# Data Mining

# Lecture 14

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Fall 2024



#### Background: Computer Vision

- Image Classification
- ILSVRC 2010 2016
- Traditional Feature Extraction Methods
- Convolution as Feature Extraction

#### Convolutional Neural Networks (CNNs)

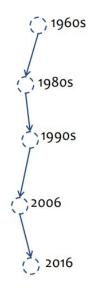
- Learning Feature Abstractions
- Common CNN Layers:
  - Convolutional Layer
  - Max-Pooling Layer
  - Fully-connected Layer (w/tensor input)
  - Softmax Layer
  - ReLU Layer
- Background: Subgradient
- Architecture: LeNet
- Architecture: AlexNet

#### Training a CNN

- SGD for CNNs
- Backpropagation for CNNs

### Motivation

Why is everyone talking about Deep Learning?



### Deep learning:

- Has won numerous pattern recognition competitions
- Does so with minimal feature engineering

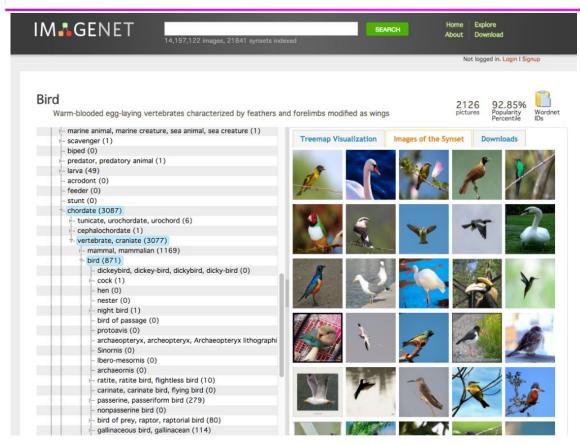
#### This wasn't always the case!

Since 1980s: Form of models hasn't changed much, but lots of new tricks...

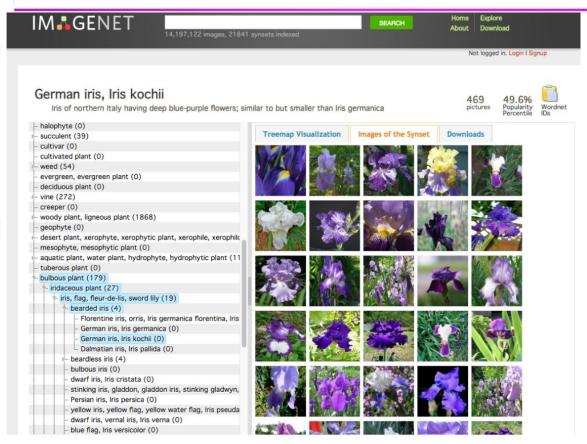
- More hidden units
- Better (online) optimization
- New nonlinear functions (ReLUs)
- Faster computers (CPUs and GPUs)

# Example: Image Classification

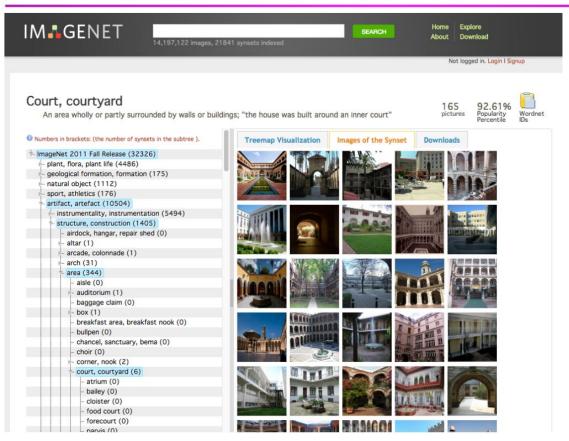
- ImageNet LSVRC-2011 contest:
  - Dataset: 1.2 million labeled images, 1000 classes
  - Task: Given a new image, label it with the correct class
  - Multiclass classification problem
- Examples from http://image-net.org/



Slides taken from https://www.cs.cmu.edu/~mgormley/courses/10601-s17/slides/lecture21-cnn.pdf



 $Slides\ taken\ from\ https://www.cs.cmu.edu/~mgormley/courses/10601-s17/slides/lecture 21-cnn.pdf$ 



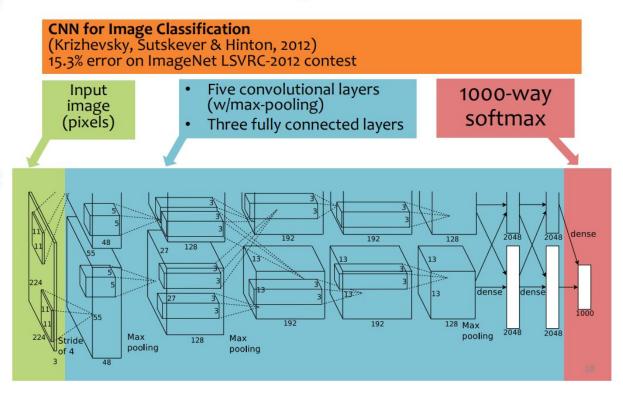
 $Slides\ taken\ from\ https://www.cs.cmu.edu/~mgormley/courses/10601-s17/slides/lecture 21-cnn.pdf$ 

# Example: Image Classification

Traditional Feature Extraction for Images:

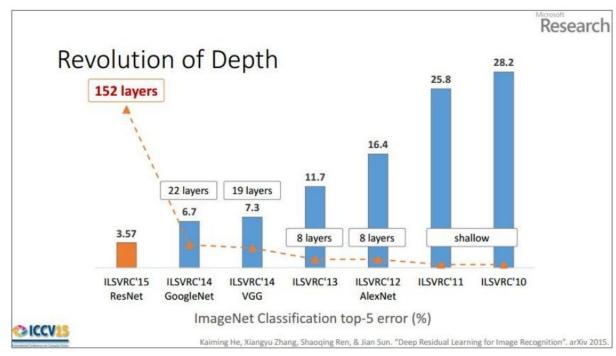
- SIFT
- HOG

# Example: Image Classification



Slides taken from https://www.cs.cmu.edu/~mgormley/courses/10601-s17/slides/lecture21-cnn.pdf

# CNNs for Image Recognition



Slides taken from https://www.cs.cmu.edu/~mgormley/courses/10601-s17/slides/lecture21-cnn.pdf

Year	CNN Architecture	Developed By
1998	LeNet	Yann LeCun et al.
2012	AlexNet	Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever
2013	ZFNet	Matthew Zeiler and Rob Fergus
2014	GoogleNet	Google
2014	VGGNet	Simonyan and Zisserman
2015	ResNet	Kaiming He
2017	DenseNet	Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger

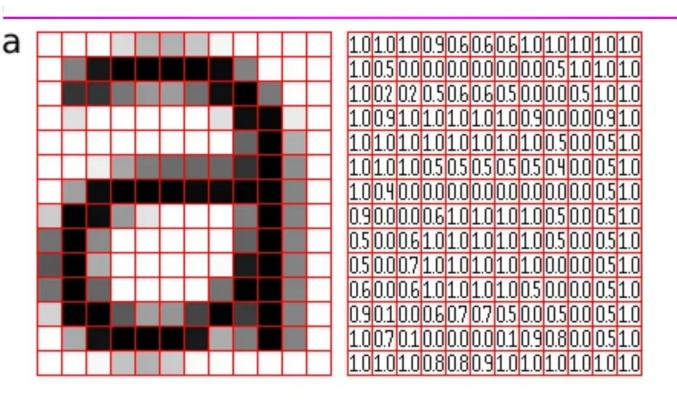
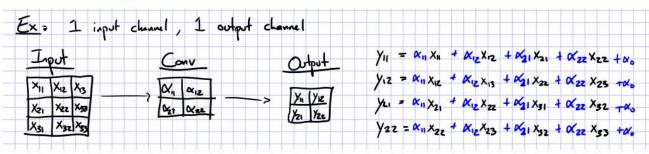


Figure 1: Representation of image as a grid of pixels

image source http://pippin.gimp.org/image\_processing/images/sample\_grid\_a\_square.png

## What's a convolution?

- Basic idea:
  - Pick a 3x3 matrix F of weights
  - Slide this over an image and compute the "inner product" (similarity) of F and the corresponding field of the image,
- Key point:
  - Different convolutions extract different types of low-level "features" from an image
  - All that we need to vary to generate these different features is the weights of F

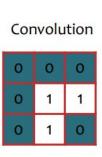


# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0	0	0	0	0	0	0
0	1	1	1	1	1	0
0	1	0	0	1	0	0
0	1	0	1	0	0	0
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0



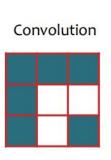
3	2	2	3	1
2	0	2	1	0
2	2	1	0	0
3	1	0	0	0
1	0	0	0	0

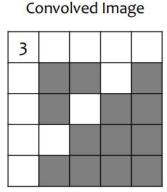
# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

			0	0	0	0
	1	1	1	1	1	0
	1		0	1	0	0
0	1	0	1	0	0	0
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0





# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0				0	0	0
0		1	1	1	1	0
0		0		1	0	0
0	1	0	1	0	0	0
О	1	1	0	0	0	0
О	1	0	0	0	0	0
0	0	0	0	0	0	0

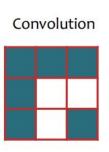


# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

Input Image

0	0				0	0
0	1		1	1	1	0
0	1		0		0	0
0	1	0	1	0	0	0
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0



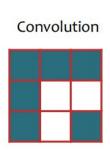
3	2	2	
			_

# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0	0	0				0
0	1	1		1	1	0
0	1	0		1		0
0	1	0	1	0	0	0
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0



# 3 2 2 3

# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0	0	0	0			
0	1	1	1		1	0
0	1	0	0		0	
0	1	0	1	0	0	0
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0



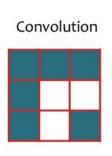
3	2	2	3	1

# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0	0	0	0	0	0	0
			1	1	1	0
	1	0	0	1	0	0
	1		1	0	0	0
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0



163	2E - 60e	25	500 1	9.1
3	2	2	3	1
2				

# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0	0	0	0	0	0	0
0				1	1	0
0		0	0	1	0	0
0		0		0	0	0
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0



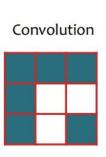
3	2	2	3	1
2	0			

# Background: Image Processing

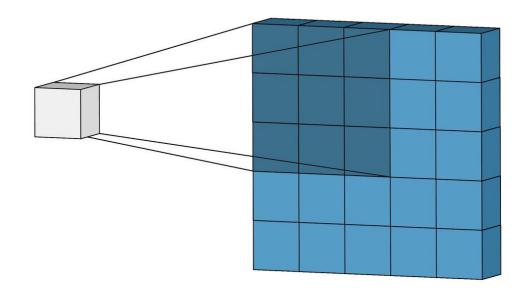
A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0	0	0	0	0	0	0
0	1	1	1	1	1	0
0	1	0	0	1	0	0
0	1	0	1	0	0	0
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0



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



# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0	0	0	0	0	0	0
0	1	1	1	1	1	0
0	1	0	0	1	0	0
0	1	0	1	0	0	0
О	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0

# Identity Convolution 0 0 0 0 1 0

#### Convolved Image

1	1	1	1	1
1	0	0	1	0
1	0	1	0	0
1	1	0	0	0
1	0	0	0	0

0

# Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

#### Input Image

0	0	0	0	0	0	0
0	1	1	1	1	1	0
0	1	0	0	1	0	0
0	1	0	1	0	0	О
0	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0

# Blurring Convolution .1 .1 .1 .1 .2 .1 .1 .1 .1

.4	.5	.5	.5	.4
.4	.2	-3	.6	-3
.5	.4	.4	.2	.1
-5	.6	.2	.1	0
.4	-3	.1	0	0

# Downsampling

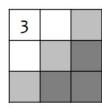
- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image

1	1	1	1	1	0
1	0	0	1	0	0
1	0	1	0	0	0
1	1	0	0	0	0
1	0	0	0	0	0
0	0	0	0	0	0

#### Convolution

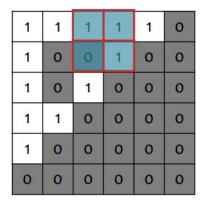




# Downsampling

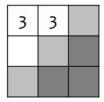
- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image



#### Convolution





# Downsampling

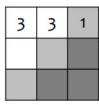
- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image

1	1	1	1	1	0
1	0	0	1	0	0
1	0	1	0	0	0
1	1	0	0	0	0
1	0	0	0	0	0
0	0	0	0	0	0

### Convolution

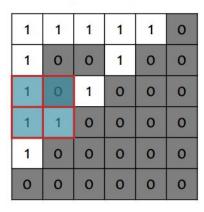




# Downsampling

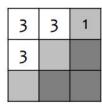
- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image



### Convolution





# Downsampling

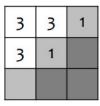
- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image

1	1	1	1	1	0
1	0	0	1	0	0
1	0	1	0	0	0
1	1	0	0	0	0
1	0	0	0	0	0
0	0	0	0	0	0

Convolution





# Downsampling

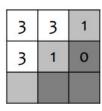
- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image

1	1	1	1	1	0
1	0	0	1	0	0
1	0	1	0	0	0
1	1	0	0	0	0
1	0	0	0	0	0
0	0	0	0	0	0

#### Convolution





# Downsampling

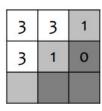
- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image

1	1	1	1	1	0
1	0	0	1	0	0
1	0	1	0	0	0
1	1	0	0	0	0
1	0	0	0	0	0
0	0	0	0	0	0

#### Convolution

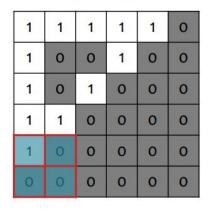




# Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image



#### Convolution



3	3	1
3	1	0
1		

# Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image

1	1	1	1	1	0
1	0	0	1	0	0
1	0	1	0	0	0
1	1	0	0	0	0
1	0	0	0	0	0
0	0	0	0	0	0





3	3	1
3	1	0
1	0	

# Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

#### Input Image

1	1	1	1	1	0
1	0	0	1	0	0
1	0	1	0	0	0
1	1	0	0	0	0
1	0	0	0	0	0
0	0	0	0	0	0

#### Convolution



3	3	1
3	1	0
1	0	0

Operation	Kernel ω	Image result g(x,y)
Identity	$\left[\begin{array}{ccc} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{array}\right]$	
Ridge or edge detection	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	

image source: https://en.wikipedia.org/wiki/Kernel\_(image\_processing)

Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9} \left[ \begin{array}{ccc} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{array} \right]$	
Gaussian blur 3 × 3 (approximation)	$\frac{1}{16} \left[ \begin{array}{ccc} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{array} \right]$	

 $image\ source: https://en.wikipedia.org/wiki/Kernel\_(image\_processing)$ 

		Γ1	4	6	4	17	
Gaussian blur 5 × 5 approximation)	$\frac{1}{256}$	$\begin{bmatrix} 4 \\ 6 \\ 4 \\ 1 \end{bmatrix}$	16 24 16 4	24 36 24 6	16 24 16 4	4 6 4 1	
Unsharp masking 5 × 5 Based on Gaussian blur with amount as 1 and threshold as 0 (with no image mask)	$\frac{-1}{256}$	1 4 6 4 1	4 16 24 16 4	$6 \\ 24 \\ -476 \\ 24 \\ 6$	4 16 24 16 4	6	

image source: https://en.wikipedia.org/wiki/Kernel\_(image\_processing)

# Convolutional Layer

**CNN** key idea:

Treat convolution matrix as parameters and learn them!

#### Input Image

0	0	0	0	0	0	0
О	1	1	1	1	1	0
0	1	0	0	1	0	0
0	1	0	1	0	0	0
О	1	1	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0



Learned Convolution

U <sub>11</sub>	U <sub>12</sub>	U <sub>13</sub>
$\theta_{21}$	$\theta_{22}$	$\theta_{23}$
$\theta_{31}$	$\theta_{32}$	$\theta_{33}$

.4	.5	.5	.5	.4
-4	.2	-3	.6	-3
.5	.4	.4	.2	.1
.5	.6	.2	.1	0
.4	.3	.1	0	0

# Downsampling by Averaging

- Downsampling by averaging used to be a common approach
- This is a special case of convolution where the weights are fixed to a uniform distribution
- The example below uses a stride of 2

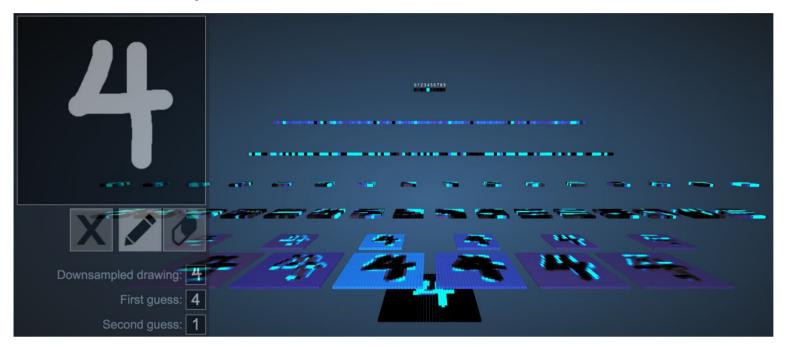
Input Image

1	1	1	1	1	0
1	0	0	1	0	0
1	0	1	0	0	0
1	1	0	0	0	0
1	0	0	0	0	0
0	0	0	0	0	0

Convolution

3/4	3/4	1/4	
3/4	1/4	0	
1/4	0	0	

# 3D Visualization of CNN

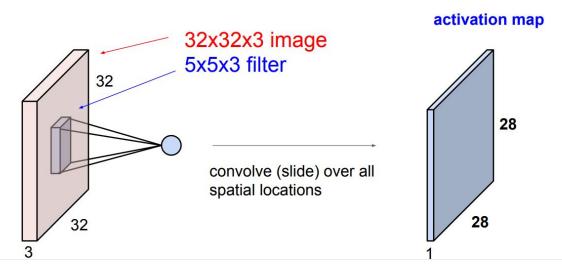


Why multiple layers?

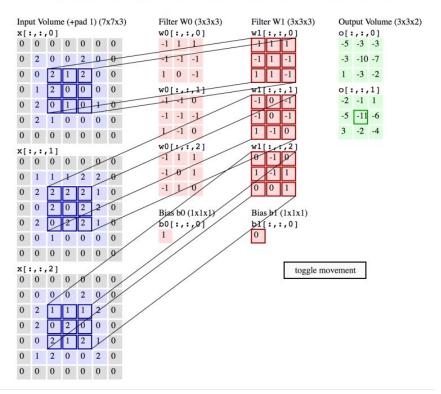
Multiple convolution layer can follow the initial convolution layer. When this happens, the structure of the CNN can become hierarchical as the later layers can see the pixels within the receptive fields of prior layers. As an example, let's assume that we're trying to determine if an image contains a bicycle. You can think of the bicycle as a sum of parts. It is comprised of a frame, handlebars, wheels, pedals, et cetera. Each individual part of the bicycle makes up a lower-level pattern in the neural net, and the combination of its parts represents a higher-level pattern, creating a feature hierarchy within the CNN.

# Convolution of a Color Image

- Color images consist of 3 floats per pixel for RGB (red, green blue) color values
- Convolution must also be 3-dimensional

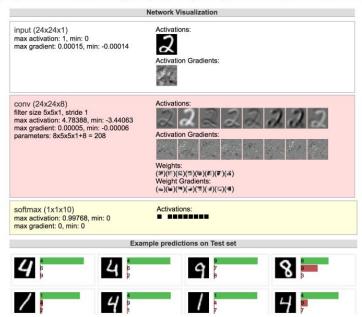


#### http://cs231n.github.io/convolutional-networks/



# MNIST Digit Recognition with CNNs (in your browser)

https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html



Link: https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html