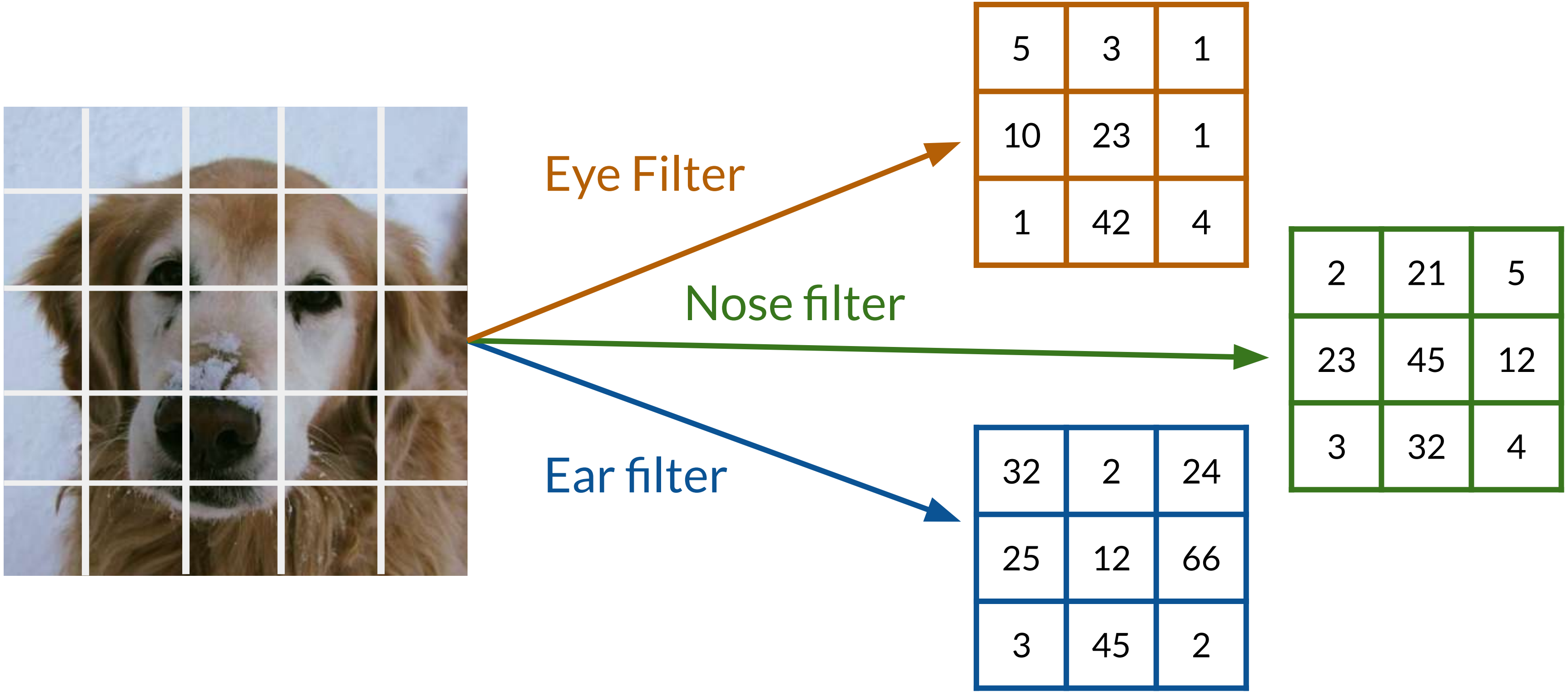
What is a convolution?



What is a convolution?



What is a convolution?



What is a convolution?

50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

0 (black) to 255 (white)

What is a convolution?

50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

$*$

Filter

1	0	-1
1	0	-1
1	0	-1

0 (black) to 255 (white)

What is a convolution?

50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

*

Filter

1	0	-1
1	0	-1
1	0	-1

Convolution

0 (black) to 255 (white)

What is a convolution?

50*1	50*0	0*-1	0	0
50*1	50*0	0*-1	0	0
50*1	50*0	0*-1	0	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

*

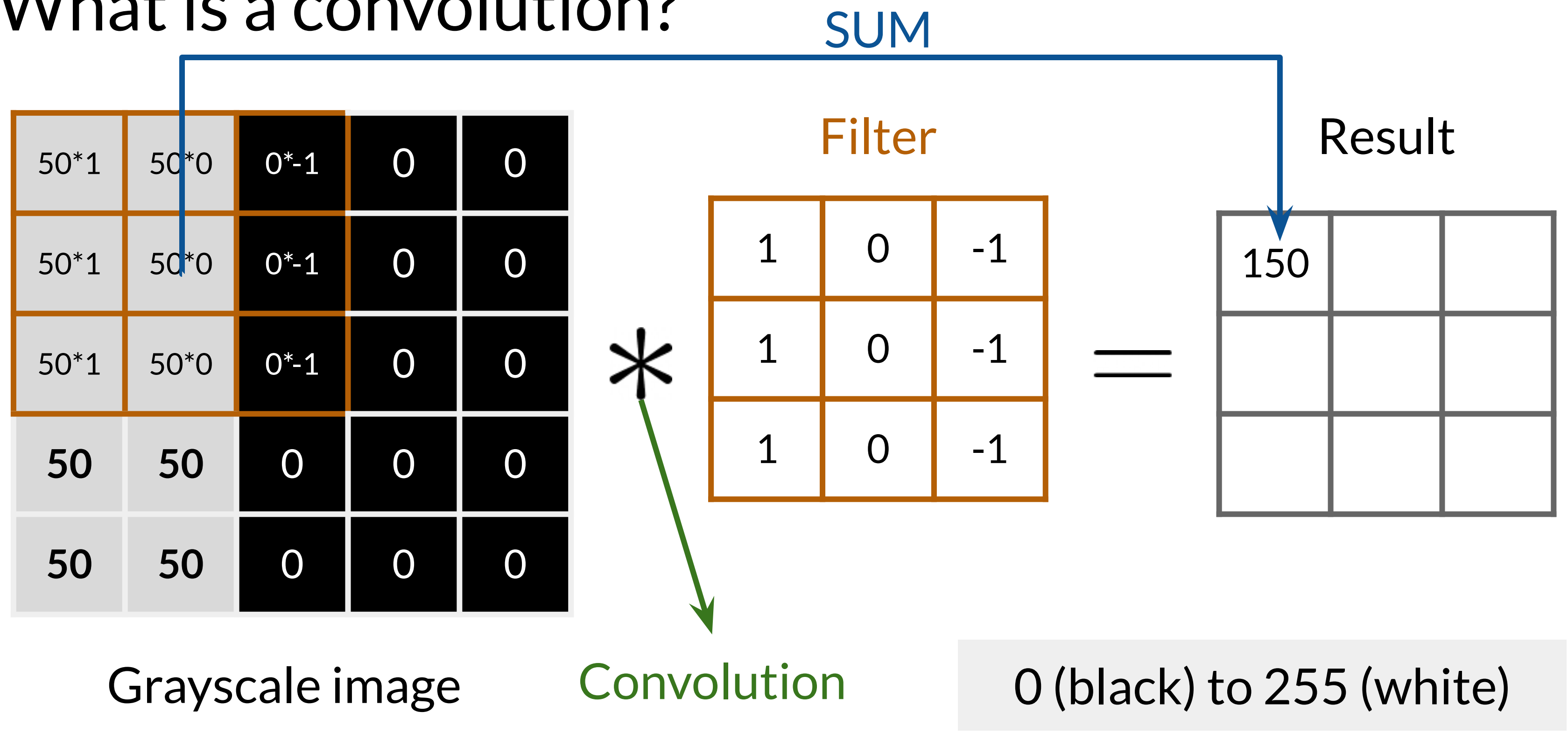
Convolution

Filter

1	0	-1
1	0	-1
1	0	-1

0 (black) to 255 (white)

What is a convolution?



What is a convolution?

50	50*1	0*0	0*-1	0
50	50*1	0*0	0*-1	0
50	50*1	0*0	0*-1	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

*

Filter

1	0	-1
1	0	-1
1	0	-1

=

Result

150	150	

Convolution

0 (black) to 255 (white)

What is a convolution?

Grayscale image

50	50	0*1	0*0	0*-1
50	50	0*1	0*0	0*-1
50	50	0*1	0*0	0*-1
50	50	0	0	0
50	50	0	0	0

$*$ Convolution

Filter

1	0	-1
1	0	-1
1	0	-1

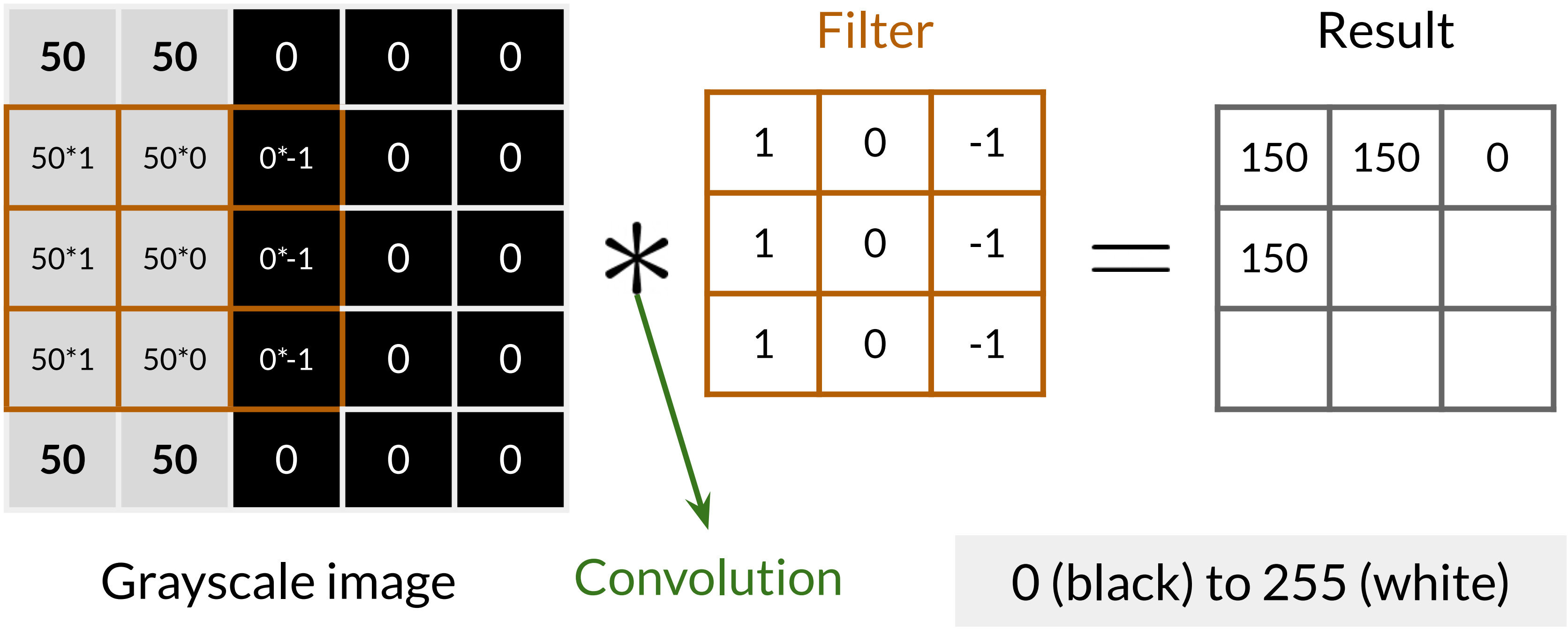
$=$

Result

150	150	0

0 (black) to 255 (white)

What is a convolution?



What is a convolution?

50	50	0	0	0
50	50*1	0*0	0*-1	0
50	50*1	0*0	0*-1	0
50	50*1	0*0	0*-1	0
50	50	0	0	0

Grayscale image

*

Convolution

Filter

1	0	-1
1	0	-1
1	0	-1

=

Result

150	150	0
150	150	

0 (black) to 255 (white)

What is a convolution?

$$
\begin{bmatrix} 50 & 50 & 0 & 0 & 0 \\ 50 & 50 & 0 & 0 & 0 \\ 50 & 50 & 0 & 0 & 0 \\ 50 & 50 & 0 & 0 & 0 \\ 50 & 50 & 0 & 0 & 0 \end{bmatrix}
*
\overset{\text{Filter}}{\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}}
=
\overset{\text{Result}}{\begin{bmatrix} 150 & 150 & 0 \\ 150 & 150 & 0 \\ 150 & 150 & 0 \end{bmatrix}}
$$

Grayscale image

Convolution

0 (black) to 255 (white)

Summary

- Convolutions are useful layers for processing images
- They scan the image to detect useful features
- Just element-wise products and sums!

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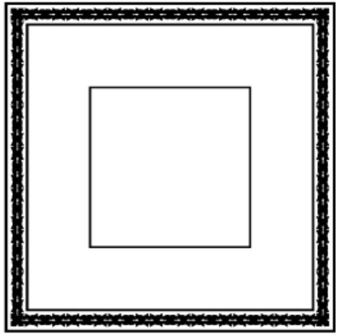
Padding and Stride

Outline

- Padding and stride
- The intuition behind padding



Stride

50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

$*$

Filter

1	0	-1
1	0	-1
1	0	-1

Stride

50*1	50*0	0*-1	0	0
50*1	50*0	0*-1	0	0
50*1	50*0	0*-1	0	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

$*$

Filter

1	0	-1
1	0	-1
1	0	-1

$=$

Result

150		

Stride

→ **1 Pixel** to the right

50	50*1	0*0	0*-1	0
50	50*1	0*0	0*-1	0
50	50*1	0*0	0*-1	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

$*$

Filter

1	0	-1
1	0	-1
1	0	-1

$=$

Result

150	150	

Stride

→ **1 Pixel** to the right

50	50	0*1	0*0	0*-1
50	50	0*1	0*0	0*-1
50	50	0*1	0*0	0*-1
50	50	0	0	0
50	50	0	0	0

Grayscale image

$*$

Filter

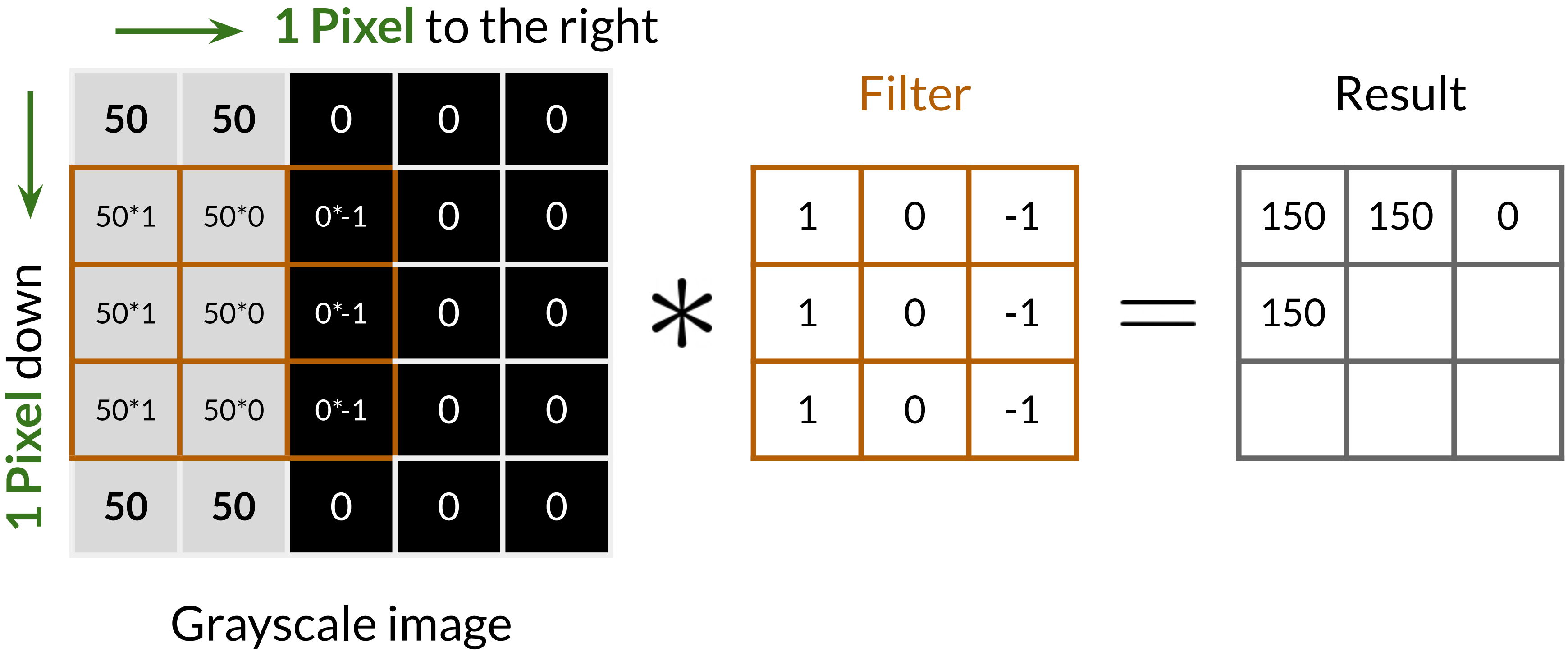
1	0	-1
1	0	-1
1	0	-1

$=$

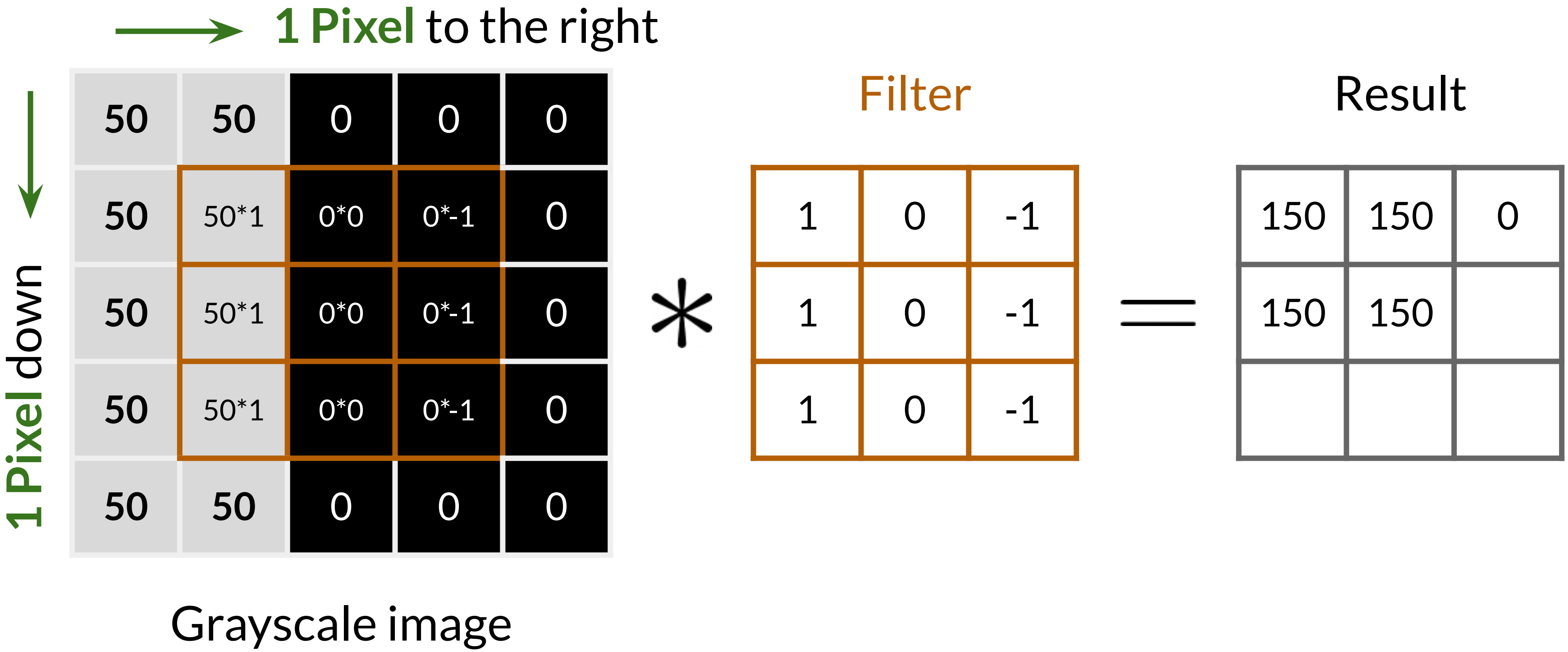
Result

150	150	0

Stride


1 Pixel to the right
1 Pixel down
50 50 0 0 0
50*1 50*0 0*-1 0 0
50*1 50*0 0*-1 0 0
50*1 50*0 0*-1 0 0
50 50 0 0 0
Grayscale image
Filter
1 0 -1
1 0 -1
1 0 -1
Result
150 150 0
150

Stride


1 Pixel to the right
1 Pixel down
50 50 0 0 0
50 50*1 0*0 0*-1 0
50 50*1 0*0 0*-1 0
50 50*1 0*0 0*-1 0
50 50 0 0 0
Filter
1 0 -1
1 0 -1
1 0 -1
Result
150 150 0
150 150
Grayscale image

Stride

1 Pixel to the right

1 Pixel down

50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

$*$

Filter

1	0	-1
1	0	-1
1	0	-1

$=$

Result

150	150	0
150	150	0
150	150	0

Stride = 1

Stride

2 Pixels to the right

2 Pixels down

50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0
50	50	0	0	0

Grayscale image

$*$

Filter

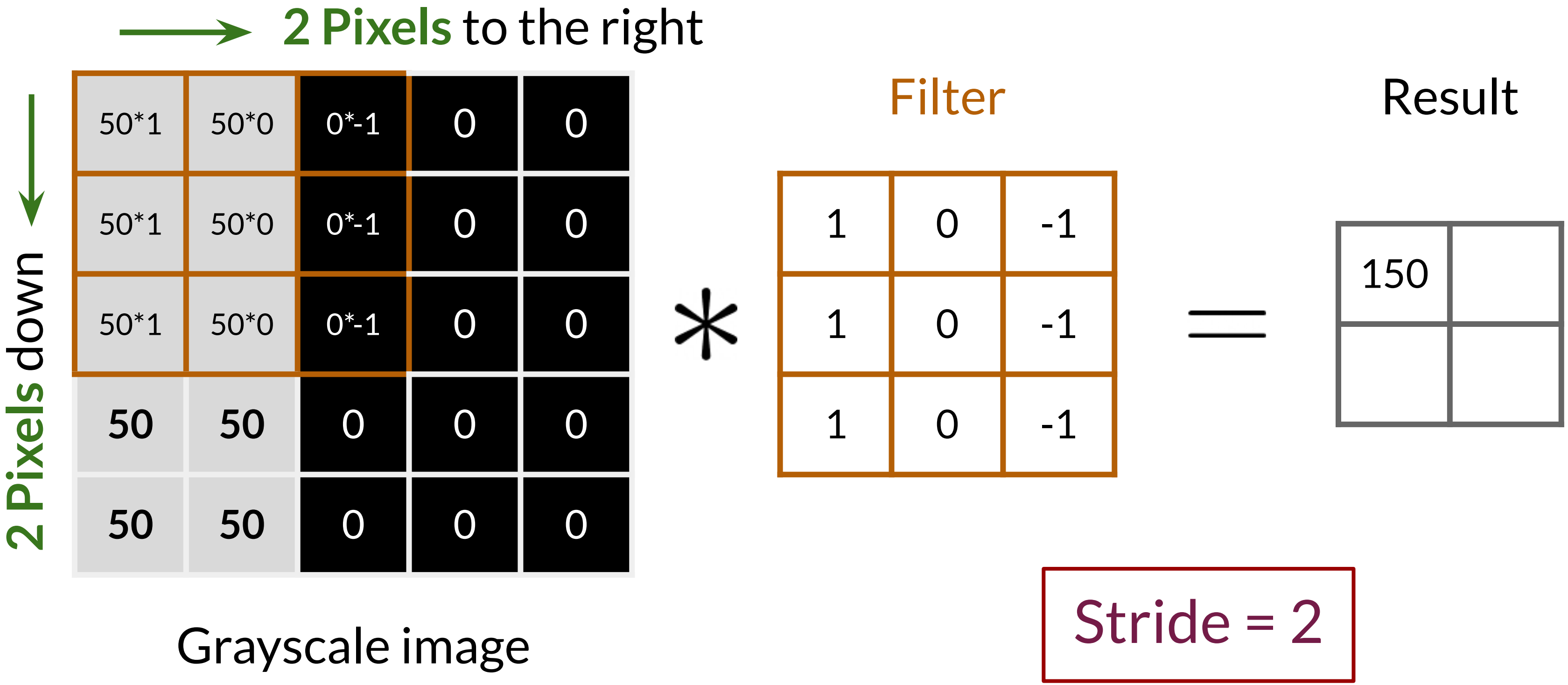
1	0	-1
1	0	-1
1	0	-1

$=$

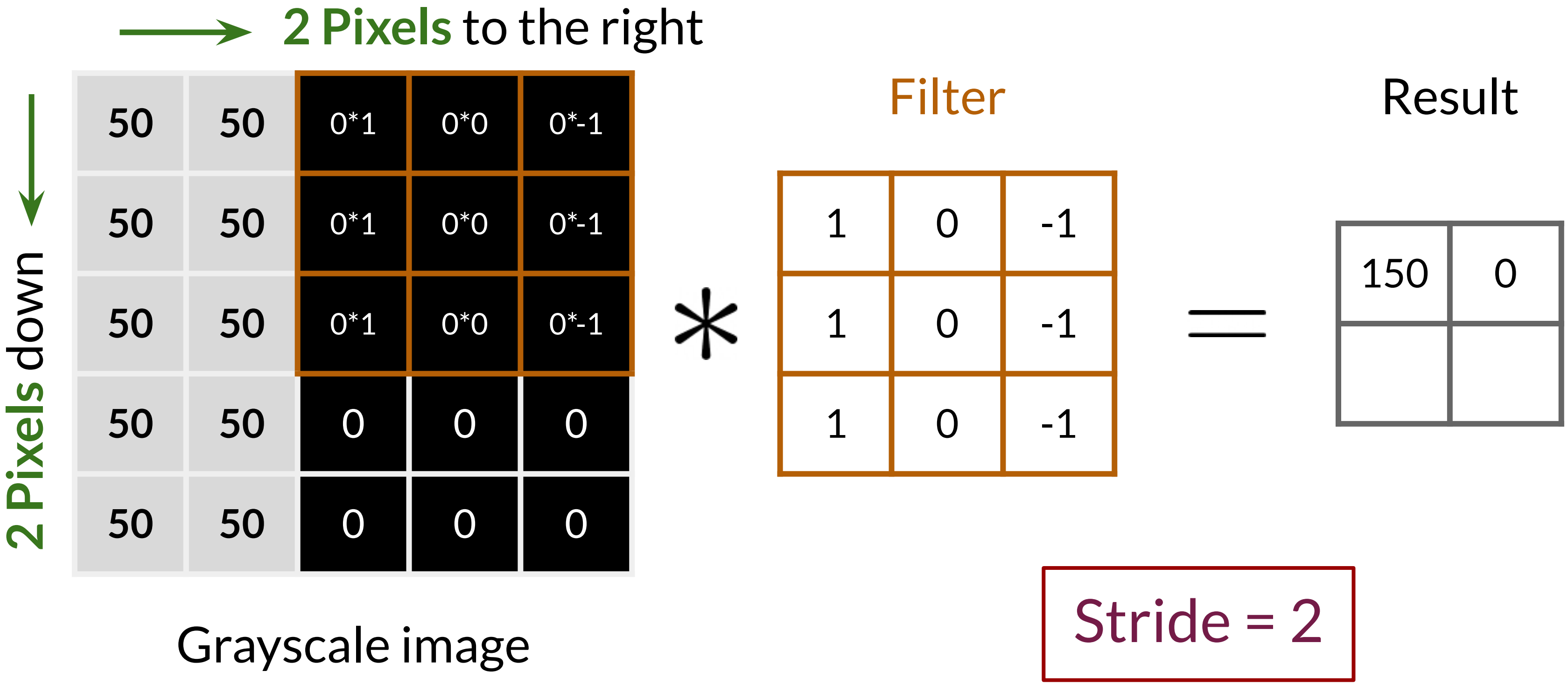
Result

Stride = 2

Stride

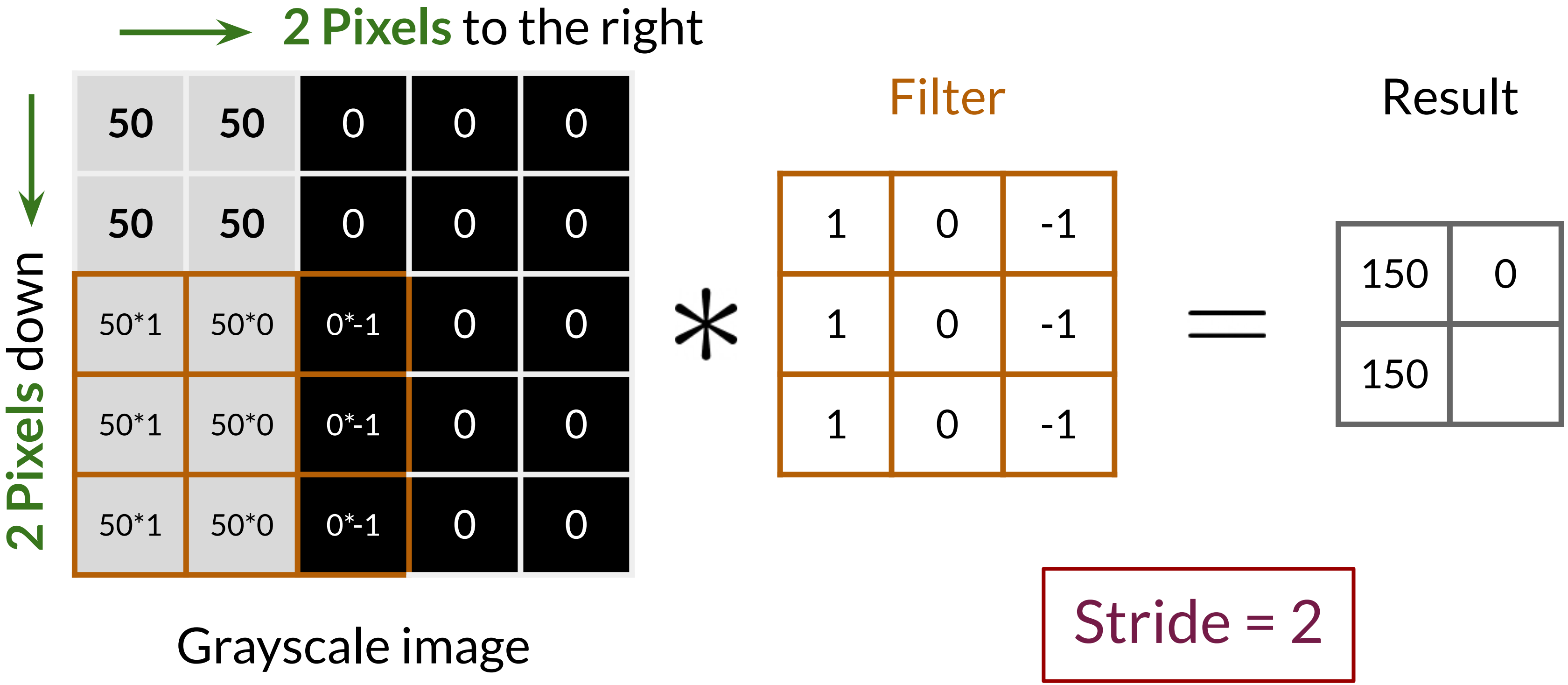

2 Pixels to the right
2 Pixels down
50*1
50*0
0*-1
0
0
50*1
50*0
0*-1
0
0
50*1
50*0
0*-1
0
0
50
50
0
0
0
50
50
0
0
0
Grayscale image
Filter
1
0
-1
1
0
-1
1
0
-1
Result
150
Stride = 2

Stride

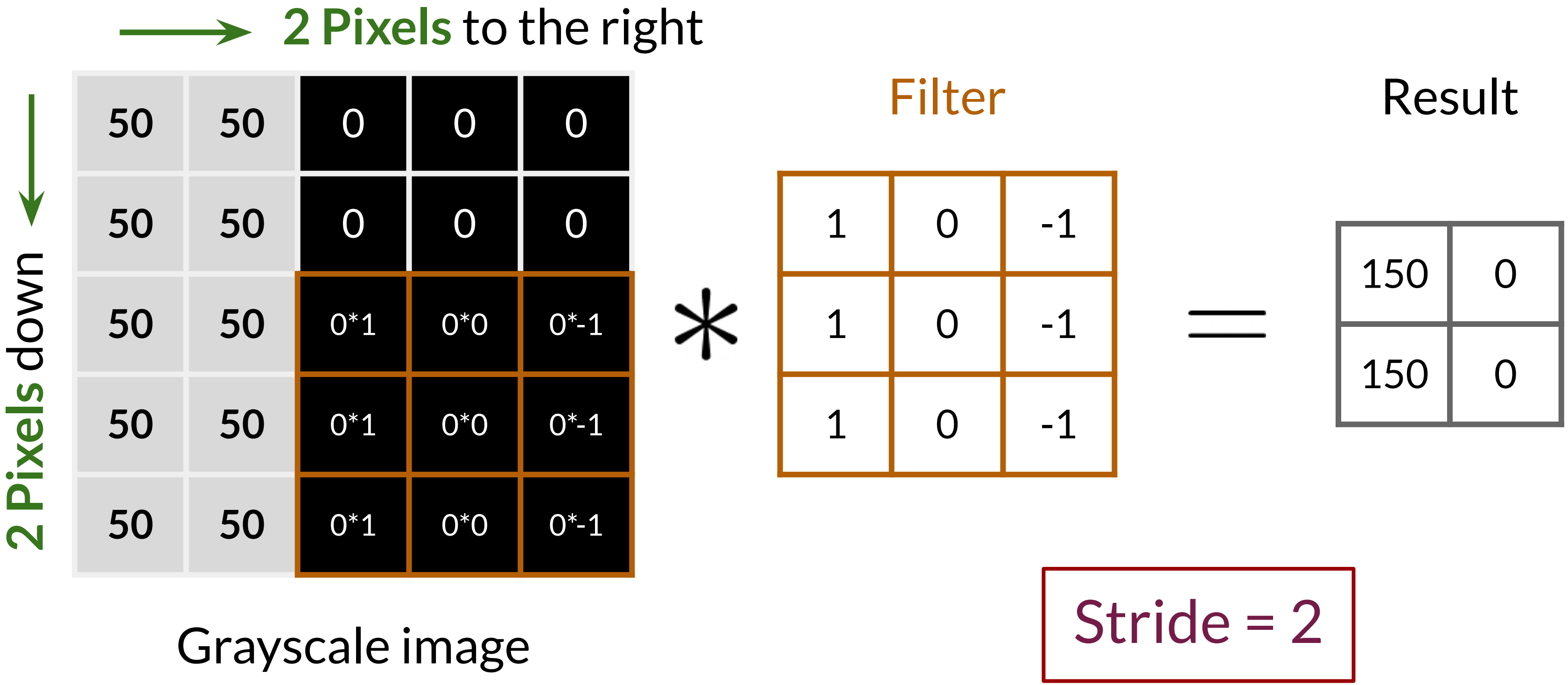


2 Pixels to the right
2 Pixels down
50 50 0*1 0*0 0*-1
50 50 0*1 0*0 0*-1
50 50 0*1 0*0 0*-1
50 50 0 0 0
50 50 0 0 0
Filter
1 0 -1
1 0 -1
1 0 -1
Result
150 0
Grayscale image
Stride = 2

Stride


2 Pixels to the right
2 Pixels down
50 50 0 0 0
50 50 0 0 0
50*1 50*0 0*-1 0 0
50*1 50*0 0*-1 0 0
50*1 50*0 0*-1 0 0
Grayscale image
Filter
1 0 -1
1 0 -1
1 0 -1
Result
150 0
150
Stride = 2

Stride


2 Pixels to the right
2 Pixels down
50 50 0 0 0
50 50 0 0 0
50 50 0*1 0*0 0*-1
50 50 0*1 0*0 0*-1
50 50 0*1 0*0 0*-1
Grayscale image
Filter
1 0 -1
1 0 -1
1 0 -1
Result
150 0
150 0
Stride = 2

Stride

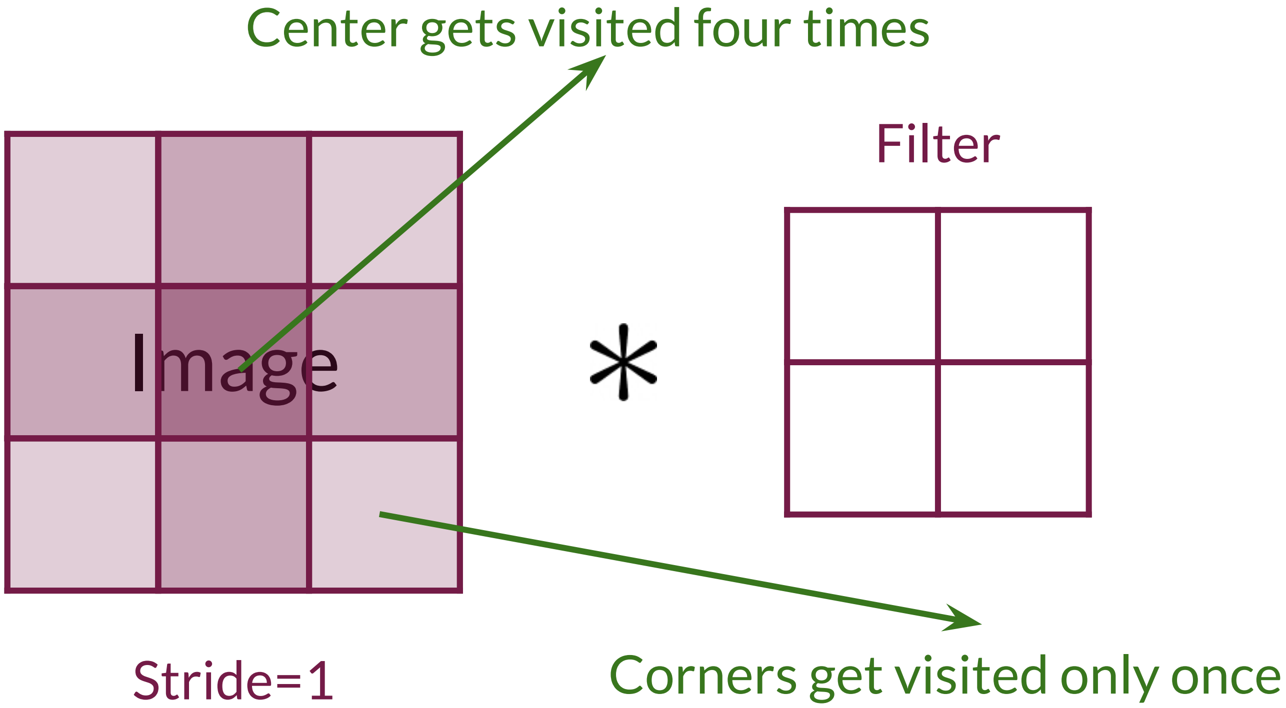
2 Pixels to the right

2 Pixels down

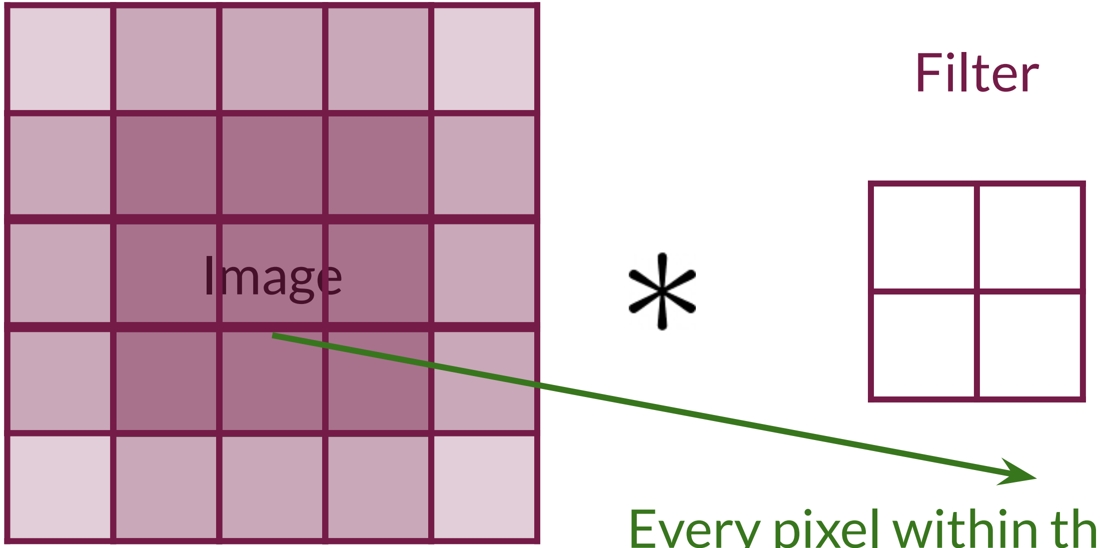
$$\underbrace{\begin{bmatrix} 50 & 50 & 0 & 0 & 0 \\ 50 & 50 & 0 & 0 & 0 \\ 50 & 50 & 0 & 0 & 0 \\ 50 & 50 & 0 & 0 & 0 \\ 50 & 50 & 0 & 0 & 0 \end{bmatrix}}_{\text{Grayscale image}} * \overset{\text{Filter}}{\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}} = \overset{\text{Result}}{\begin{bmatrix} 150 & 0 \\ 150 & 0 \end{bmatrix}}$$

Stride = 2

Padding


Center gets visited four times
Filter
Image
*
Stride=1
Corners get visited only once

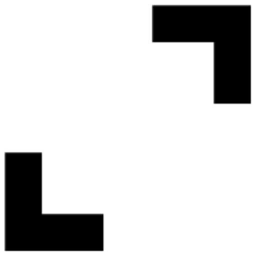
Padding



Every pixel within the image gets visited the same number of times

Summary

- Stride determines how the filter scans the image
- Padding is like a frame on the image
- Padding gives similar importance to the edges and the center



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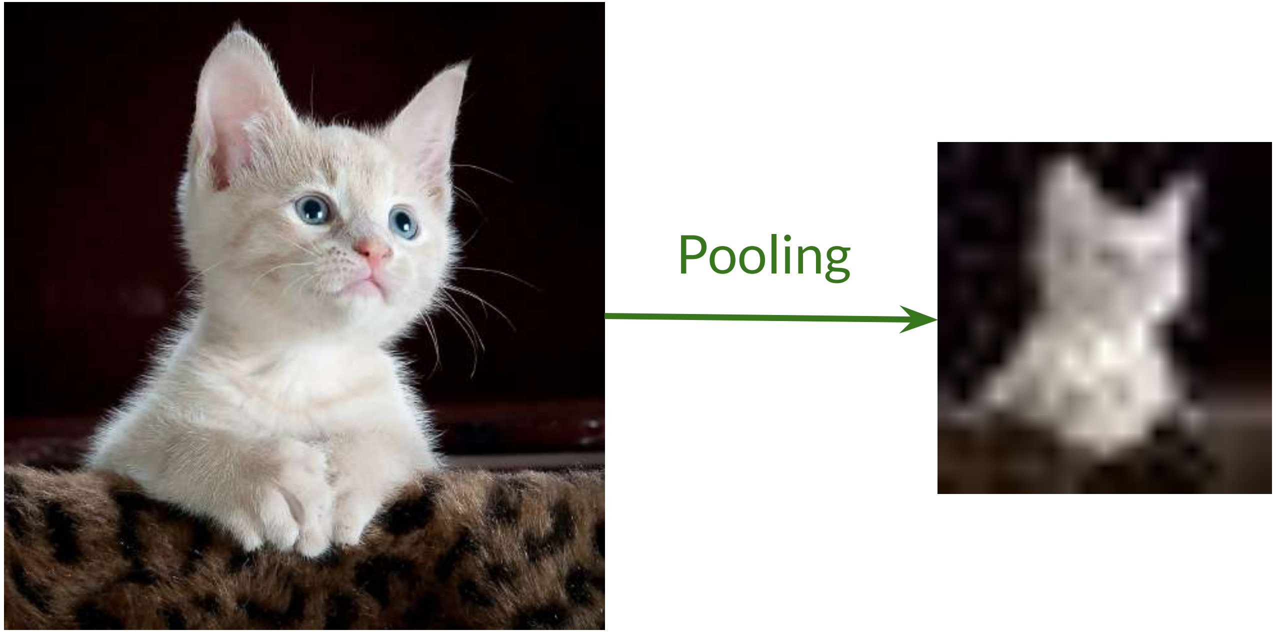
Pooling and Upsampling

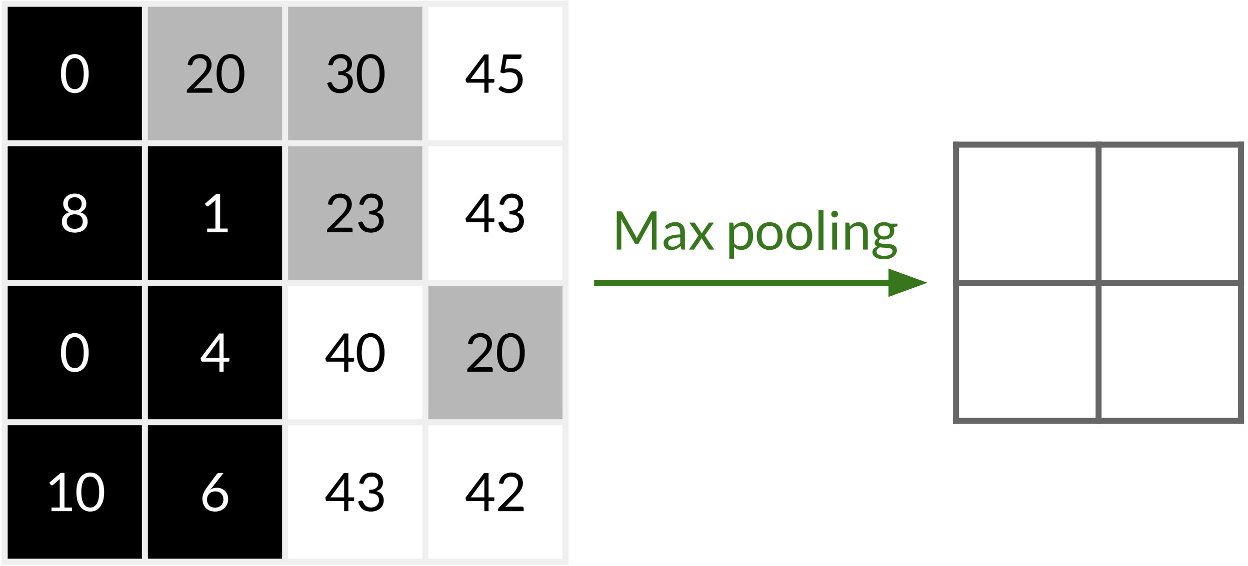
Outline

- Pooling
- Upsampling and its relation to pooling

Pooling



Max Pooling

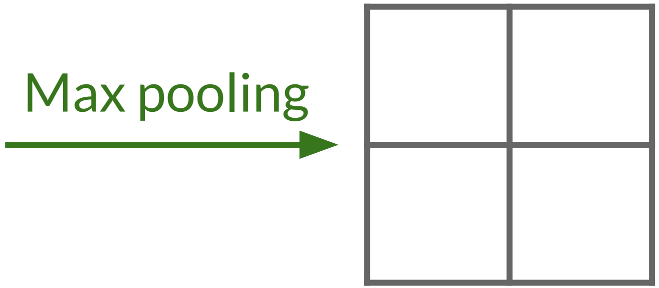


4x4 input to 2x2 output

Max Pooling

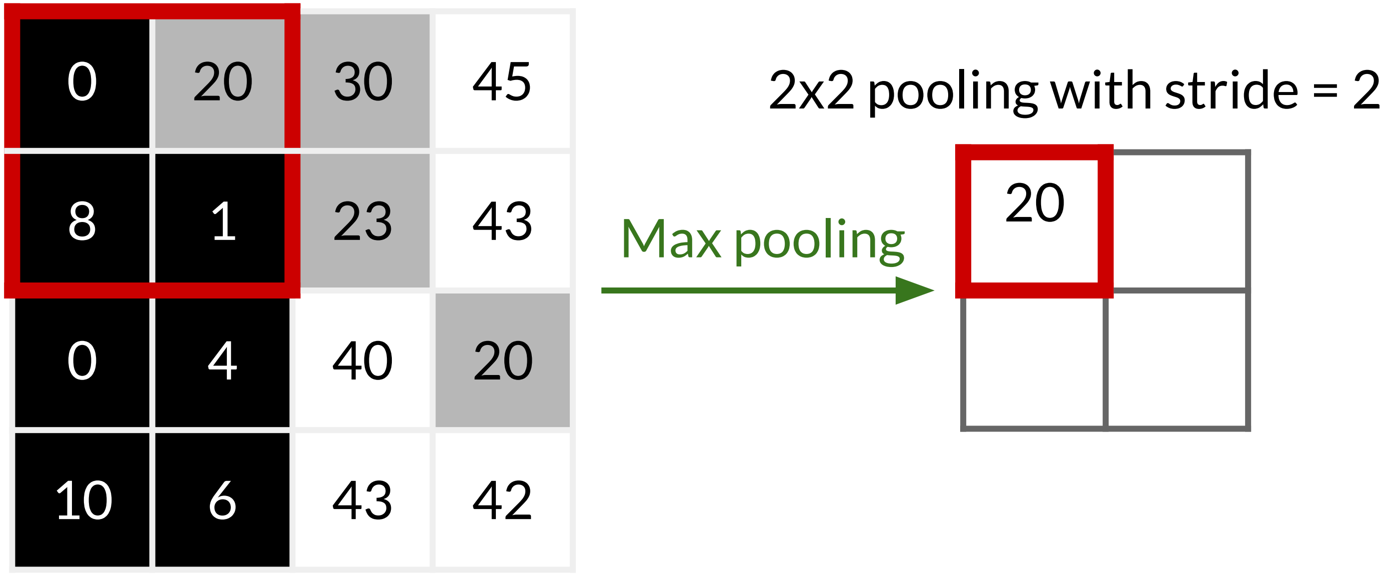
0	20	30	45
8	1	23	43
0	4	40	20
10	6	43	42

2x2 pooling with stride = 2



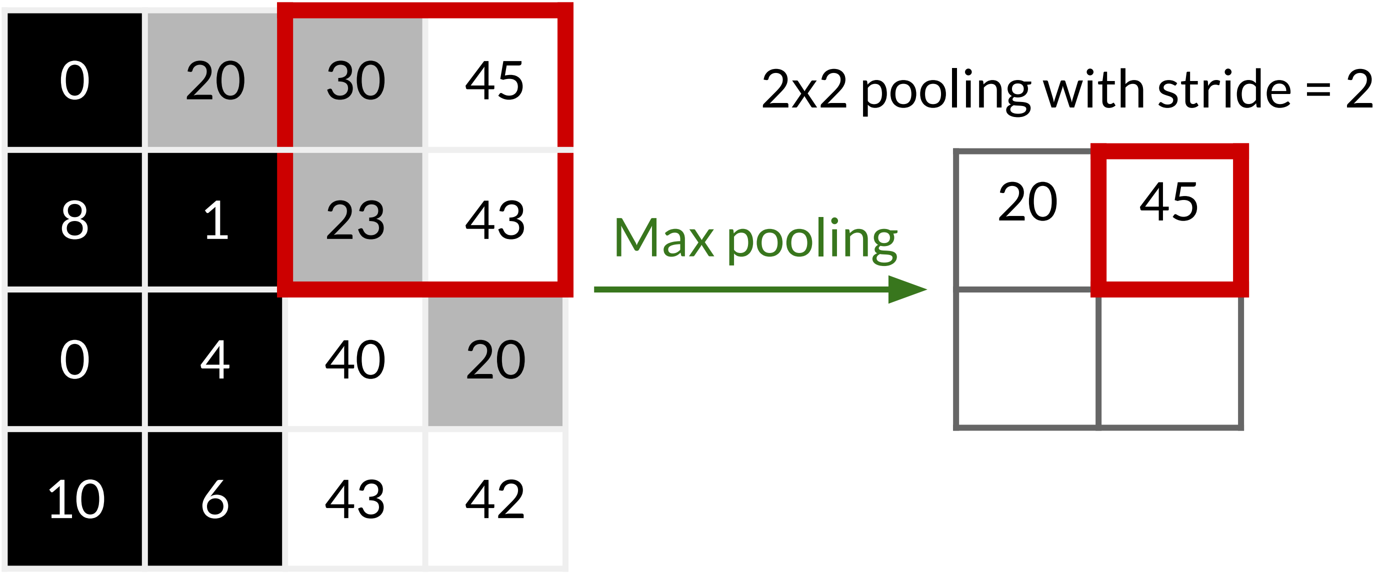
4x4 input to 2x2 output

Max Pooling



4x4 input to 2x2 output

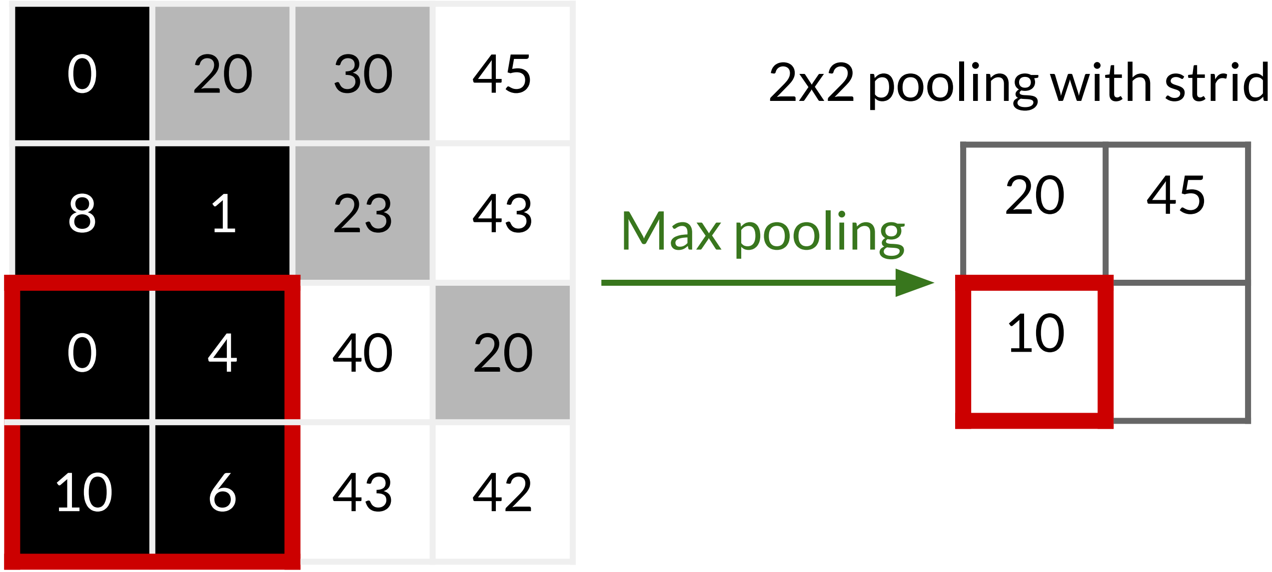
Max Pooling



4x4 input to 2x2 output

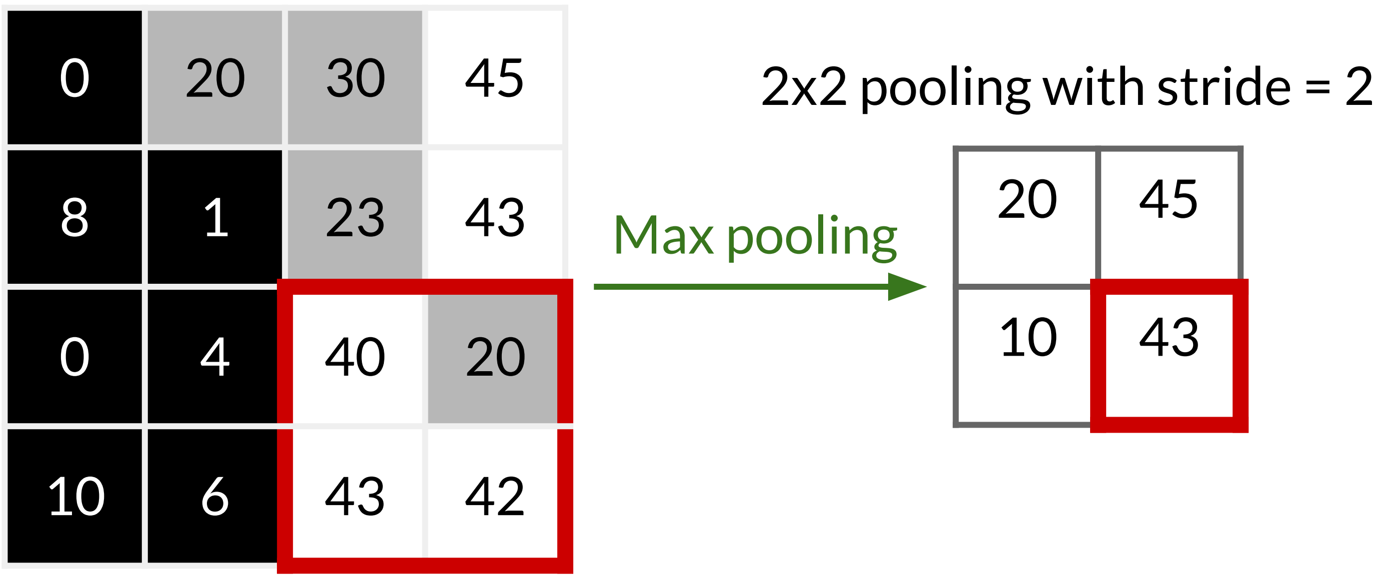
Max Pooling

2x2 pooling with stride = 2



4x4 input to 2x2 output

Max Pooling



4x4 input to 2x2 output

Max Pooling

0	20	30	45
8	1	23	43
0	4	40	20
10	6	43	42

Max pooling →

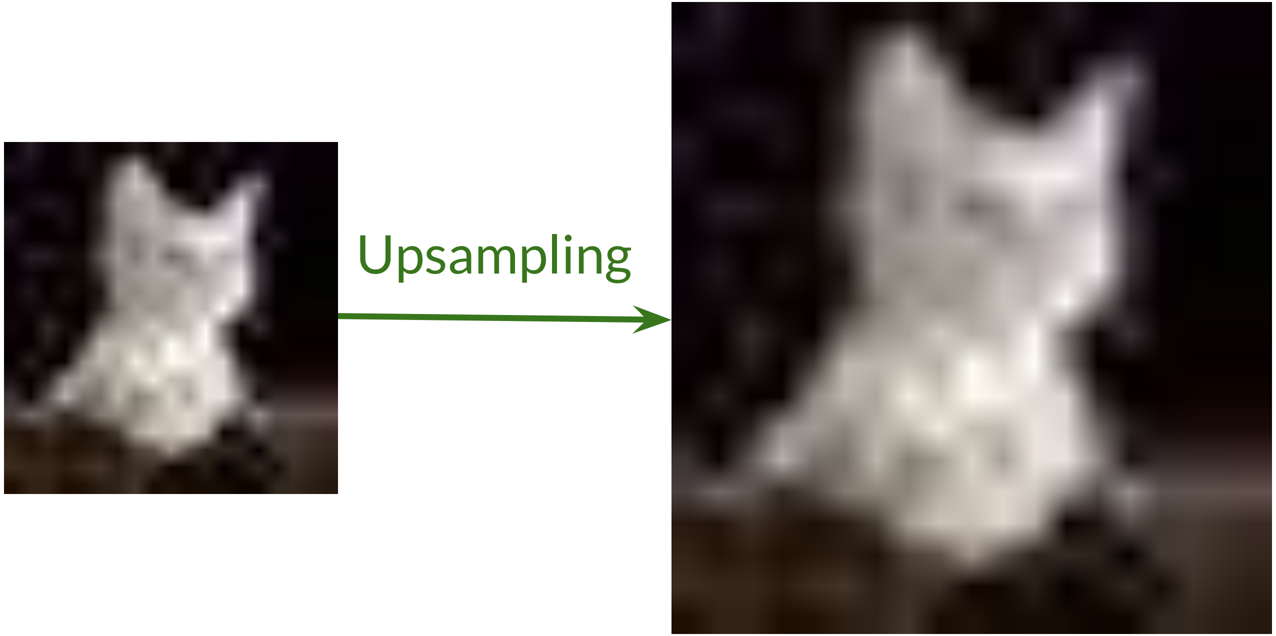
2x2 pooling with stride = 2

20	45
10	43

4x4 input to 2x2 output

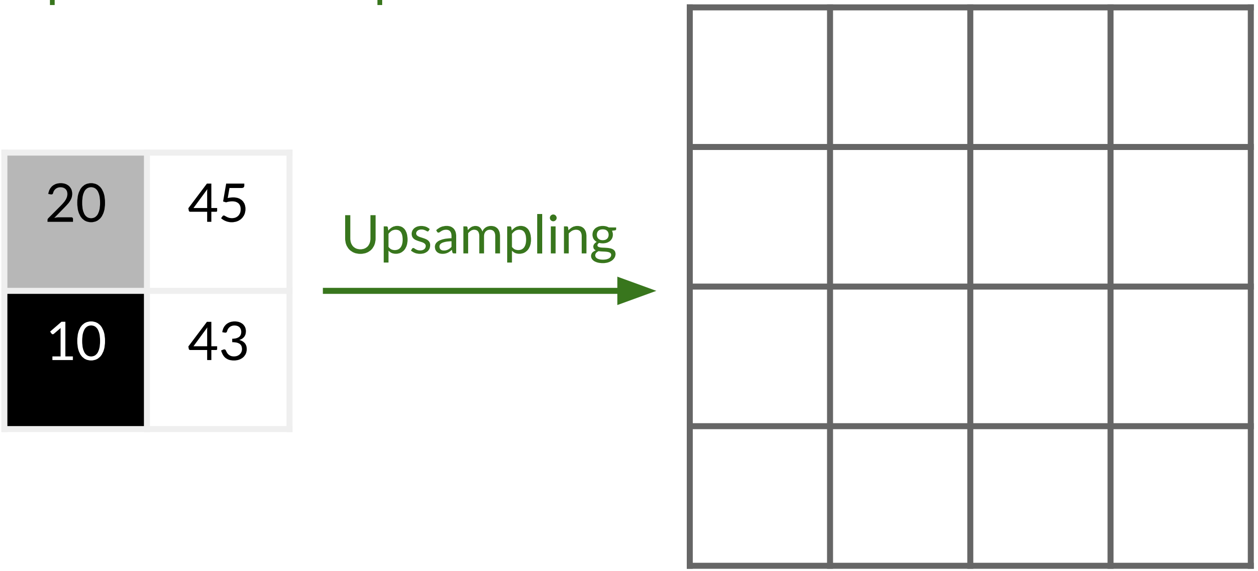
Other types include:
1. Average pooling
2. Min pooling

Upsampling



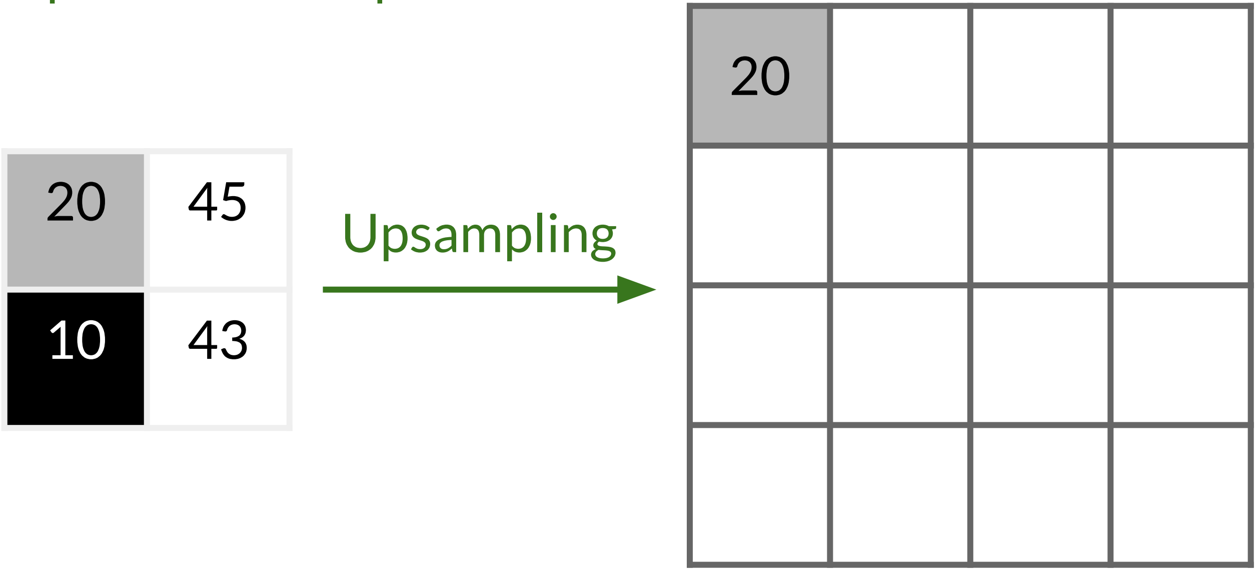
Upsampling: Nearest Neighbors

2x2 input to 4x4 output



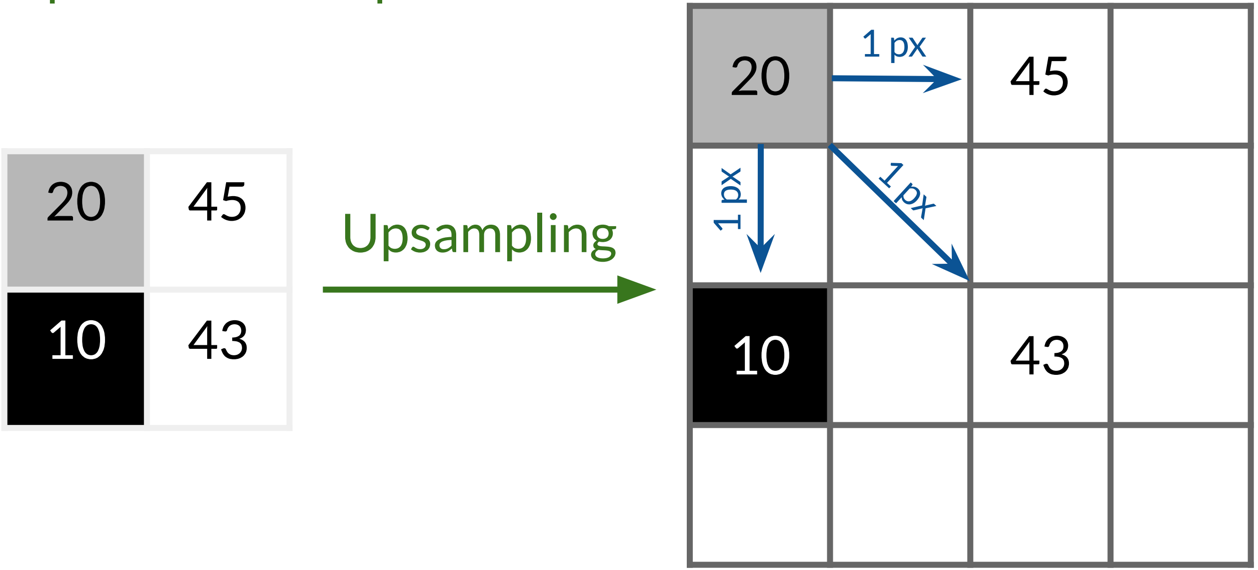
Upsampling: Nearest Neighbors

2x2 input to 4x4 output



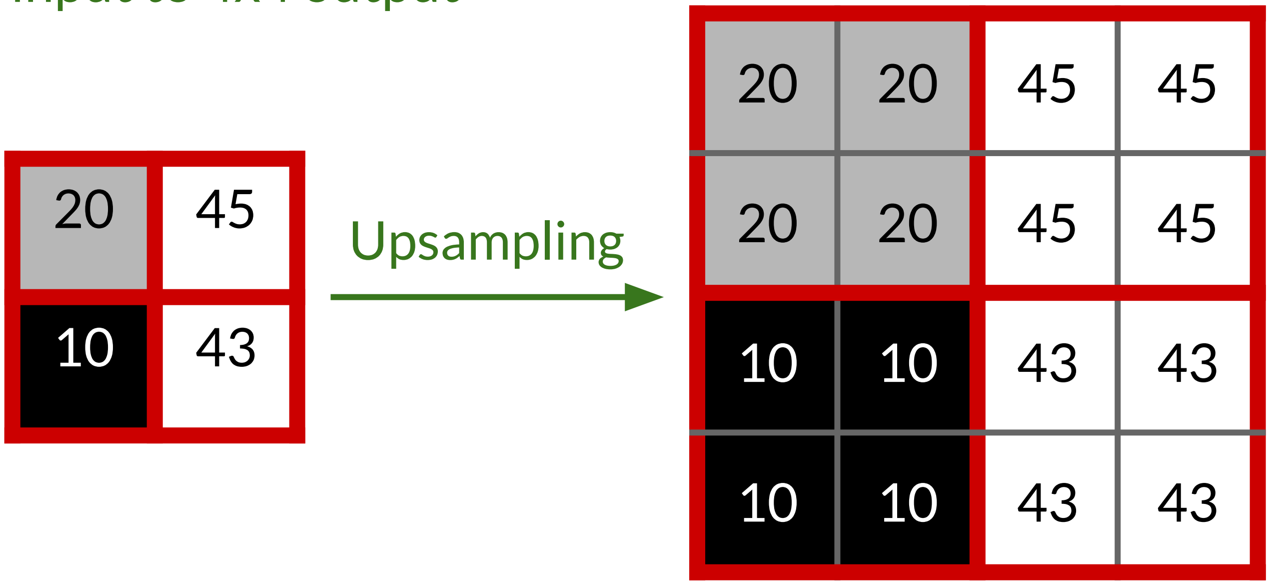
Upsampling: Nearest Neighbors

2x2 input to 4x4 output



Upsampling: Nearest Neighbors

2x2 input to 4x4 output



Upsampling: Nearest Neighbors

2x2 input to 4x4 output

20	45
10	43

Upsampling →

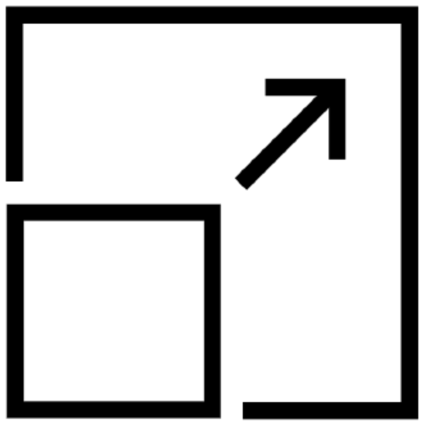
20	20	45	45
20	20	45	45
10	10	43	43
10	10	43	43

Other types include:

1. Linear interpolation
2. Bi-linear interpolation

Summary

- Pooling reduces the size of the input
- Upsampling increases the size of the input
- No learnable parameters!



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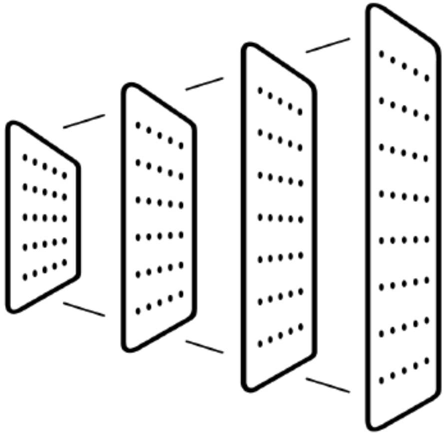
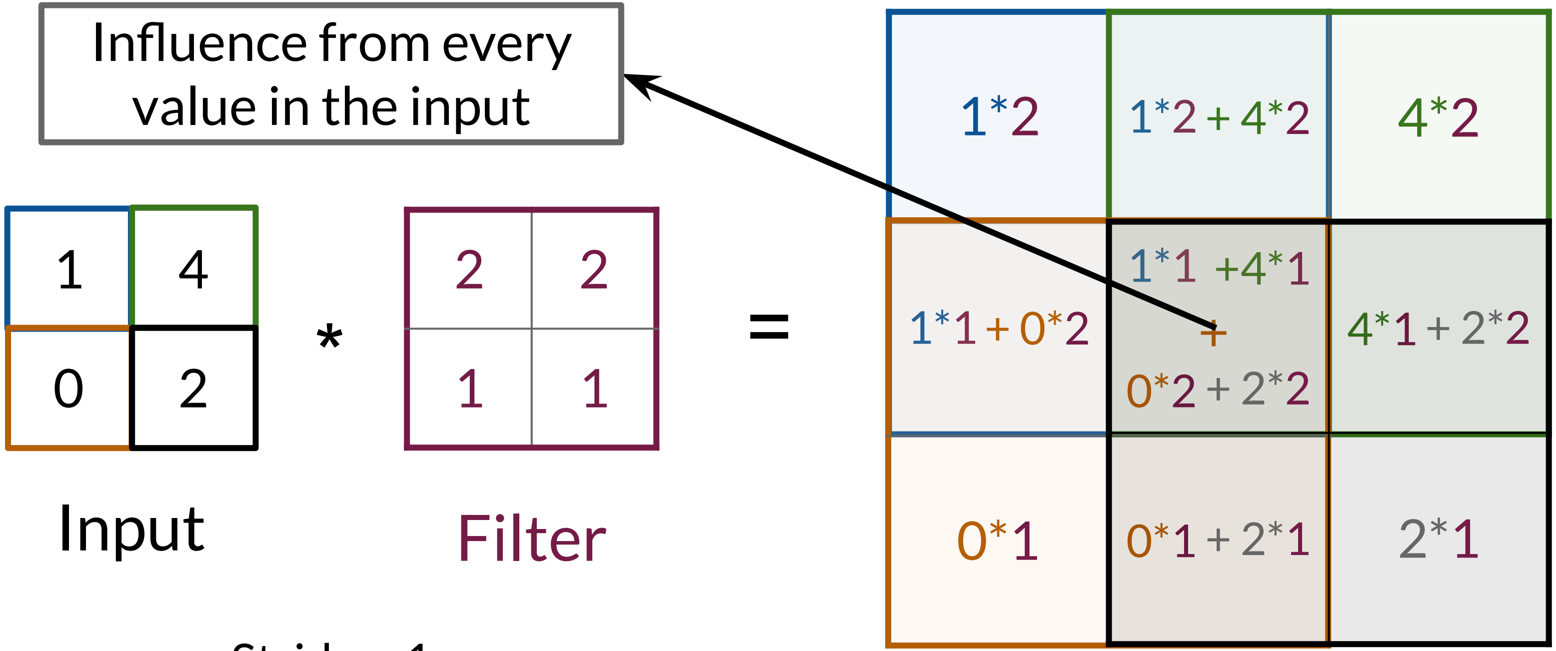
Transposed Convolutions

Outline

- Transposed convolutions as an upsampling technique
- Issues with transposed convolutions



Transposed Convolution



Stride = 1

Transposed Convolution

Influenced by just one value

Input

1	4
0	2

*

Filter

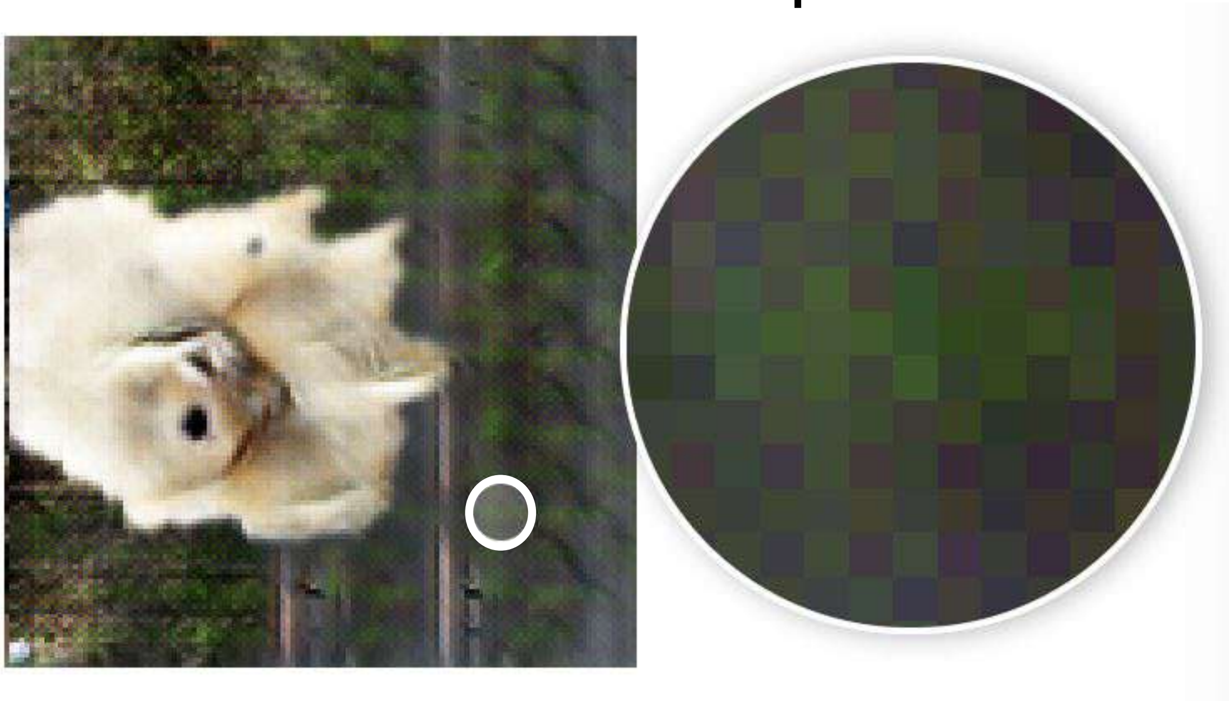
2	2
1	1

=

1*2	1*2 + 4*2	4*2
1*1 + 0*2	1*1 +4*1 + 0*2 + 2*2	4*1 + 2*2
0*1	0*1 + 2*1	2*1

Stride = 1

The Problems with Transposed Convolution



Checkerboard Pattern

Available from: http://doi.org/10.23915/distill.00003

Summary

- Transposed convolutions upsample
- They have learnable parameters
- Problem: results have a checkerboard pattern