Introduction to Computer Vision

13. Deep Learning

UCLA – CS 188 – Fall 2019

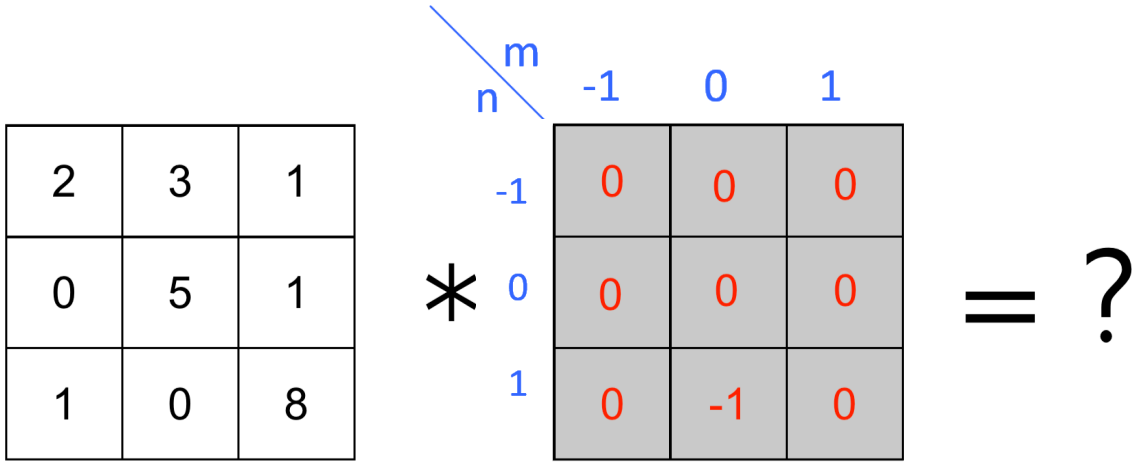
Fabien Scalzo, Ph.D.

Week 1			26-Sep	**Introduction**
Week 2	1-Oct	**Basic Image Processing**	3-Oct	**Feature Extraction and Classification**
Week 3	8-Oct	**Feature Tracking/Optical Flow**	10-Oct	**SVD, 2D camera model, projective plane**
Week 4	15-Oct	**2D Image transformations, RANSAC**	17-Oct	**Euclidean geometry, rigid body motion**
Week 5	22-Oct	**Epipolar Geometry**	24-Oct	**3D Cameras and processing**
Week 6	29-Oct	**Midterm**	31-Oct	**3D Cameras and processing**
Week 7	5-Nov	**Learning from data**	7-Nov	**Neural Networks**
Week 8	12-Nov	**Deep Learning**	14-Nov	**Deep Learning**
Week 9	19-Nov	**Object Detection**	21-Nov	**Generative Models**
Week 10	26-Nov	**Guest Lecture (Nikhil Naik)**	28-Nov	
Week 11	3-Dec	**Applications**	5-Dec	**Recap**
Week 12	10-Dec		12-Dec	**Final**

- Convolution
- Back-propagation
- Limitations of Gradient Descent
- Limitations of Neural Networks in Computer Vision
- Deep Learning
  - Convolutional Neural Networks
  - Convolutional Encoder-decoder

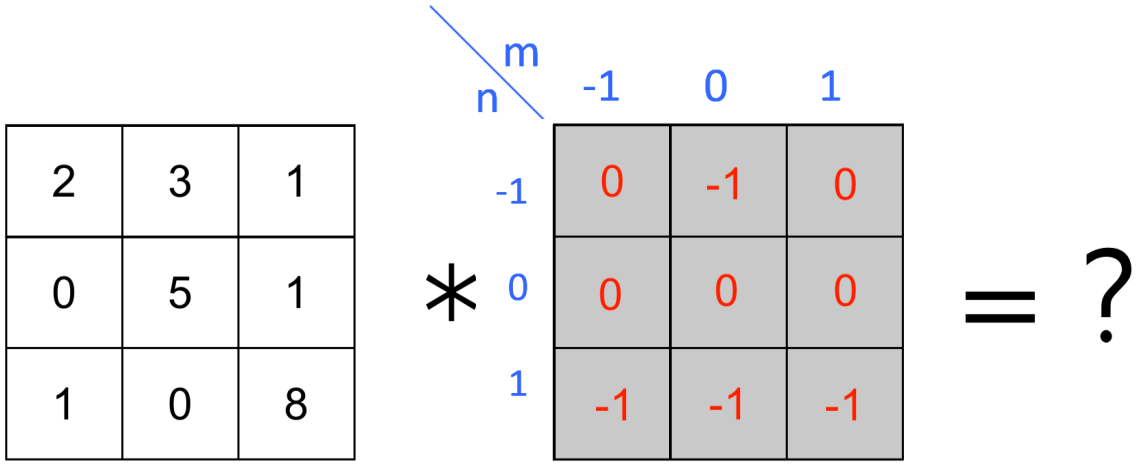
2D Convolution

$$I'(x,y) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} I(x-i, y-j) \,.\, filter(i,j)$$

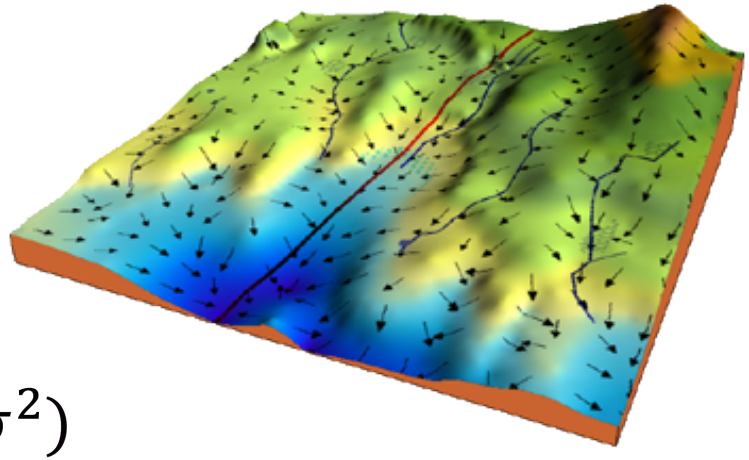


2D Convolution

$$I'(x,y) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} I(x-i, y-j) \,.\, filter(i,j)$$



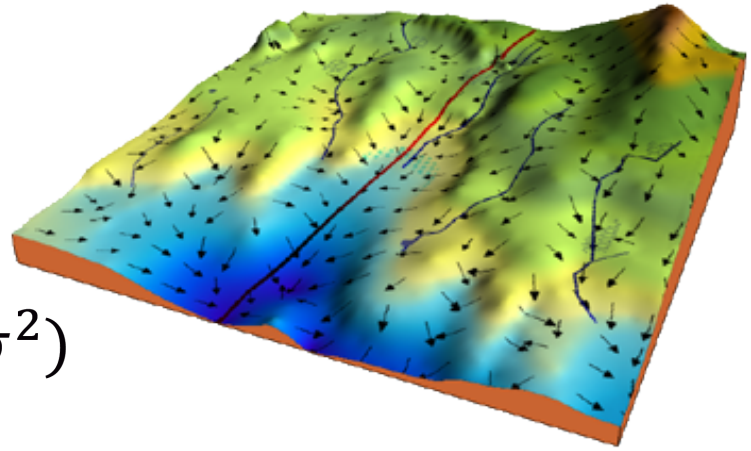
Gradient Descent



Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
4. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Return weights

Gradient Descent



Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
   - Propagate input forward
   - Backpropagate
4. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Return weights

Chain rule

If h(x) is a composite function defined by h(x) = g(f(x)), and f and g are differentiable, then h(x) is differentiable and h' is given by the product:

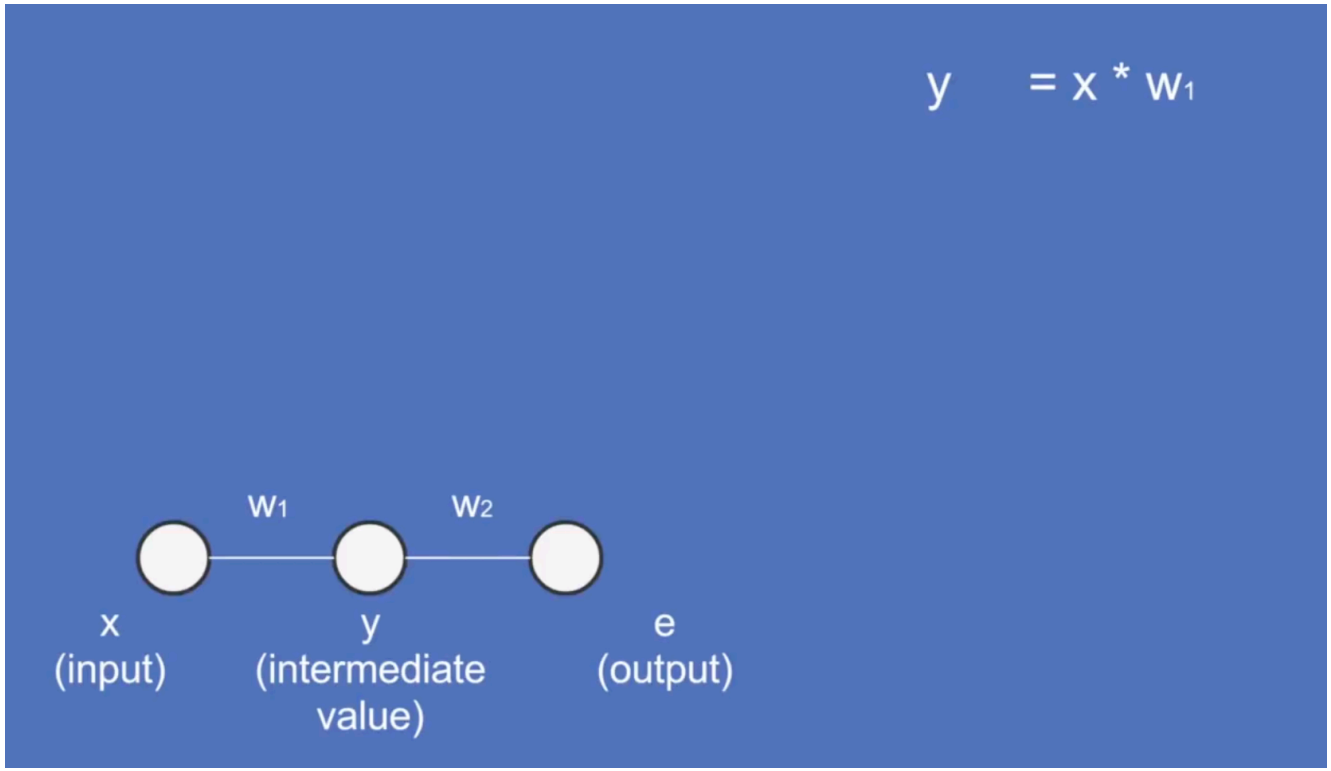
$$(h(x))' = (g(f(x)))' = g'(f(x)) \cdot f'(x)$$

derive the outside, keep the inside

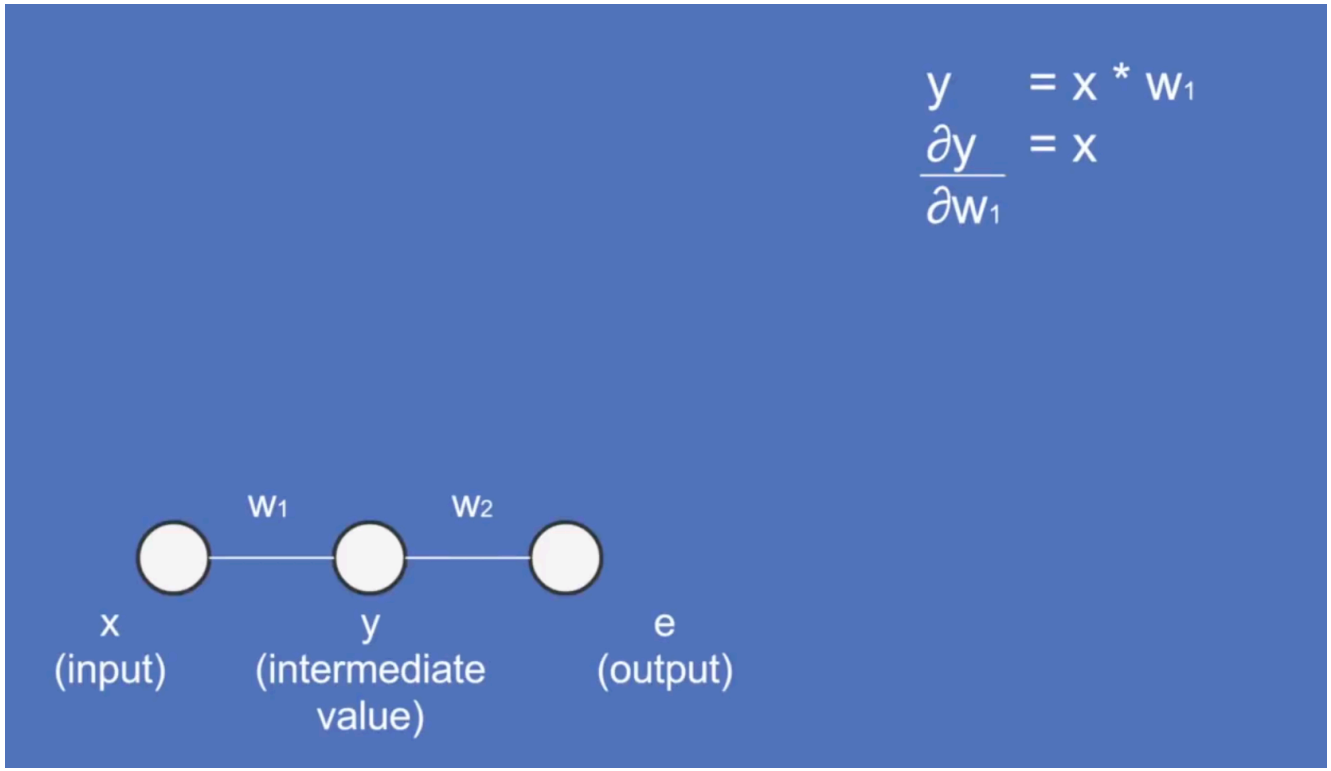
derive the inside

$$\frac{\partial h}{\partial x} = \frac{\partial h}{\partial g} \cdot \frac{\partial g}{\partial x}$$

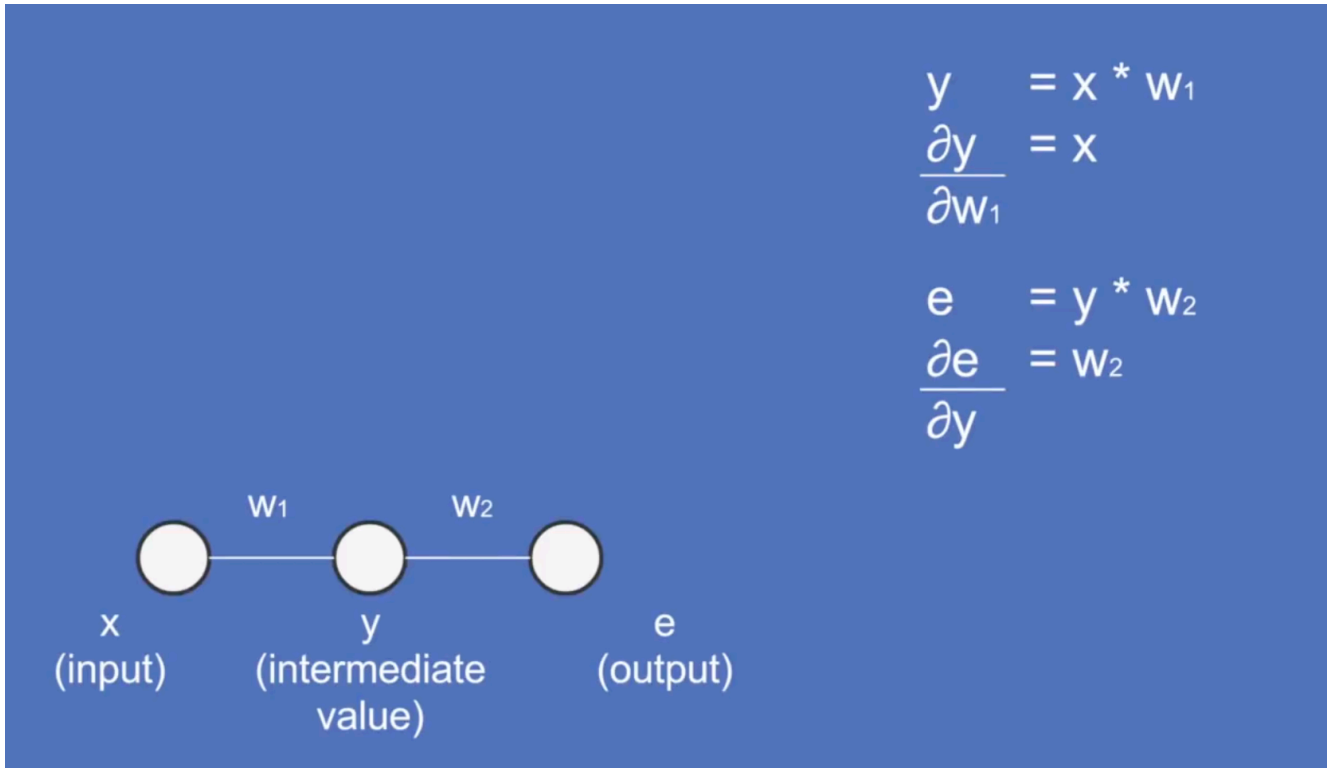
Chain rule



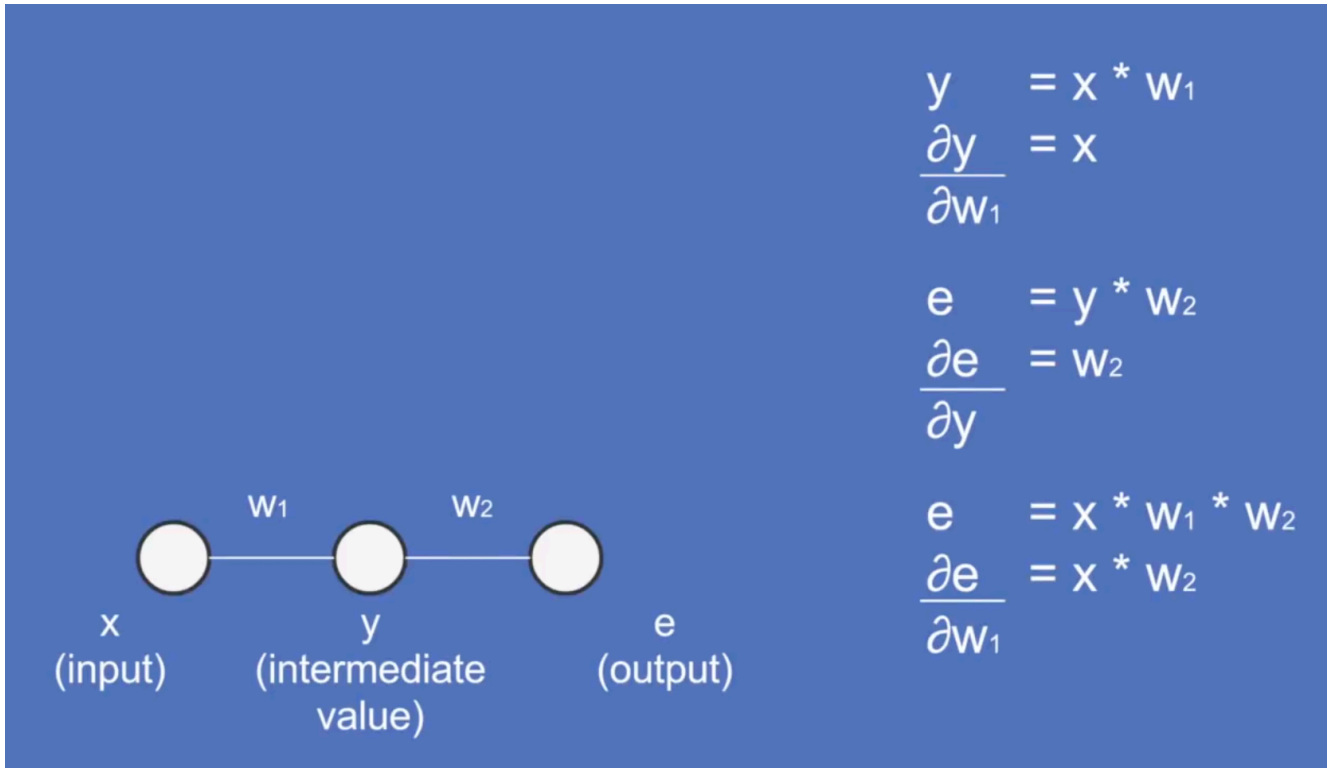
Chain rule



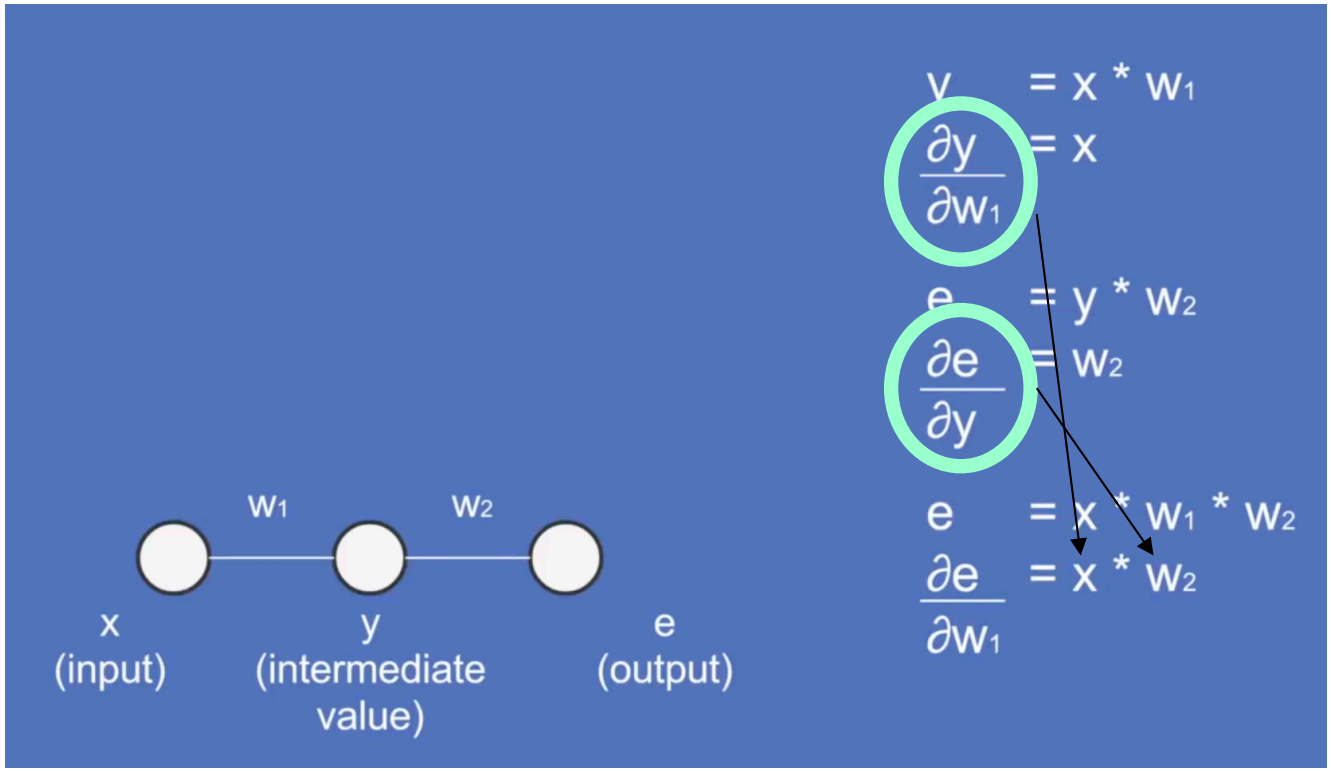
Chain rule


y = x * w1
∂y/∂w1 = x
e = y * w2
∂e/∂y = w2
w1
w2
x
(input)
y
(intermediate
value)
e
(output)

Chain rule


w1
w2
x
(input)
y
(intermediate
value)
e
(output)
y = x * w1
∂y/∂w1 = x
e = y * w2
∂e/∂y = w2
e = x * w1 * w2
∂e/∂w1 = x * w2

Chain rule


w1
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x
(input)
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y = x * w1
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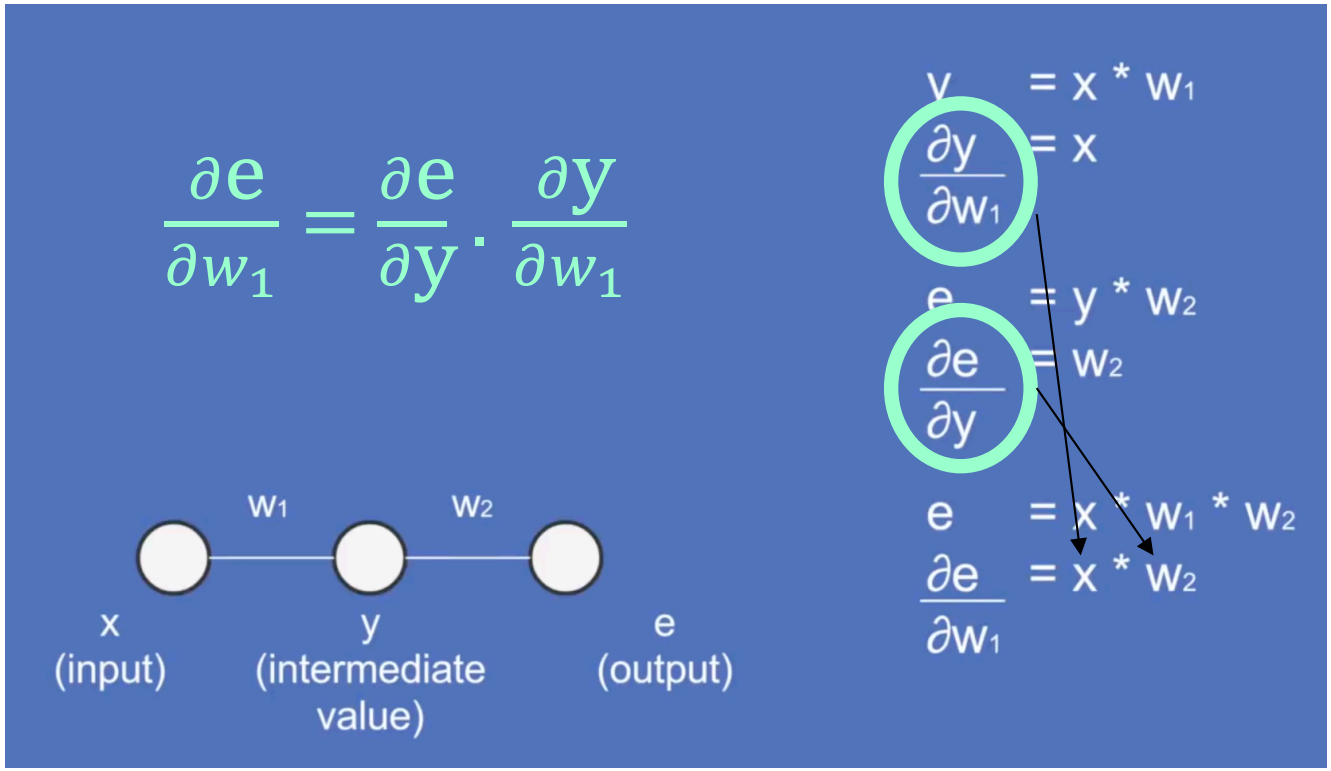
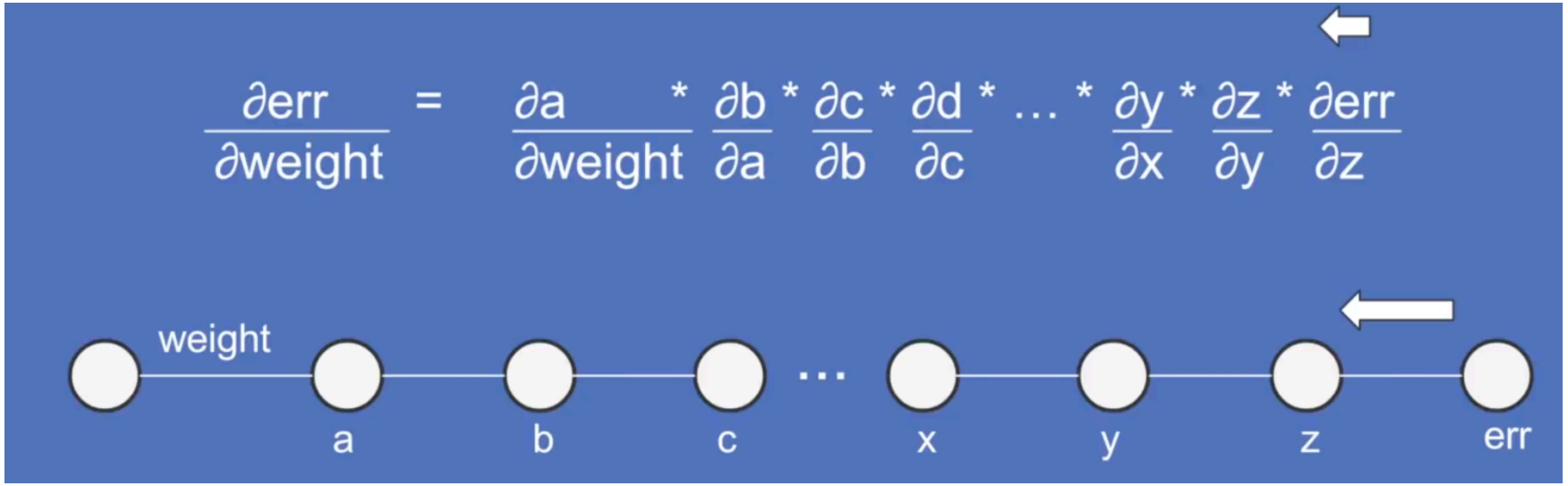
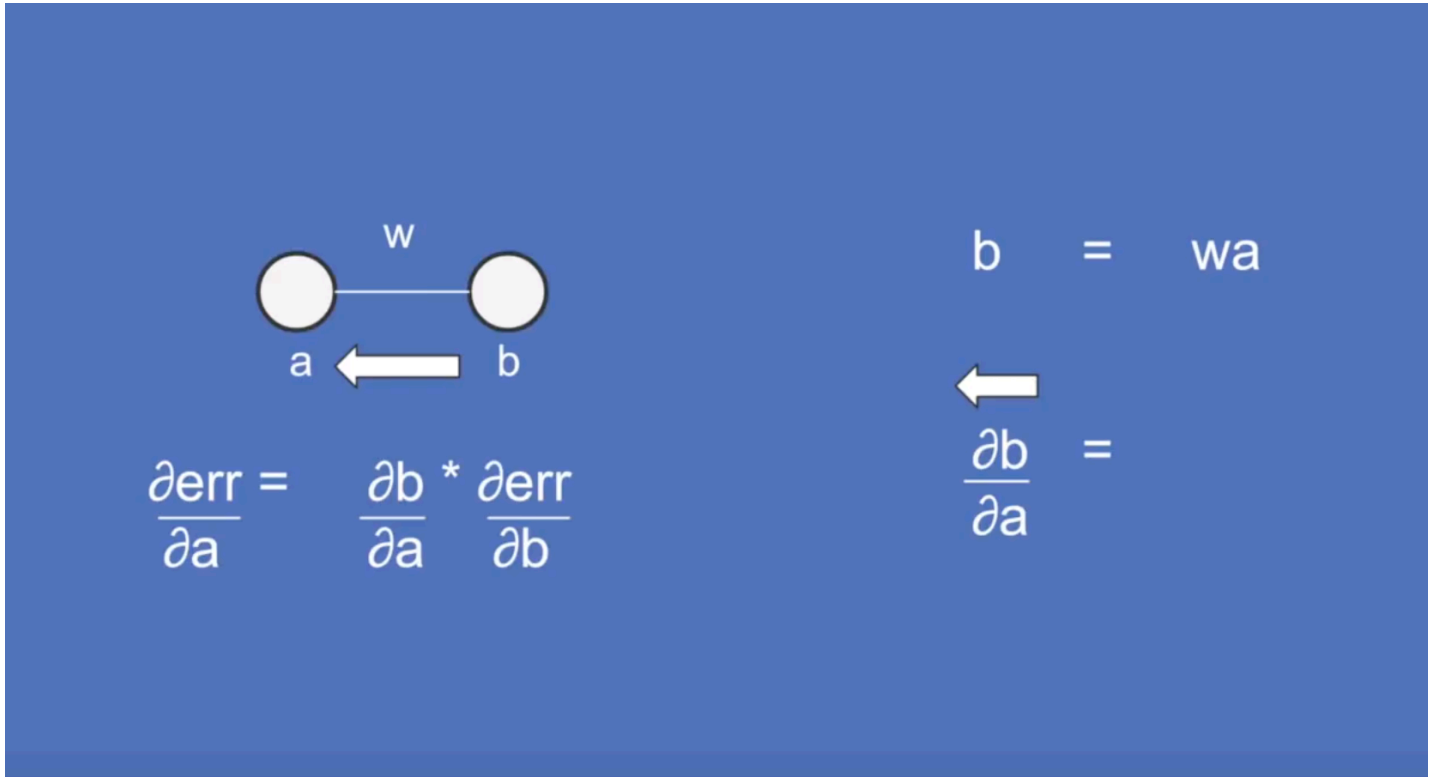
Chain rule


$\frac{\partial e}{\partial w_1} = \frac{\partial e}{\partial y} \cdot \frac{\partial y}{\partial w_1}$
y = x * w1
∂y/∂w1 = x
e = y * w2
∂e/∂y = w2
e = x * w1 * w2
∂e/∂w1 = x * w2
w1
w2
x
(input)
y
(intermediate value)
e
(output)

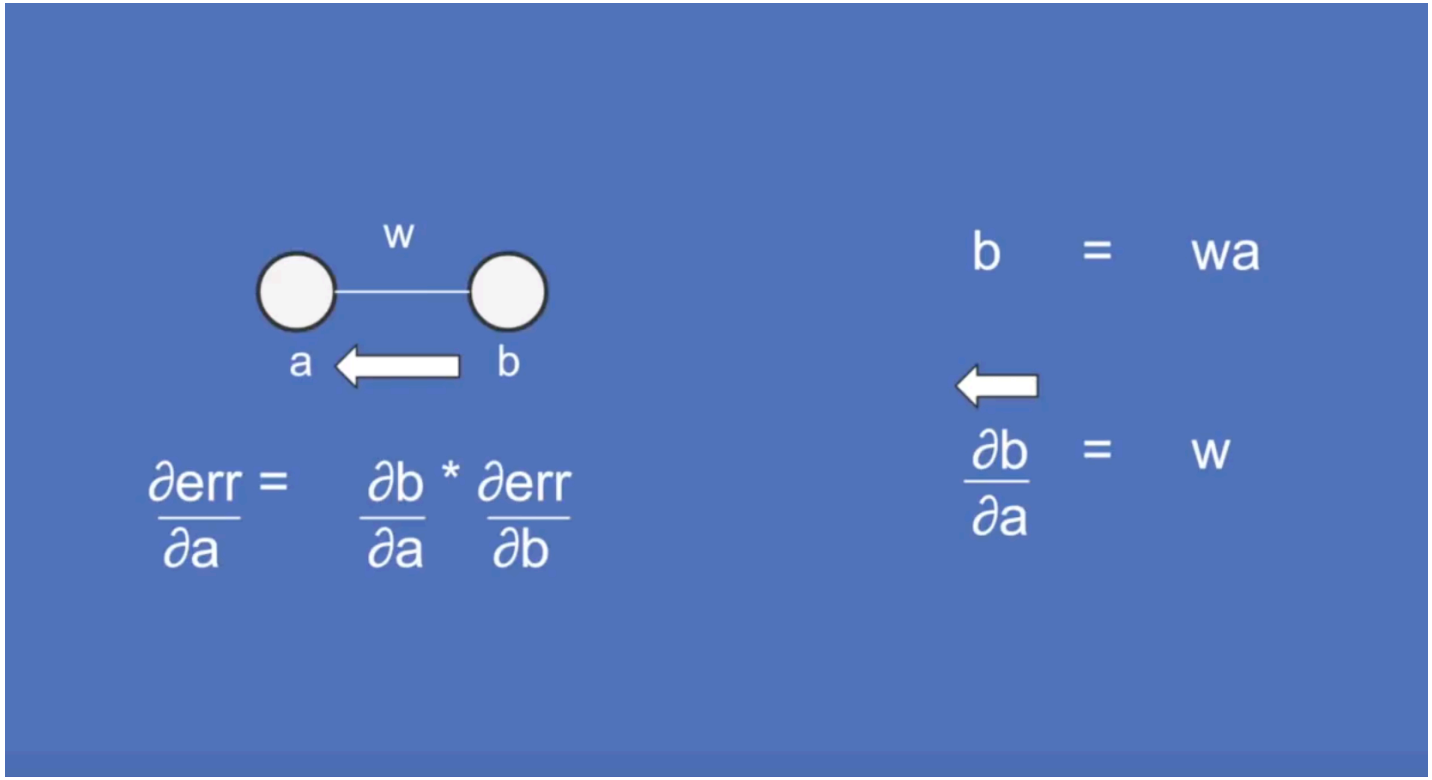
Chain Rule



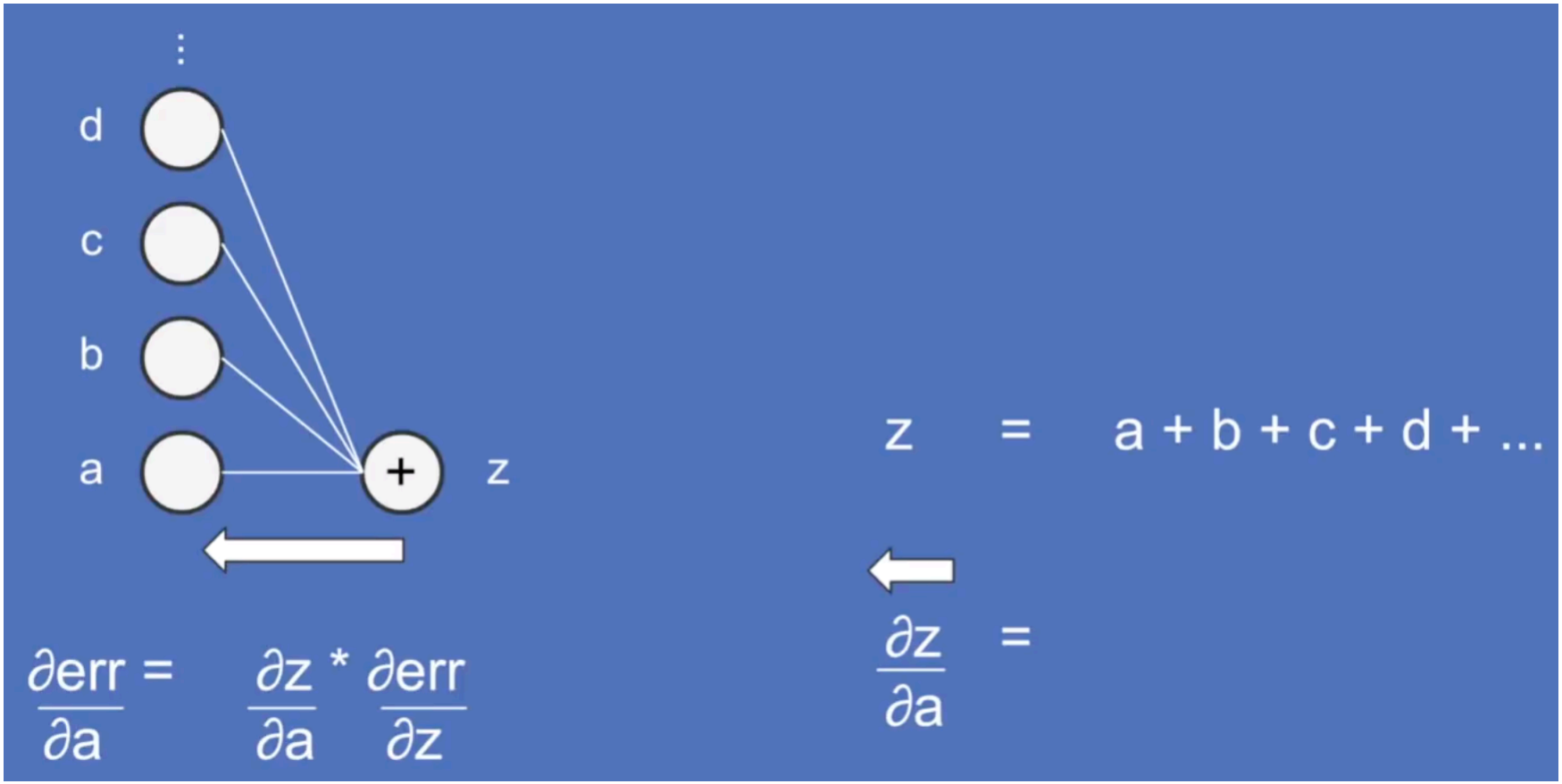
Chain rule


w
a
b
b = wa
$\frac{\partial err}{\partial a} = \frac{\partial b}{\partial a} * \frac{\partial err}{\partial b}$
$\frac{\partial b}{\partial a} =$

Chain rule


w
a
b
b = wa
$\frac{\partial err}{\partial a} = \frac{\partial b}{\partial a} * \frac{\partial err}{\partial b}$
$\frac{\partial b}{\partial a} = w$

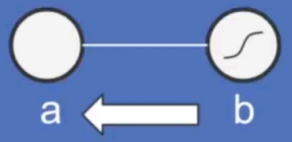
Chain rule



Chain rule

$$b = \frac{1}{1 + e^{-a}} = \sigma(a)$$

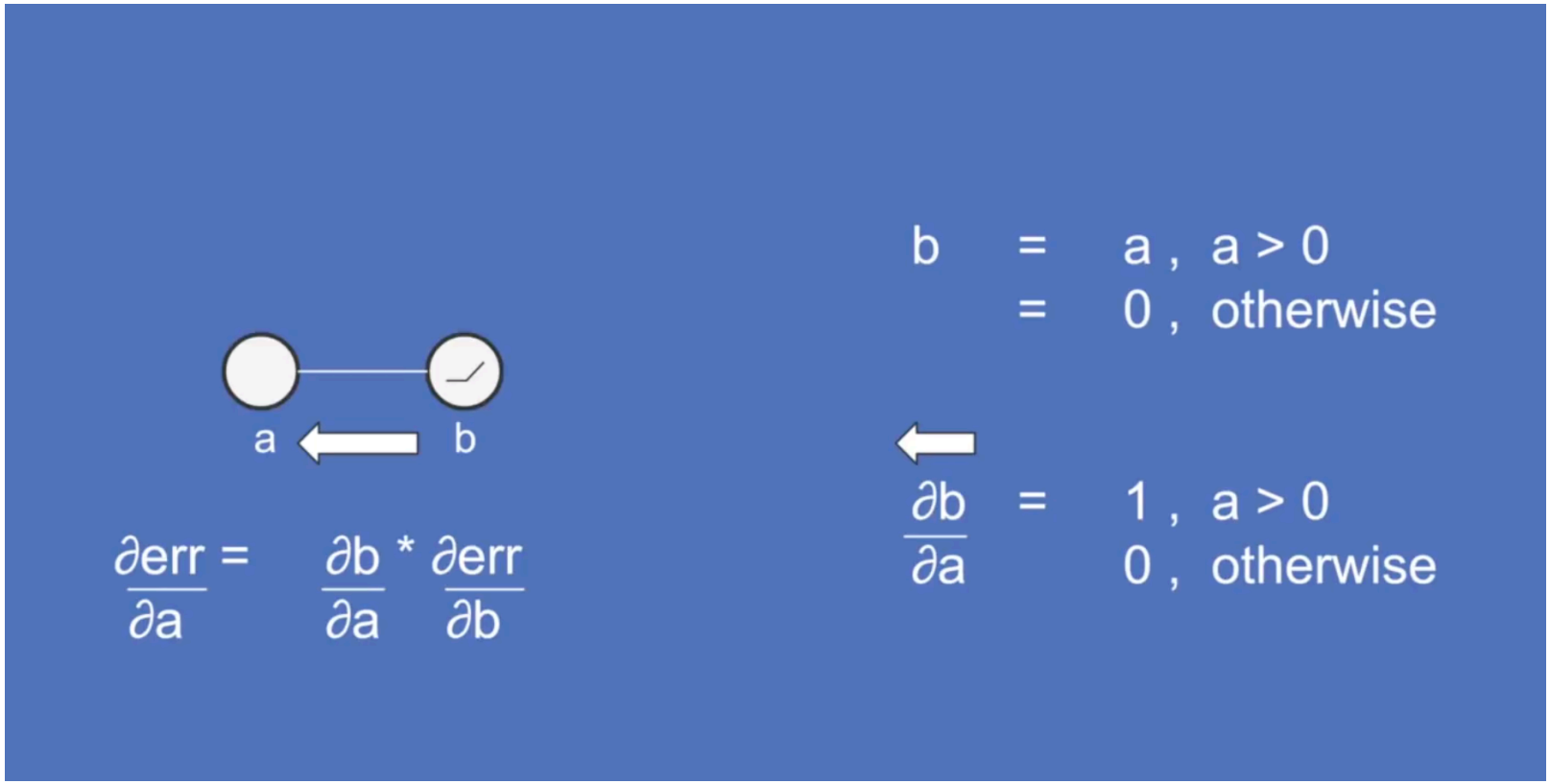
Because math is beautiful / dumb luck:



$$\frac{\partial err}{\partial a} = \frac{\partial b}{\partial a} * \frac{\partial err}{\partial b}$$

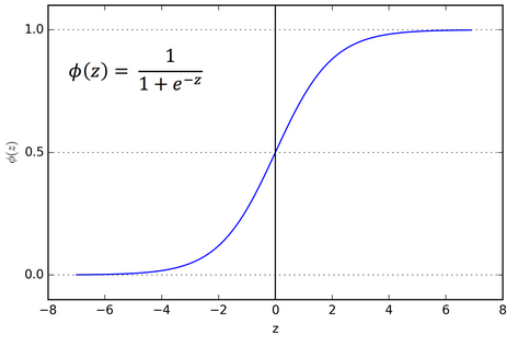
$$\frac{\partial b}{\partial a} = \sigma(a) * (1 - \sigma(a))$$

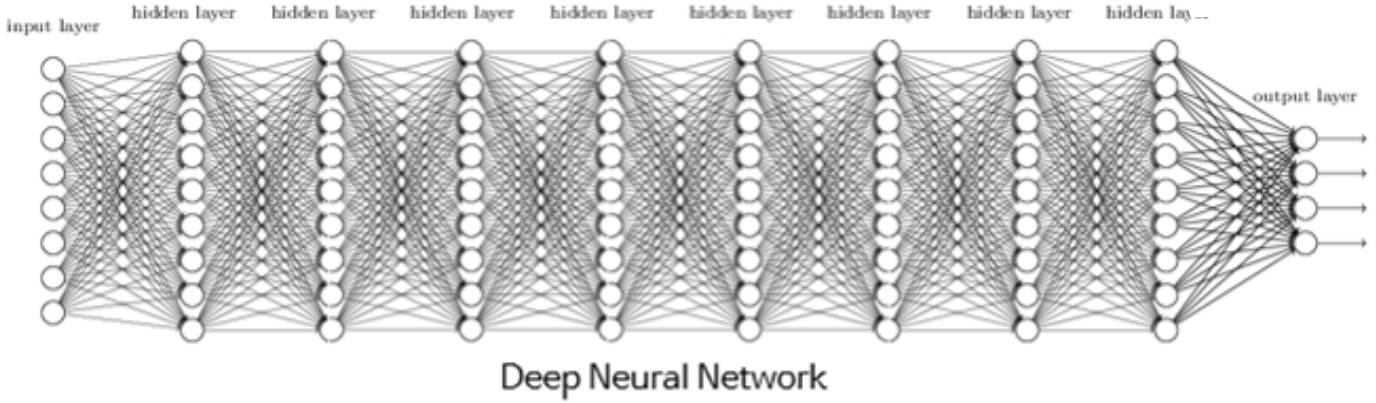
Chain rule

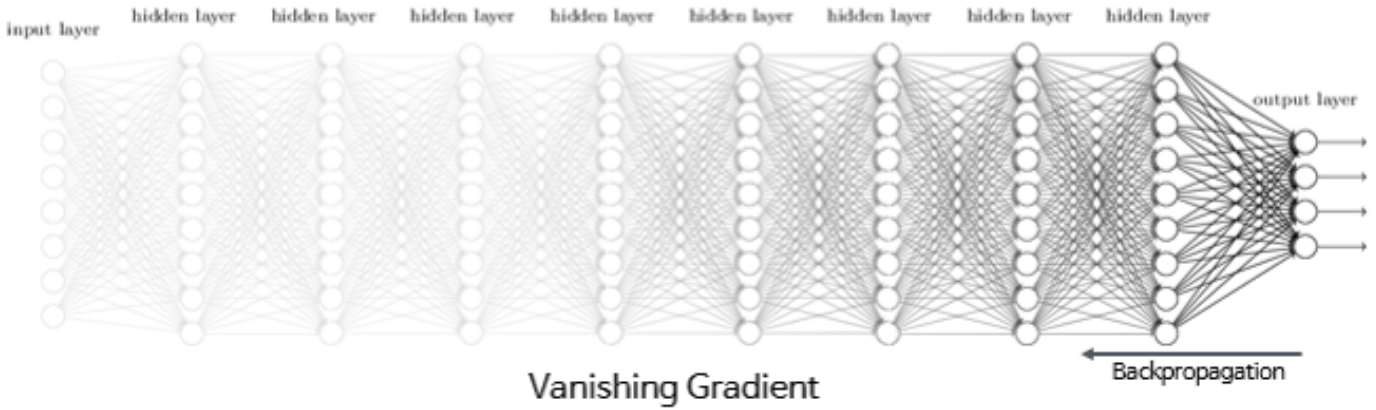


Limitations of Gradient Descent

- Activation function: Sigmoid







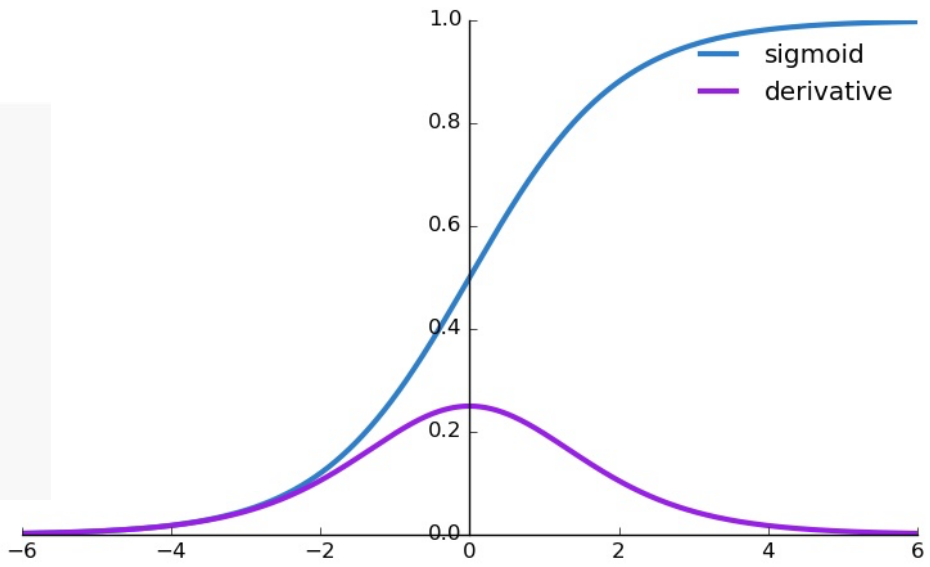
Vanishing gradient

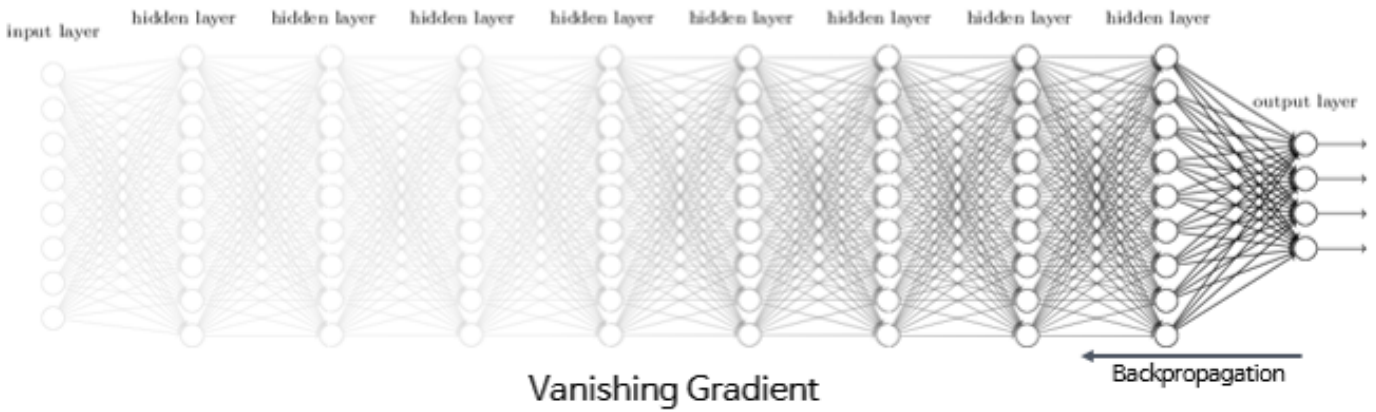
The sigmoid function is defined as follows

$$\sigma(x) = \frac{1}{1 + e^{-x}}.$$

This function is easy to differentiate because

$$\frac{d\sigma(x)}{d(x)} = \sigma(x) \cdot (1 - \sigma(x)).$$

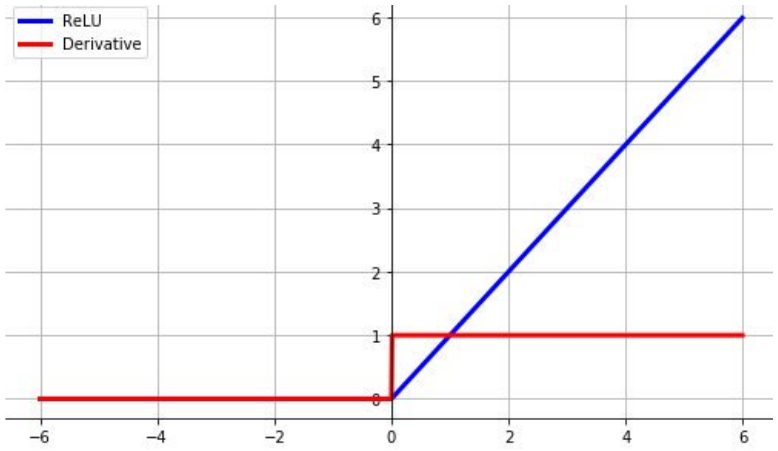




Vanishing Gradient

Vanishing gradient : Solution 1

ReLU activation function



Vanishing gradient : Solution 2

(mini-)batch normalization (BN)

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

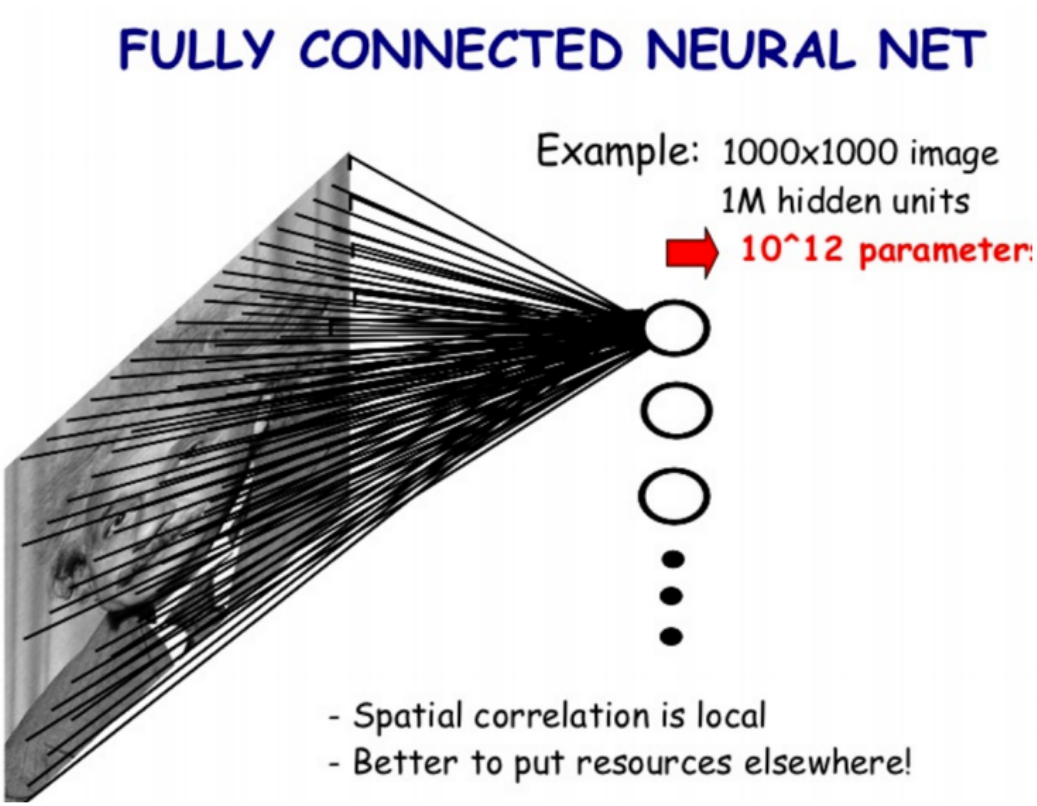
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

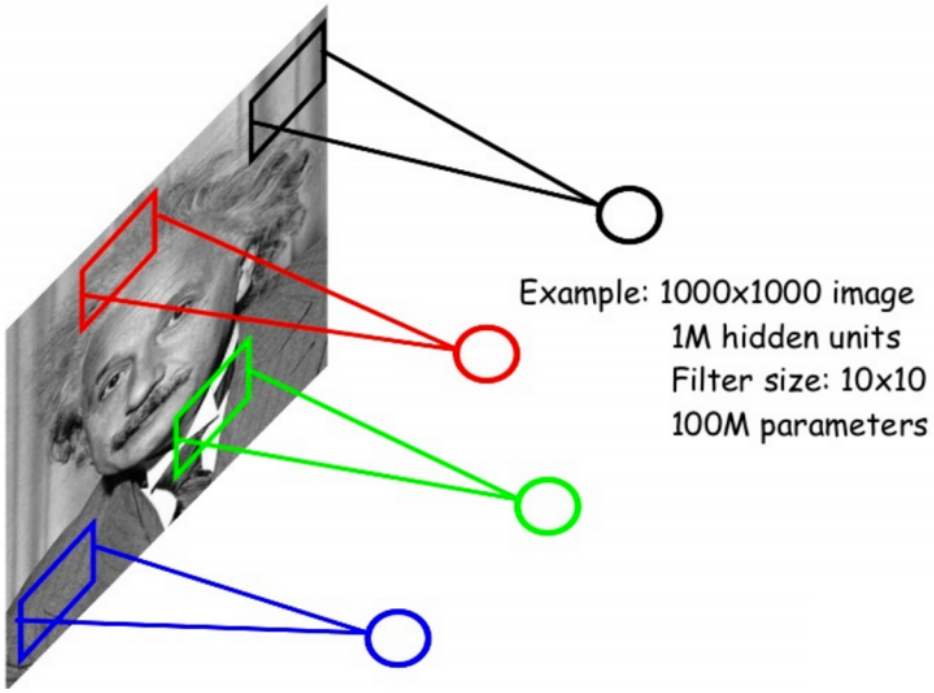
$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

FULLY CONNECTED NEURAL NET

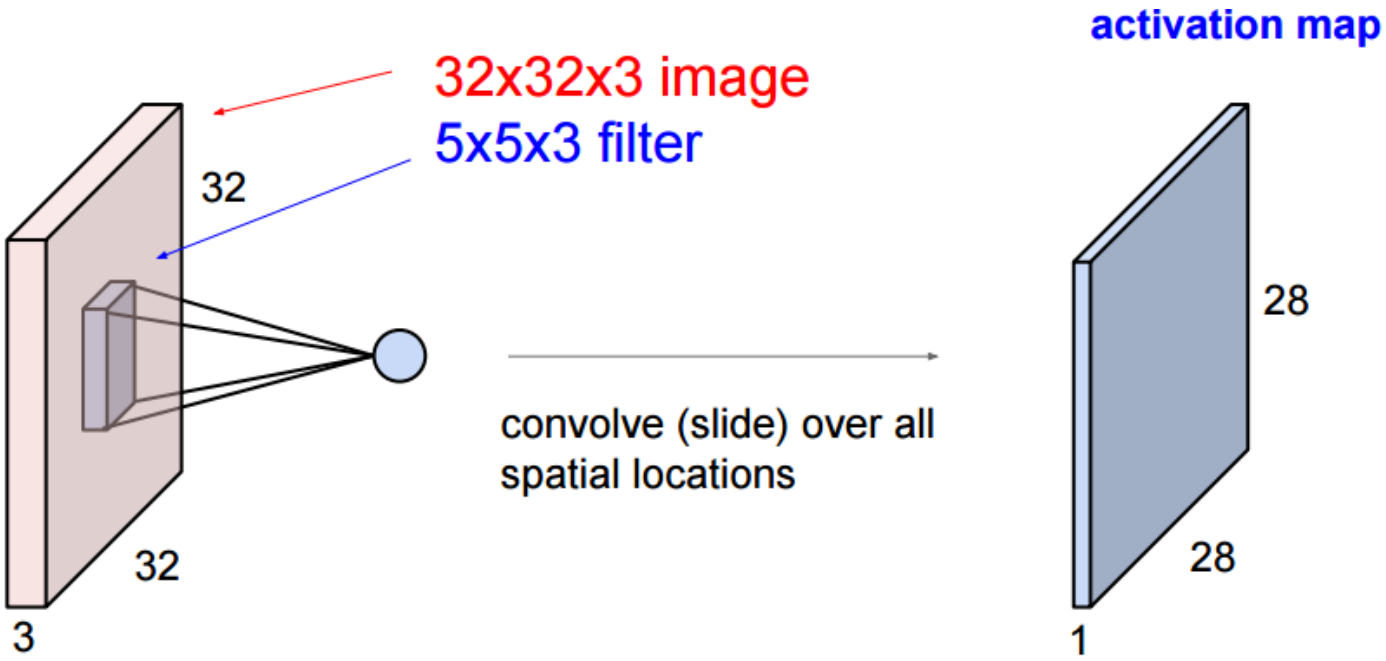


LOCALLY CONNECTED NEURAL NET

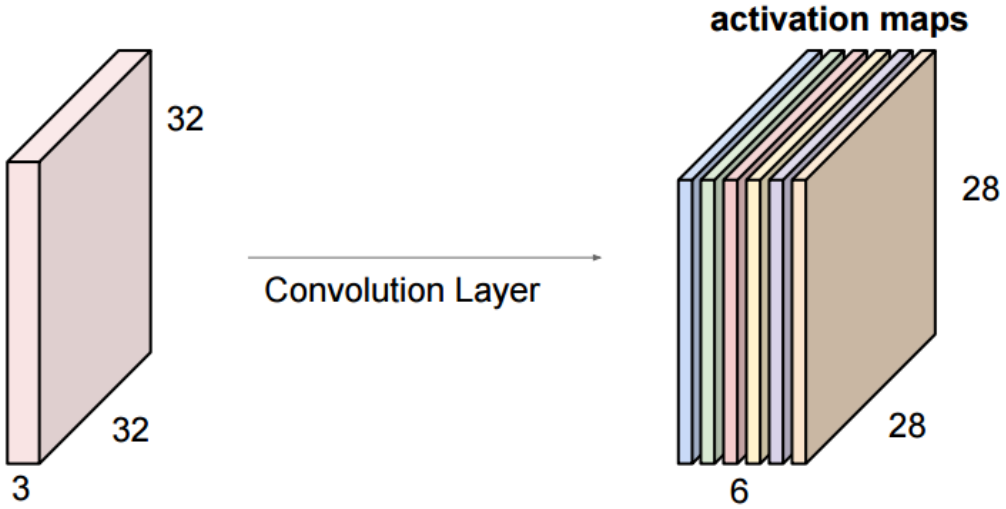


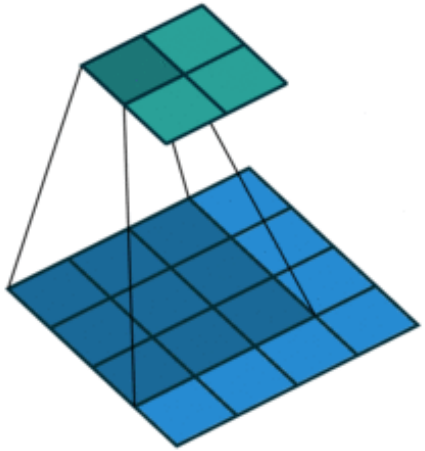
Example: 1000x1000 image
1M hidden units
Filter size: 10x10
100M parameters

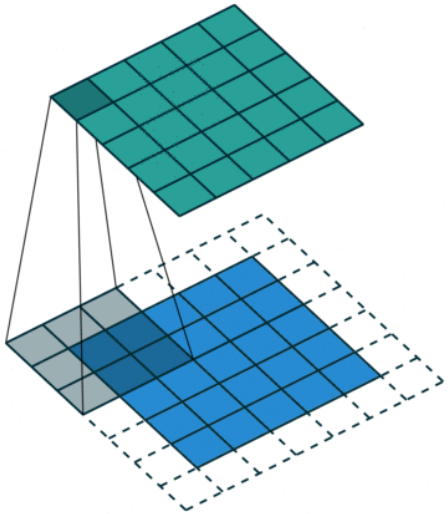
Convolution Layer



Convolution layer

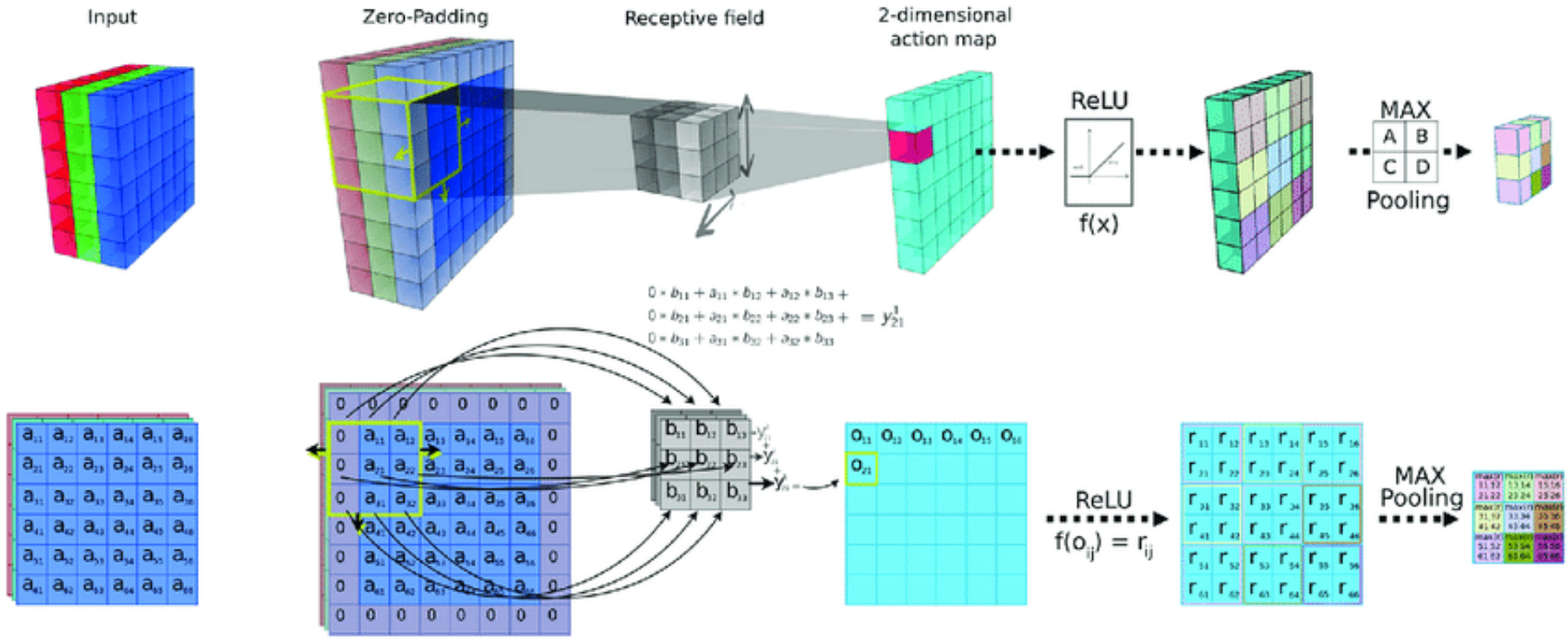




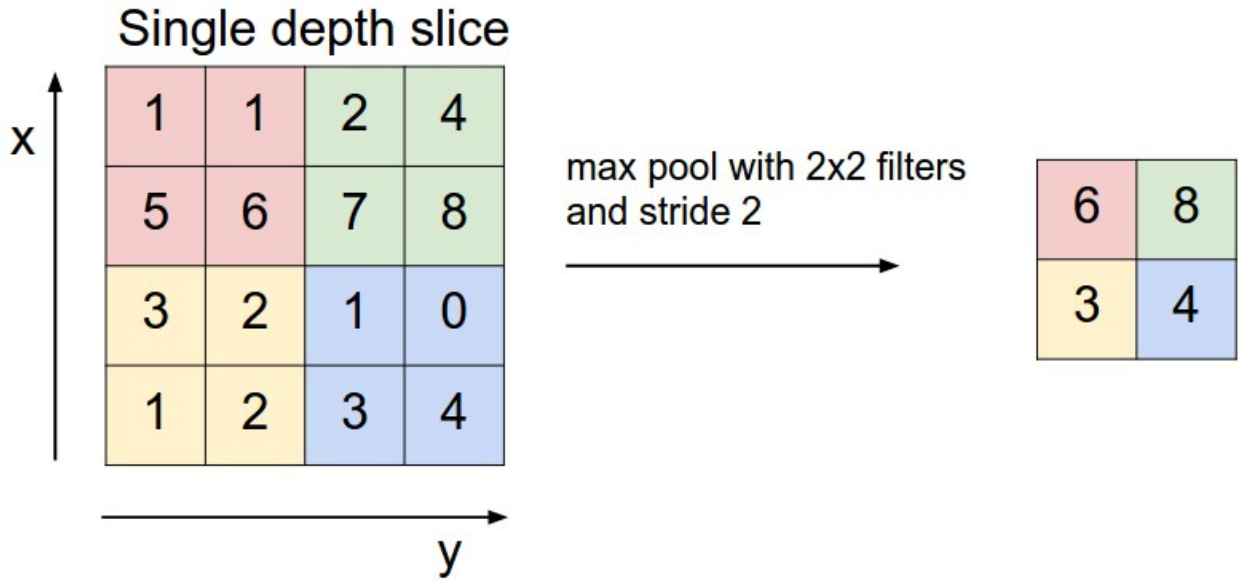


Convolution layer

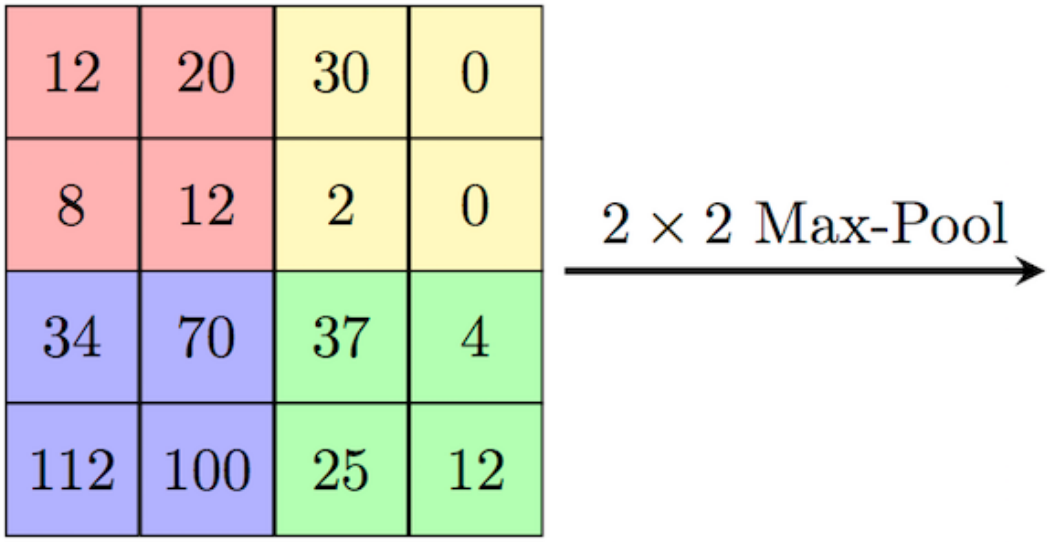
- Parametrized by: height, width, depth, stride, padding, number of filters, type of activation function



Pooling layer (i.e. sub-sampling)



Pooling layer (i.e. sub-sampling)



Dropout layer

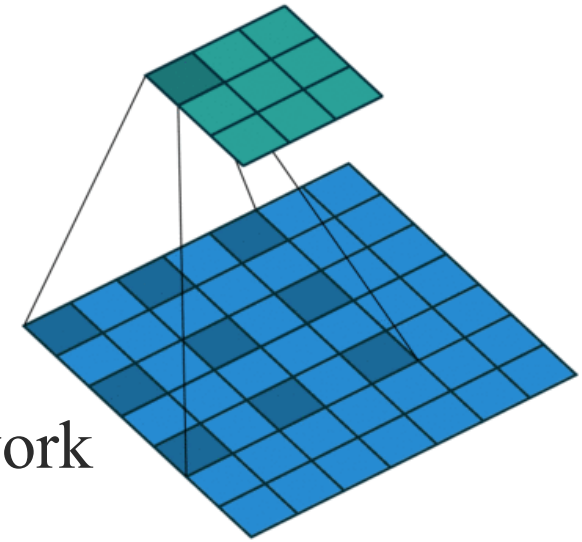
- Dropout consists in randomly setting a fraction rate of input units to 0.

Flatten layer

- Convert the input to a 1D array.

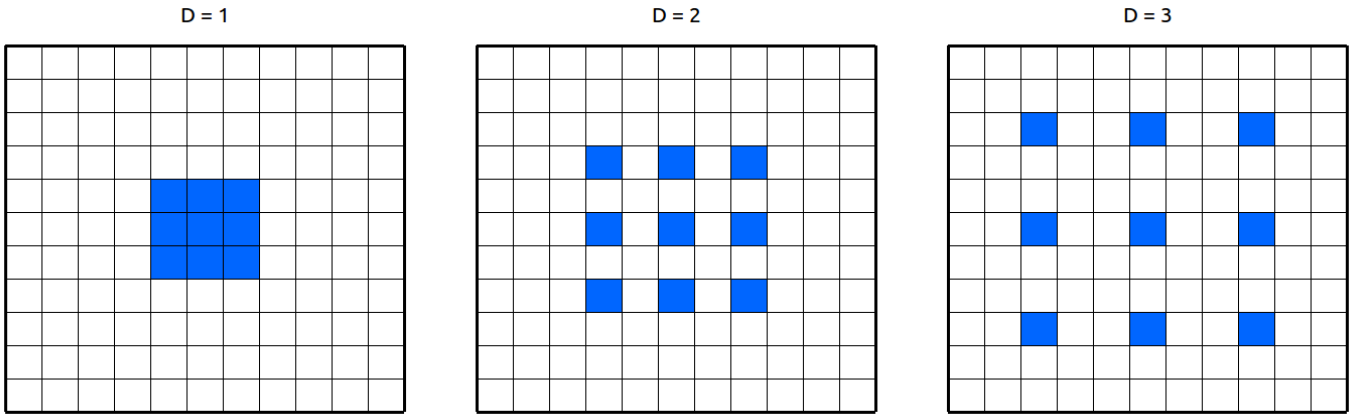
Batch Normalization (BN), Noise Layer

Dilated Convolution

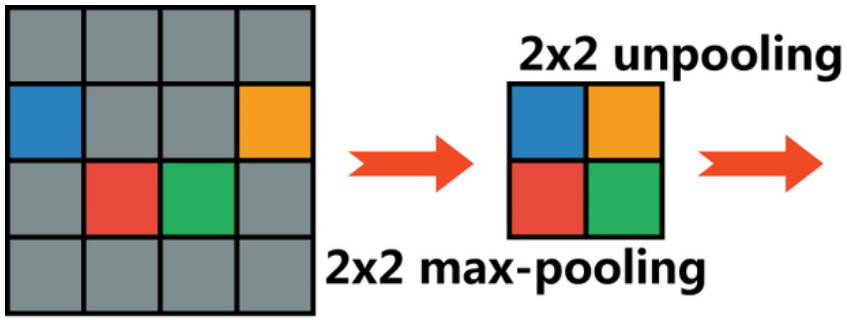


Dilating the filter means expanding its size filling the empty positions with 0.

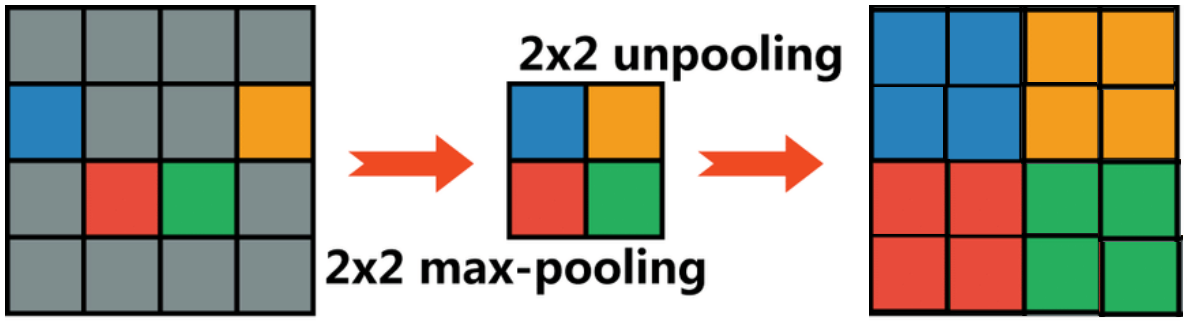
A way of increasing receptive view of the network while keeping the number of weights constant.



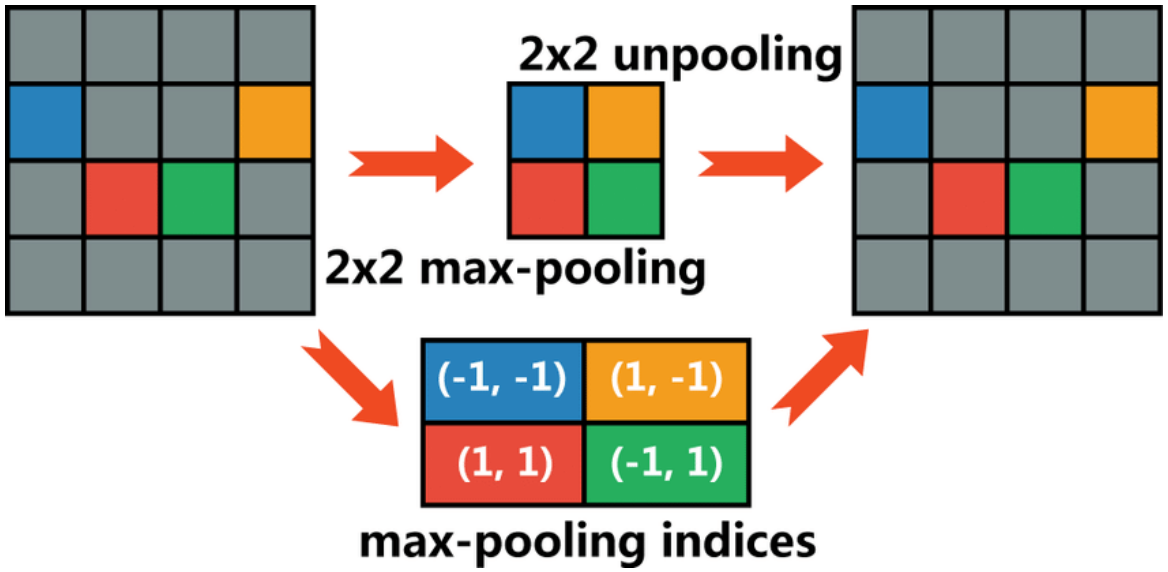
Unpooling



Unpooling (Nearest Neighbor)



Max-Unpooling



Max Pooling
Remember which element was max!

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

Input: 4 x 4

5	6
7	8

Output: 2 x 2

Rest of the network

Max Unpooling
Use positions from pooling layer

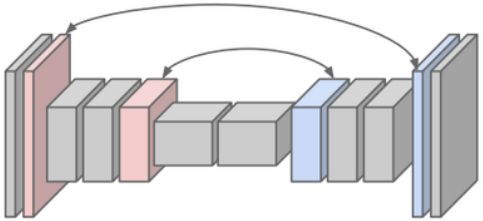
1	2
3	4

Input: 2 x 2

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

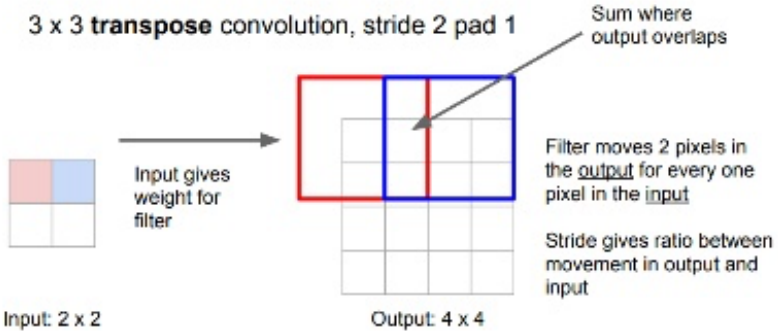
Output: 4 x 4

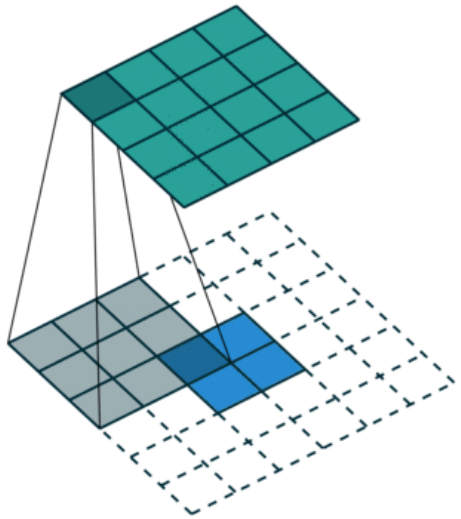
Corresponding pairs of downsampling and upsampling layers

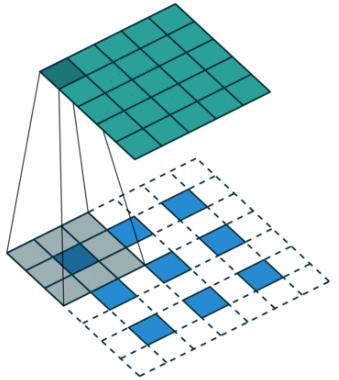


Learned Up-Sampling (~~Deconvolution~~)

- Also called transposed convolution







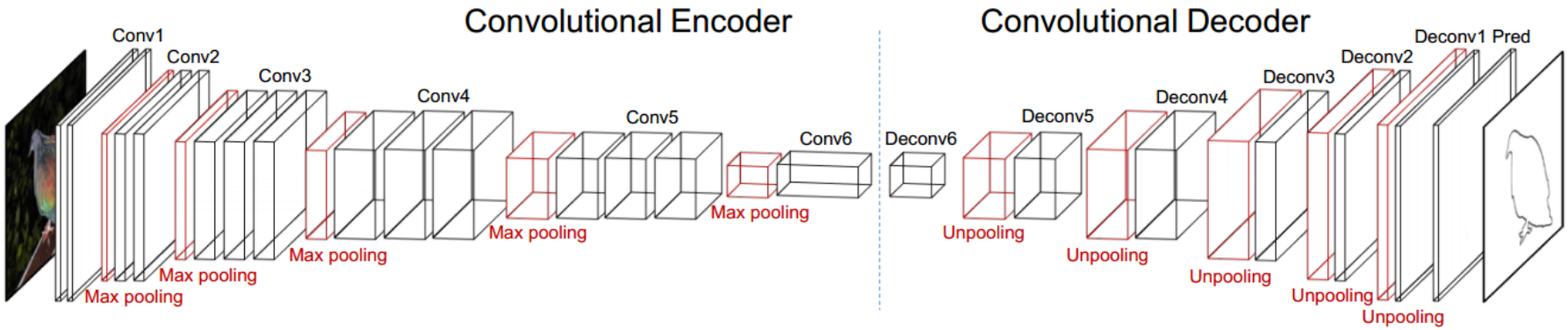
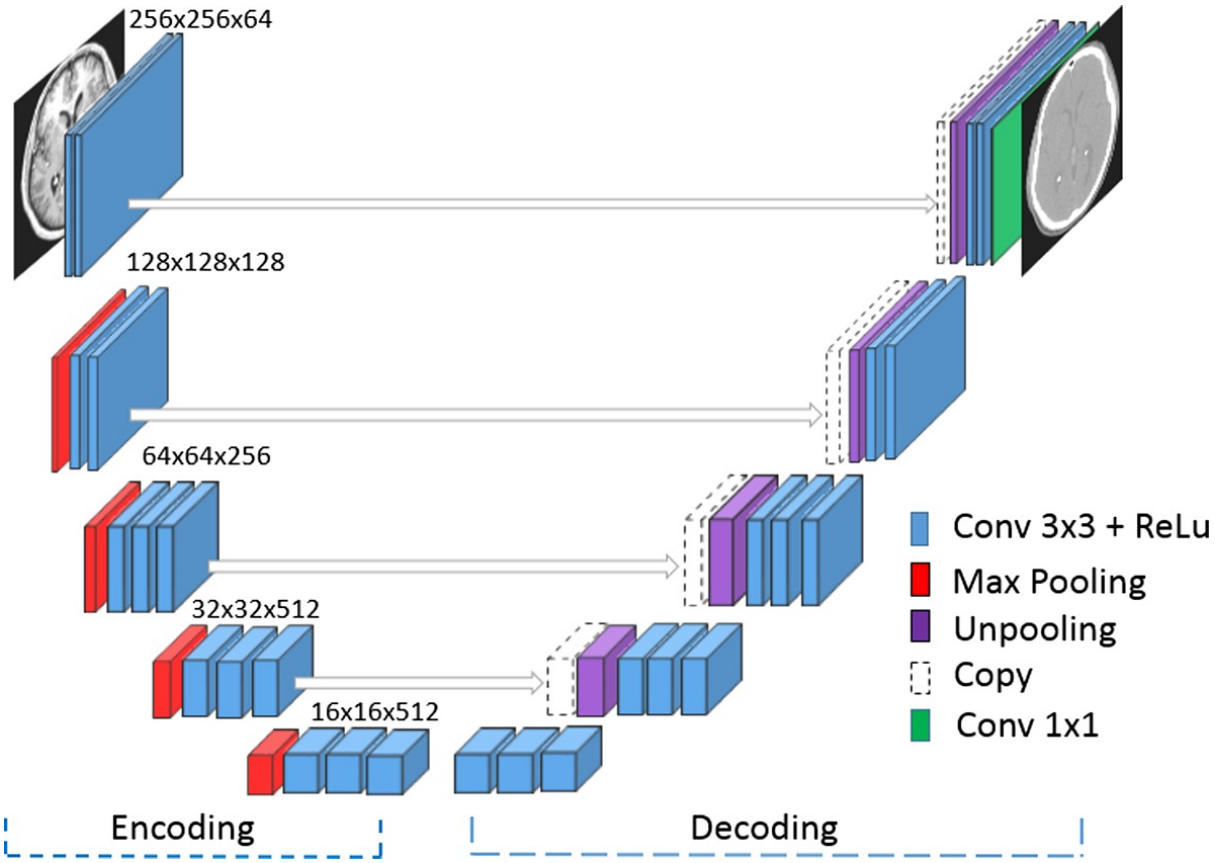


Figure 2. Architecture of the proposed fully convolutional encoder-decoder network.

MR-based synthetic CT generation using a deep convolutional neural network method



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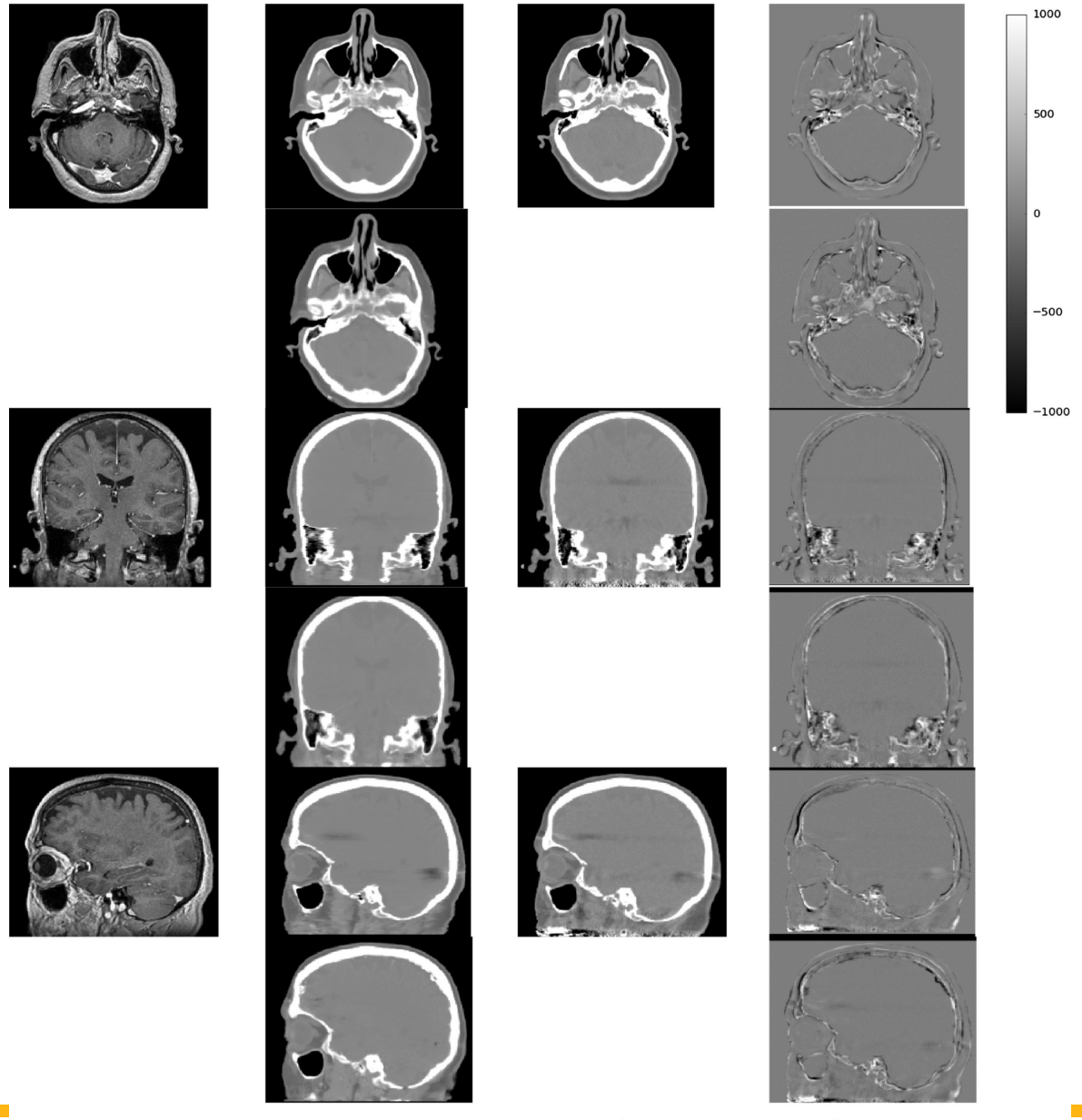
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500
0
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−1000
MR
sCT
Real CT
Difference Map