

# Convolutional Neural Networks – 02506

## Spring 2020

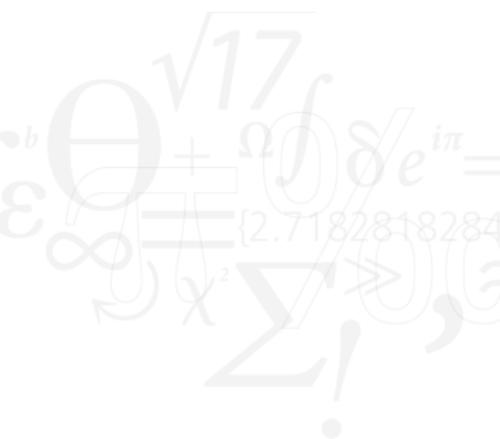
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DTU Compute

Advanced Image Analysis

April 2020

$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^{(i)}(x)$$



Outline



Learning objectives

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Principle

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Forward propagation

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Backpropagation

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Exercise

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More

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Learning objectives

Principle

Forward propagation

Backpropagation

Exercise

More

# Learning objectives

- ▶ Understand the principles of convolutional neural networks
- ▶ Perform image classification using a convolutional neural network library
- ▶ Understand the different parameters used in the convolutional neural network
- ▶ Understand the principles of learning parameters of convolutional neural networks

$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^{(i)}(x)$$


Some images from: [www.cs.toronto.edu/~rgrosse/csc321/lec11.pdf](http://www.cs.toronto.edu/~rgrosse/csc321/lec11.pdf)

# Convolutional neural networks

- ▶ You now know deep neural networks with fully connected layers
- ▶ What is a convolutional neural network? How is it different?
- ▶ What makes them especially suited for images?
- ▶ What are the parameters in convolutional neural networks?
- ▶ How are the parameters learned?

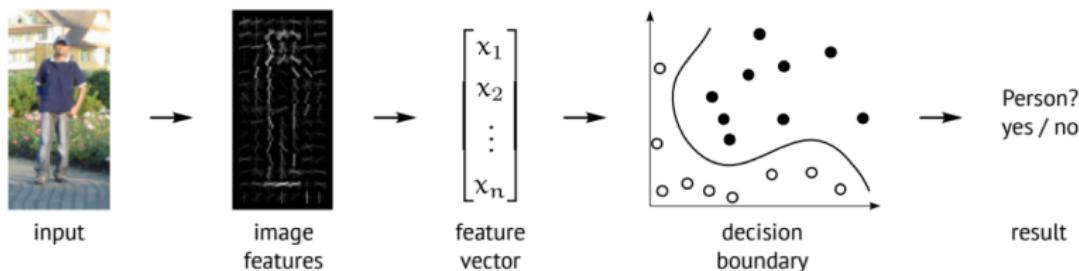
$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^{(i)}(x)$$

## Suggested reading material

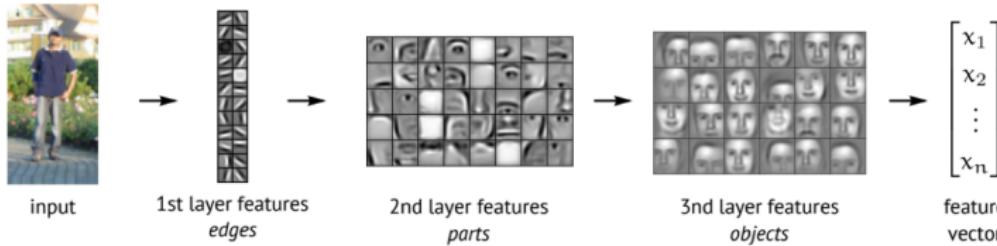
- Goodfellow, Bengio, and Courville. Deep Learning, Chapter 9.

# Motivation

- ▶ Feature engineering – e.g. SIFT

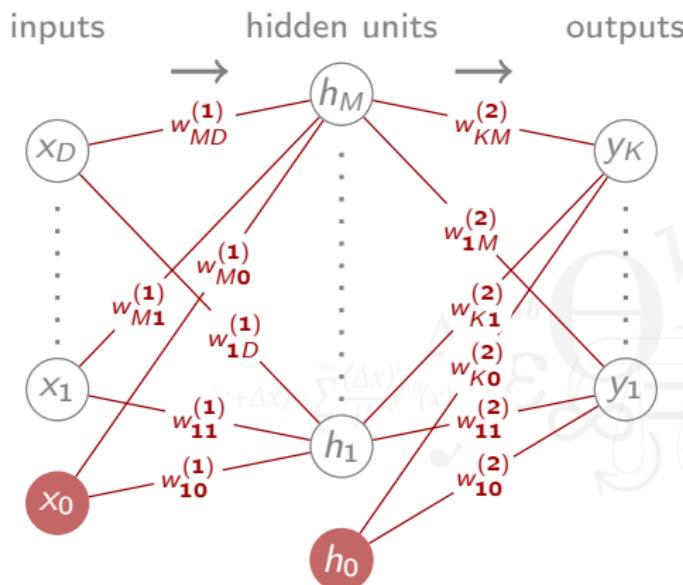


- ▶ Deep convolutional neural network



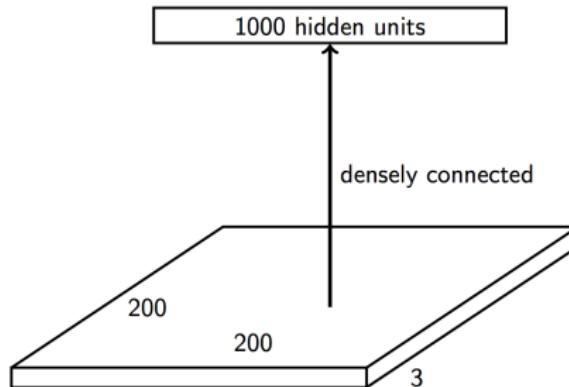
# Learning deep neural networks

## ► Fully connected neural networks



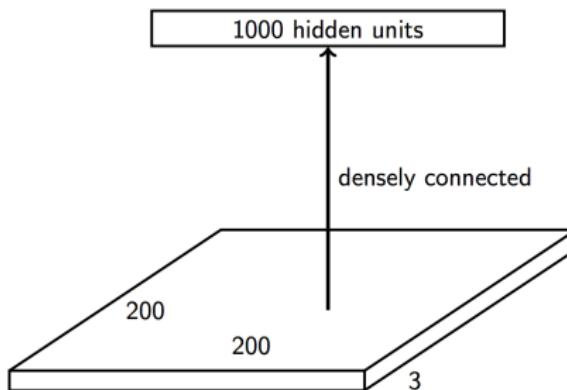
# Images

- ▶ What happens when we get to larger images?



# Images

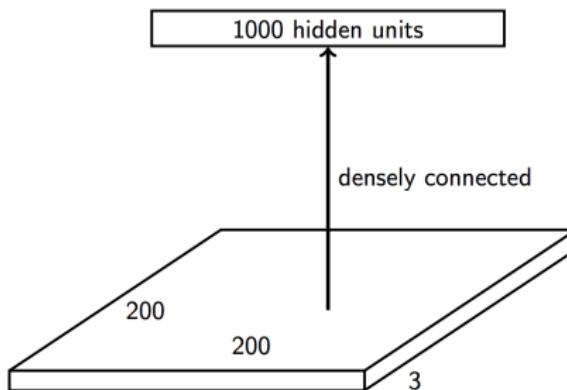
- ▶ What happens when we get to larger images?



- ▶ Number of pixels:  $200 \times 200 \times 3 = 120000$
- ▶ Number of weights:  $120000 \times 1000 = 120000000$

# Images

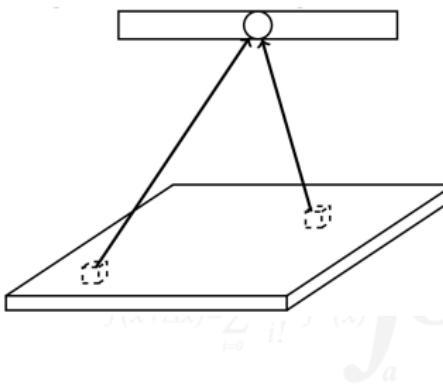
- ▶ What happens when we get to larger images?



- ▶ Number of pixels:  $200 \times 200 \times 3 = 120000$
- ▶ Number of weights:  $120000 \times 1000 = 120000000$
- ▶ How can we avoid this explosion?

# Images

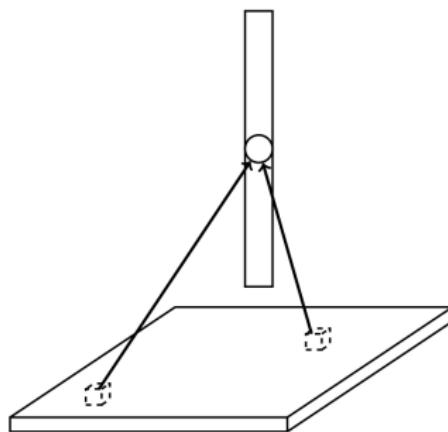
- ▶ Each neuron is connected to all pixels
- ▶ Far away pixels – not correlated



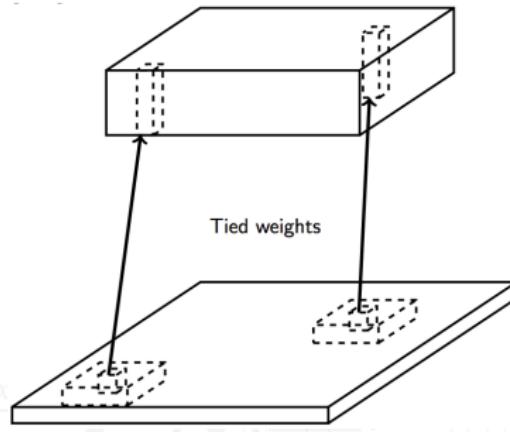
- ▶ Look locally and share weights!
- ▶ Use layers to correlate features at longer distances.

# Fully connected vs convolutional

Fully connected



Convolutional neural network



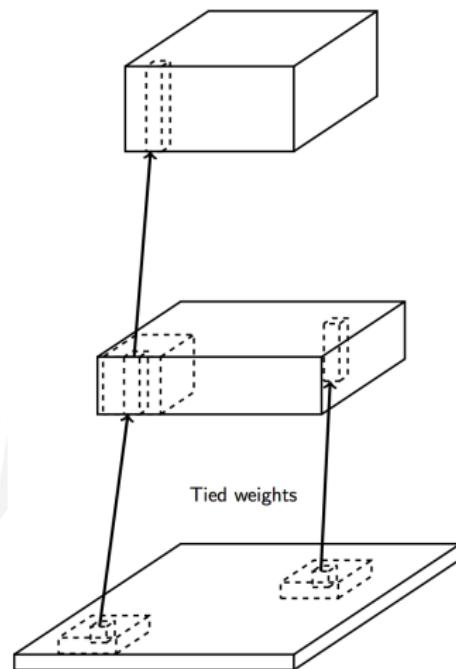
- ▶ Each neuron looks in the entire image

- ▶ Each column of hidden units only looks at a patch

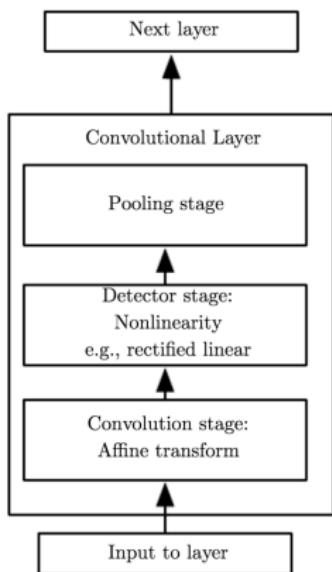
# Deep convolutional neural network

- ▶ Build a network based on convolutions
- ▶ Parameters are the convolution weights – shared over the image
- ▶ Filters are tensors (a set of small volumes)
- ▶ Forward propagation as a series of convolutions
- ▶ Layer operations: Convolutions (weighted average), activation, pooling

$$f(x+\Delta x) = \sum_{l=0}^{\infty} \frac{(\Delta x)^l}{l!} f^{(l)}(x)$$



# Forward propagation



► Steps in each layer:

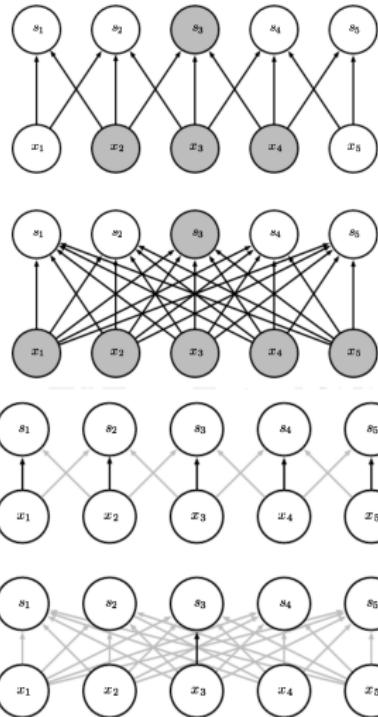
- Convolution
- Nonlinear map
- Pooling

$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^{(i)}(x)$$

# Convolution

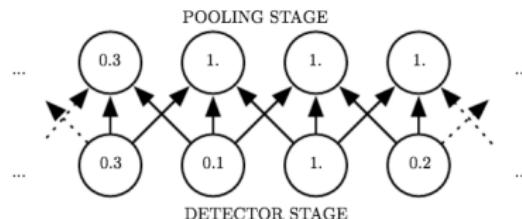
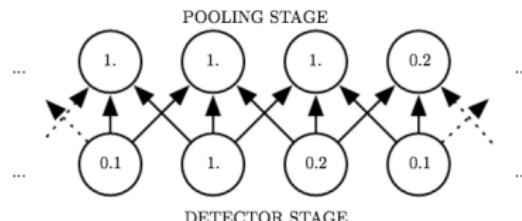
- ▶ Weighted average
- ▶ Sparse interactions
- ▶ Shared weights
- ▶ Typically one bias per filter
- ▶ Filters as tensors (a set of small volumes)
- ▶ Zero padding to avoid shrinkage of image

$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^i$$



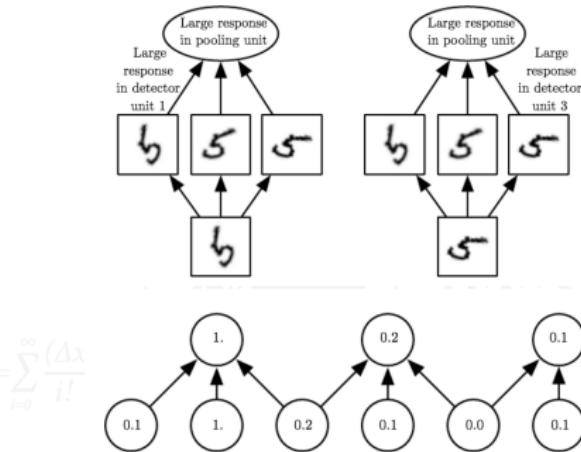
# Pooling

- ▶ Max pooling
- ▶ Average, weighted average, etc. are also possible
- ▶ Introduces invariance – translation, different features
- ▶ Possibility for down-sampling



# Pooling

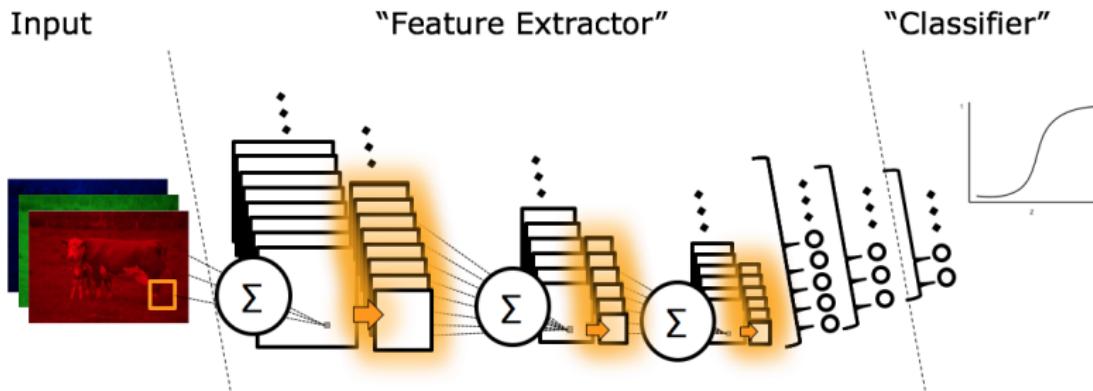
- ▶ Max pooling
- ▶ Average, weighted average, etc. are also possible
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$$\sum_{l=0}^{\infty} \frac{(\Delta x)^l}{l!}$$

# Network architecture

- ▶ Large number of layers
  - ▶ GoogLeNet – 22 layers
  - ▶ VGGnet – 19 layers
  - ▶ 2015 Microsoft – 152 layers



# Backpropagation

## ► MLP backpropagation

$$\frac{\partial L}{\partial z_i^l} = \delta_j^l$$

$$\delta_j^l = a'(z_i^l) \sum_k w_{ki}^{l+1} \delta_k^{l+1}$$

$$\frac{\partial L}{\partial w_{ij}^l} = \delta_i^l h_i^{l-1}$$

## ► CNN backpropagation

$$\frac{\partial L}{\partial z_i^l} = \delta_i^l$$

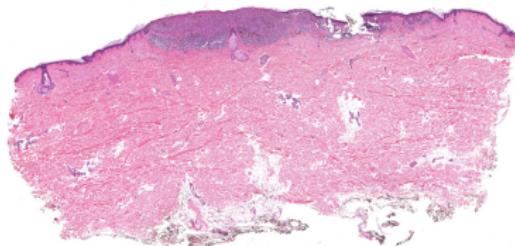
$$\delta_i^l = a'(z_i^l) \sum_k w_{ki}^{l+1} \delta_k^{l+1}$$

$$\frac{\partial L}{\partial w_{ij}^l} = \sum_{m,n} \delta_m^l h_n^{l-1}$$

## ► Can be implemented using convolutions

# Problem

## ► Whole-slide imaging<sup>1</sup>



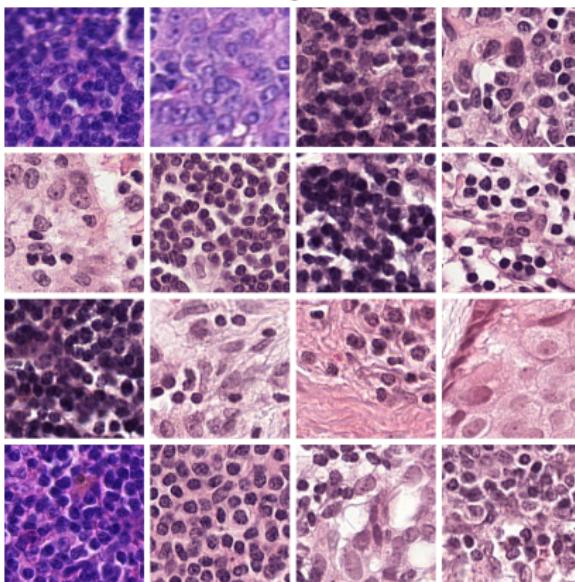
$$f(x+\Delta x) = \sum_{i=0}^n \frac{(x+\Delta x)^i}{i!} f^{(i)}(x)$$

<sup>1</sup>Obtained from: <http://www.cs.unc.edu/~mn/?q=content/image-analysis-histopathology-melanoma-classification>, <http://www.sysmex.co.nz/the-9th-asia-pacific-congress-recap/>

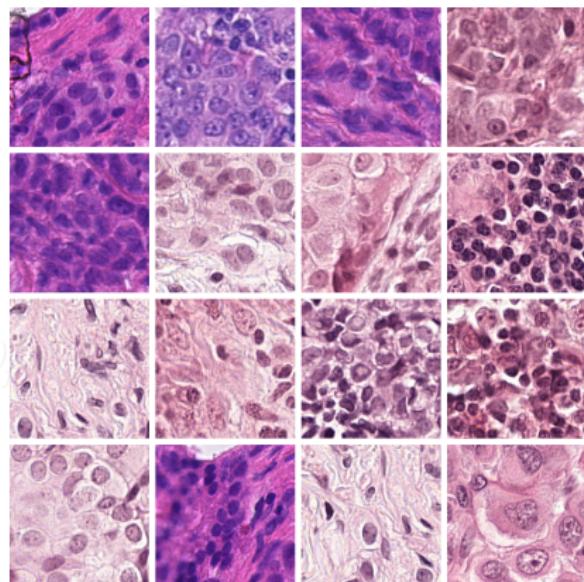
# Data

## ► CEMELYON17 competition<sup>2</sup>

Healthy tissue



Cancer Tissue



<sup>2</sup> Obtained from: <https://camelyon17.grand-challenge.org/>

## Exercise: Pre-trained network for classification

- ▶ Now sparse connections through convolution
- ▶ Now use others implementation – MatConvNet library (<http://www.vlfeat.org/matconvnet/>) or Keras (<https://keras.io/>)
- ▶ Problem – image classification using  $k$ -nearest neighbor
- ▶ Investigate an already trained network
- ▶ Use a simple classifier on the output features

# 02514 Deep learning for Computer Vision

- ▶ Recognition – classification
- ▶ Image generation
- ▶ Segmentation
- ▶ Runs in 3 weeks period in June

$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^{(i)}(x)$$

# MNIST competition – remember the prize!

- ▶ MNIST classification
- ▶ Competition – not insignificant eatable prize for winning team (probably some post easter theme!)

5	0	4	1	9	2	1	3	1	4
3	5	3	6	1	7	2	8	6	9
4	0	9	1	1	2	4	3	2	7
3	8	6	9	0	5	6	0	7	6
1	8	7	9	3	9	8	5	9	3
3	0	7	4	9	8	0	9	4	1
4	4	6	0	4	5	6	1	0	0
1	7	1	6	3	0	2	1	1	7
8	0	2	6	7	8	3	9	0	4
6	7	4	6	8	0	7	8	3	1

