Hasso Plattner Institut
Digital Engineering · Universität Potsdam

Medical Images: Neural Networks

Borchert, Konak, Dr. Schapranow

Data Management for Digital Health

Winter 2020

Agenda

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Medical Use Cases

Biology Recap

Oncology

Infectious Diseases & Care

Technology Foundation

Data Sources

Data Formats

Processing and Analysis

Software Architectures

Machine Learning

Data

Prediction + Probability

Medical Images: Neural Networks

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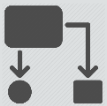
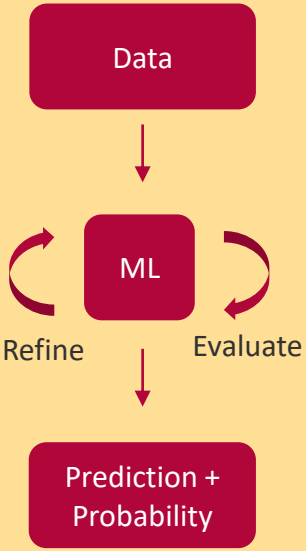


Software Architectures

Machine Learning



Medical Images: Neural Networks

Data Management for Digital Health, Winter 2020

Agenda

- Diagnostic Radiology & Computer-aided Diagnosis
- Computer Vision
- Convolutional Neural Network (CNN)
  - Convolution Layer
  - Pooling Layer
  - Fully Connected Layer
  - Backpropagation

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- **Diagnostic Radiology & Computer-aided Diagnosis**
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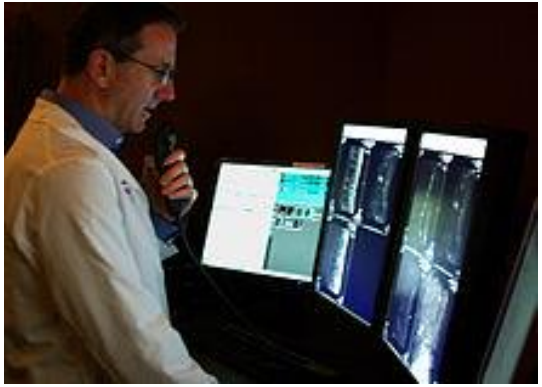
State of the Art
Analysis of Images – Diagnostic Radiology

- Core of clinical decision-making in modern medicine
- Medical specialization that involves undertaking a range of imaging procedures to obtain images of the inside of the body
- Diagnostic radiologist carefully interprets images to diagnose illness and injury
- A radiologist interprets medical images on a PACS workstation
- Diagnostic radiologists know when an imaging test can help answer a question about a symptom, disease, injury or treatment and which tests will get the best result for each patient

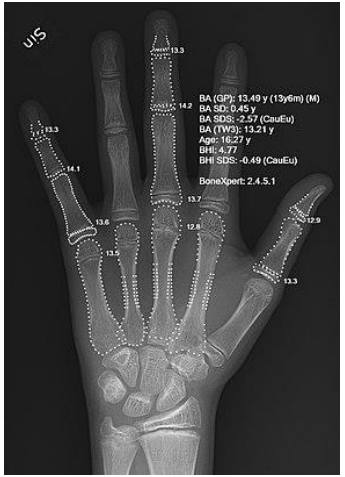


https://en.wikipedia.org/wiki/Radiology

Computer-aided Diagnosis (CAD)

- Use of a computer-generated output as an assisting tool for a clinician to make a diagnosis
- Different from automated computer diagnosis, in which the end diagnosis is based on a computer algorithm only
- As an early form of artificial intelligence, computer aided diagnosis systems have been used extensively within radiology for many years

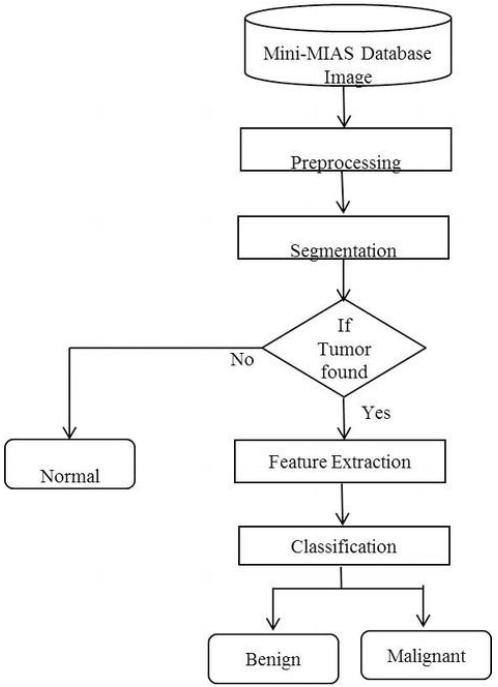
X-ray of the hand of a 16.27 year old male, with automatic calculation of bone age by BoneXpert, taken because of delayed puberty. The bone age is 13.49 by the Greulich and Pyle algorithm, and 13.21 by the third Tanner Whitehouse algorithm. From this, a final height of 188.3±3.6 cm could be estimated



https://en.wikipedia.org/wiki/Computer-aided_diagnosis#/media/File:X-ray_of_a_hand_with_automatic_bone_age_calculation.jpg

Applications of CAD System

- Most common applications → Breast cancer on mammography and pulmonary nodules on chest CT
- Traditionally relied on manual feature engineering based on domain knowledge
- Newer approaches are employing machine learning to discover latent features within imaging data
- CAD often used for both computer-aided detection and computer-aided diagnosis
  - Computer-aided detection (CADe): Marks specific areas of images that may seem abnormal, designed to reduce the risk of missing pathologies of interest
  - Computer-aided diagnosis (CADx): Helps a practitioner assess and classify pathology in medical images



https://www.intechopen.com/books/breast-imaging/computer-aided-diagnosis-medical-image-analysis-techniques

Summary

- Computer-aided detection (CADe) and computer-aided diagnosis (CADx) are emerging technologies to help radiologists interpret medical images
- In screening mammography, CADe can help radiologists avoid overlooking a cancer, while CADx can help radiologists decide whether a biopsy is warranted when reading a diagnostic mammogram
- CADe outputs the location of potential cancers, while CADx outputs the likelihood that a known lesion is malignant

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Questions?

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Computer Vision

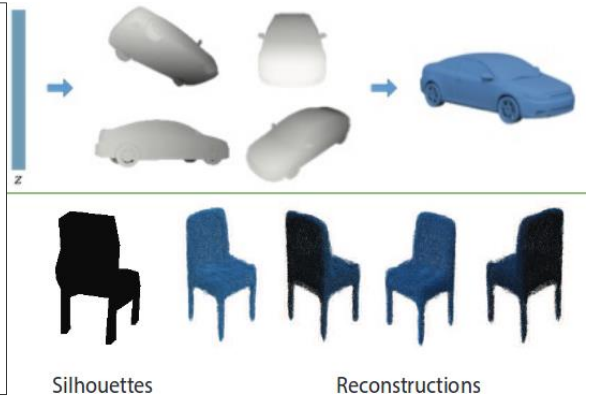
Computer vision for people counter purposes in public places, malls, shopping centers

Interdisciplinary scientific field that deals with how computers can gain high-level understanding from digital images or videos

New iPad includes lidar sensor

Tracking of vehicles movement using Python (cvlib library)

Learning 3D shapes has been a challenging task in computer vision. Recent advances in deep learning have enabled researchers to build models that are able to generate and reconstruct 3D shapes from single or multi-view depth maps or silhouettes seamlessly and efficiently



Images: https://en.wikipedia.org/wiki/Computer_vision

Neural Networks are State of the Art in Computer Vision Medical Imaging

Springer Link

Review Article | Published: 04 August 2019

Current applications and future directions of deep learning in musculoskeletal radiology

Pauley Chea & Springer Link

Skeletal Radiolog

1416 Accesses | Published: 21 November 2019

Using deep learning techniques in medical imaging: a systematic review of applications on CT and PET

Springer Inês Domingues, Gisèle Pereira, Pedro Martins, Hugo Duarte, João Santos & Pedro Henriques Abreu

Artificial Intelligence Review 53, 4093–4160(2020) | Cite this article

Original Paper | 1836 Accesses | 7 Citations | Metrics

Deep learning applications in pulmonary medical imaging: recent updates and insights on COVID-19

Hanan Farhat, George E. Sakr & Rima Kilany

Machine Vision and Applications 31, Article number: 53 (2020) | Cite this article

2434 Accesses | 1 Citations | 4 Altmetric | Metrics

Google Scholar deep learning ct image

Artikel

Ungefähr 24.200 Ergebnisse (0,11 Sek.)

Beliebige Zeit
Seit 2021
Seit 2020
Seit 2017
Zeitraum wählen...

Nach Relevanz sortieren

Rapid ai development cycle for the coronavirus (covid-19) pandemic: Initial results for automated detection & patient monitoring using **deep learning ct image** analysis
O Gozes, M Frid-Adar, H Greenspan ... - arXiv preprint arXiv ..., 2020 - arxiv.org
Purpose: Develop AI-based automated **CT image** analysis tools for detection, quantification, and tracking of Coronavirus; demonstrate they can differentiate coronavirus patients from non-patients. Materials and Methods: Multiple international datasets, including from Chinese ...
☆ 99 Zitiert von: 240 Ähnliche Artikel Alle 3 Versionen »

[HTML] COVID-19 pneumonia diagnosis using a simple 2D **deep learning** framework with a single chest **CT image**: model development and validation
H Ko, H Chung, WS Kang, KW Kim, Y Shin... - Journal of medical ..., 2020 - jmir.org
Background: Coronavirus disease (COVID-19) has spread explosively worldwide since the beginning of 2020. According to a multinational consensus statement from the Fleischner Society, computed tomography (**CT**) is a relevant screening tool due to its higher sensitivity ...
☆ 99 Zitiert von: 21 Alle 9 Versionen »

[HTML] A **deep learning** system to screen novel coronavirus disease 2019 pneumonia
X Xu, X Jiang, C Ma, P Du, X Li, S Lv, L Yu, Q Ni... - Engineering, 2020 - Elsevier
... According to the previous dataset assignment, the training and validation sets had 528 **CT** samples, which were equivalent to 10 161 ... **Deep learning** model for classification ... relative distance from the edge was used as an extra weight for the model in order to **learn** the relative ...
☆ 99 Zitiert von: 328 Ähnliche Artikel Alle 5 Versionen

Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with **CT images**
Y Song, S Zheng, L Li, X Zhang, X Zhang, Z Huang... - medRxiv, 2020 - medrxiv.org
Background A novel coronavirus (COVID-19) has emerged recently as an acute respiratory syndrome. The outbreak was originally reported in Wuhan, China, but has subsequently been spread world-widely. As the COVID-19 continues to spread rapidly across the world ...
☆ 99 Zitiert von: 131 Ähnliche Artikel Alle 5 Versionen »

[PDF] A **deep learning** algorithm using **CT images** to screen for Corona Virus Disease (COVID-19)
S Wang, B Kang, J Ma, X Zeng, M Xiao, J Guo, M Cai... - MedRxiv, 2020 - medrxiv.org
Background: To control the spread of Corona Virus Disease (COVID-19), screening large numbers of suspected cases for appropriate quarantine and treatment measures is a priority. Pathogenic laboratory testing is the diagnostic gold standard but it is time consuming with ...
☆ 99 Zitiert von: 269 Ähnliche Artikel Alle 3 Versionen »

[HTML] A **deep learning** approach to characterize 2019 coronavirus disease (COVID-19) pneumonia in chest **CT images**
Q Ni, ZY Sun, L Qi, W Chen, Y Yang, L Wang... - European ..., 2020 - Springer

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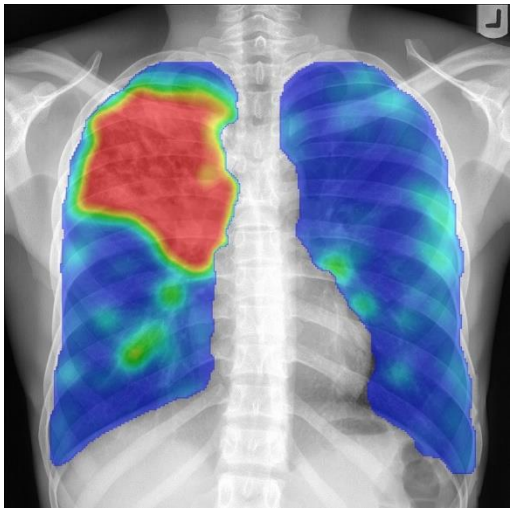
Medical Images: Neural Networks

Data Management for Digital Health, Winter 2020

Computer Vision Opportunities in Medical Imaging

- Amongst different healthcare fields, medical images make the highest volume of data
- Inside that data are valuable insights
- Scope of data often surpasses the possibilities of traditional analysis
- Human interpretation is limited and prone to errors due to various factors including stress, lack of context, lack of expertise
- Deep learning applications can process data and extract valuable insights at higher speeds with much more accuracy
- The primary type of deep learning application for medical image analysis is a convolutional neural network (CNN)



https://medium.com/analytics-vidhya/detecting-anomalies-in-x-ray-using-cnn-1e4c2e49f23a

Medical Images: Neural Networks

Summary

- Implementation of deep learning into medical image analysis can improve on the main requirements for the proceedings
- Provide high accuracy image processing
- It can help doctors to process data and analyze test results more thoroughly

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Questions?

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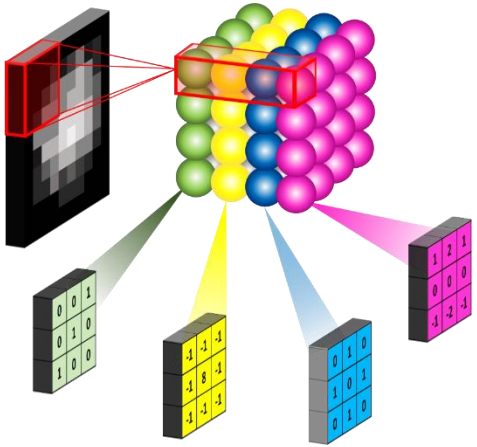
Convolutional Neural Network (CNN)

- In 1995, Yann LeCun and Yoshua Bengio introduced the concept of Convolutional Neural Networks
- Convolutional Neural Networks or CNNs, are a special kind of neural network for processing data that has a known, grid-like topology
- Examples include time-series data → can be thought of as a 1D grid; and image data → can be thought of as a 2D grid of pixels

Convolutional Neural Network (CNN)

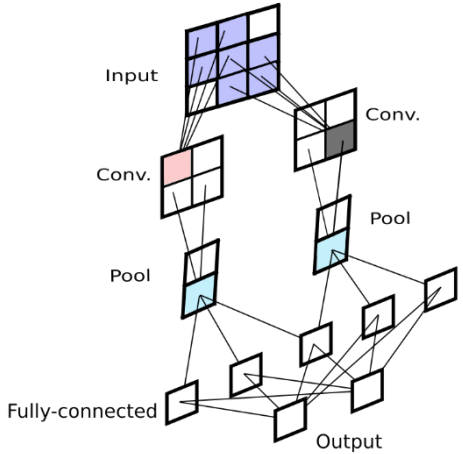
- Name “convolutional neural network” indicates that the network employs a mathematical operation called **convolution**
- Convolution is a specialized kind of linear operation
- CNNs are very similar to ordinary Neural Networks — they are made up of neurons that have learnable weights and biases
- Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity



https://www.hiclipart.com/search?clipart=convolutional+neural+network

Convolutional Neural Network (CNN)

- CNN is a combination of two basic building blocks:
  1. **The Convolution Block** — Consists of the Convolution Layer and the Pooling Layer. This layer forms the essential component of *Feature-Extraction*
  2. **The Fully Connected Block** — Consists of a fully connected simple neural network architecture. This layer performs the task of *Classification* based on the input from the convolutional block.



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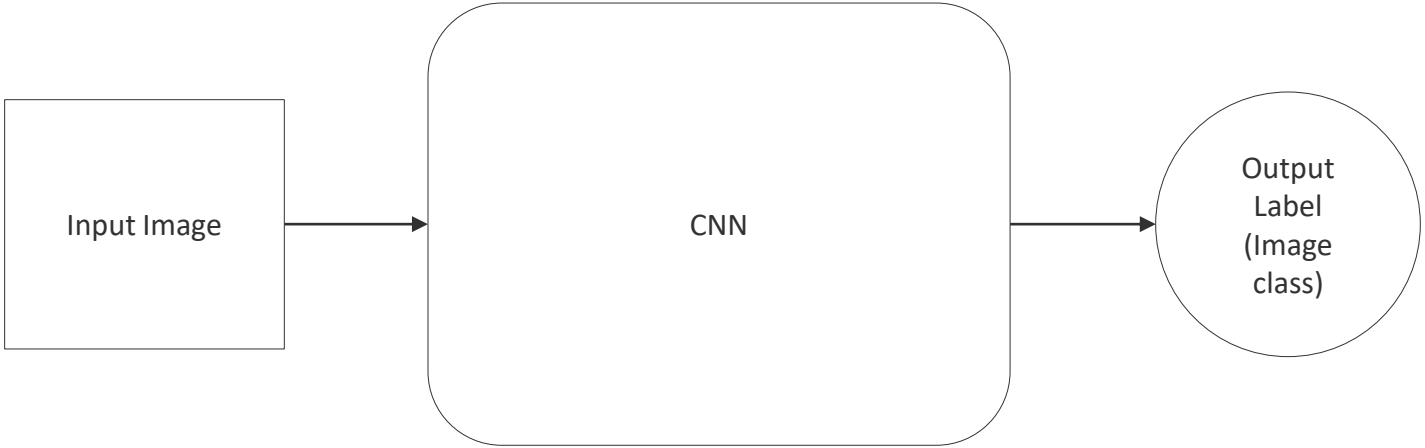
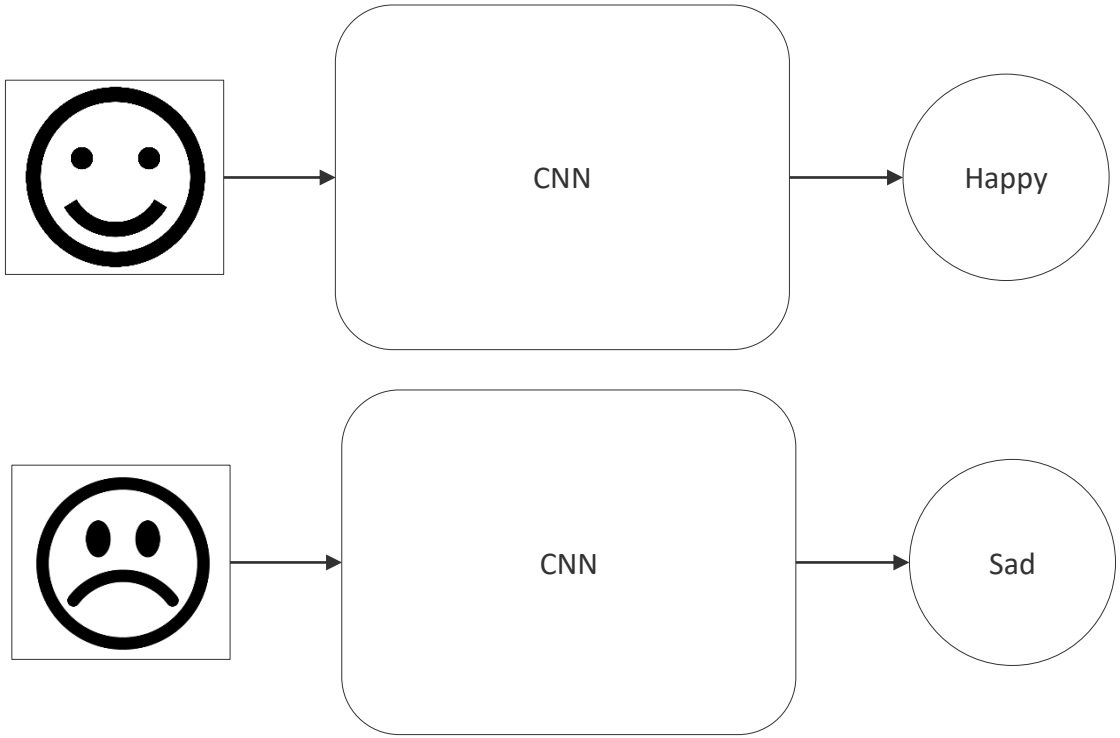
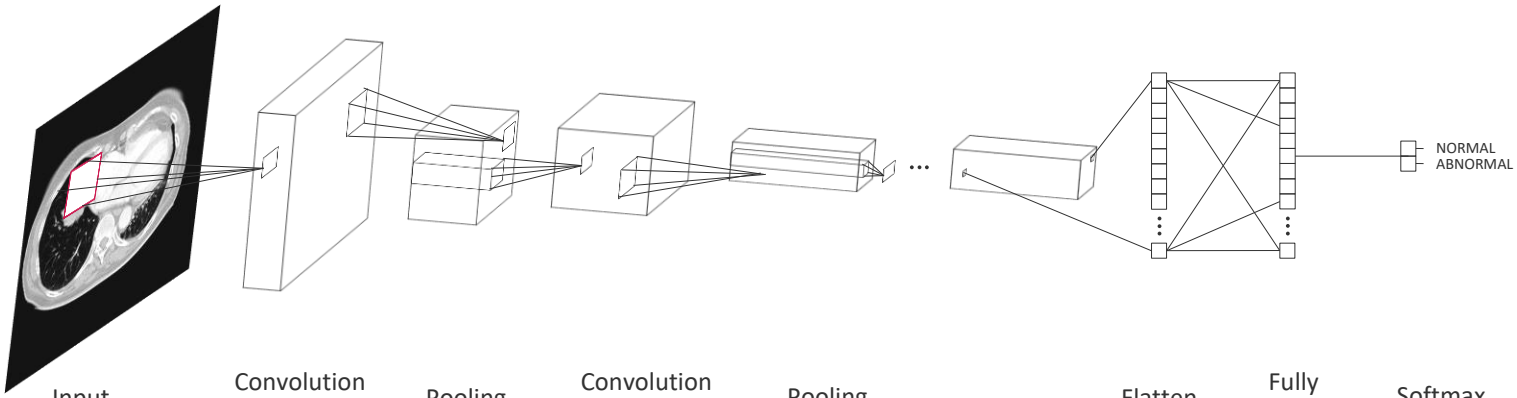
CNN
Classification



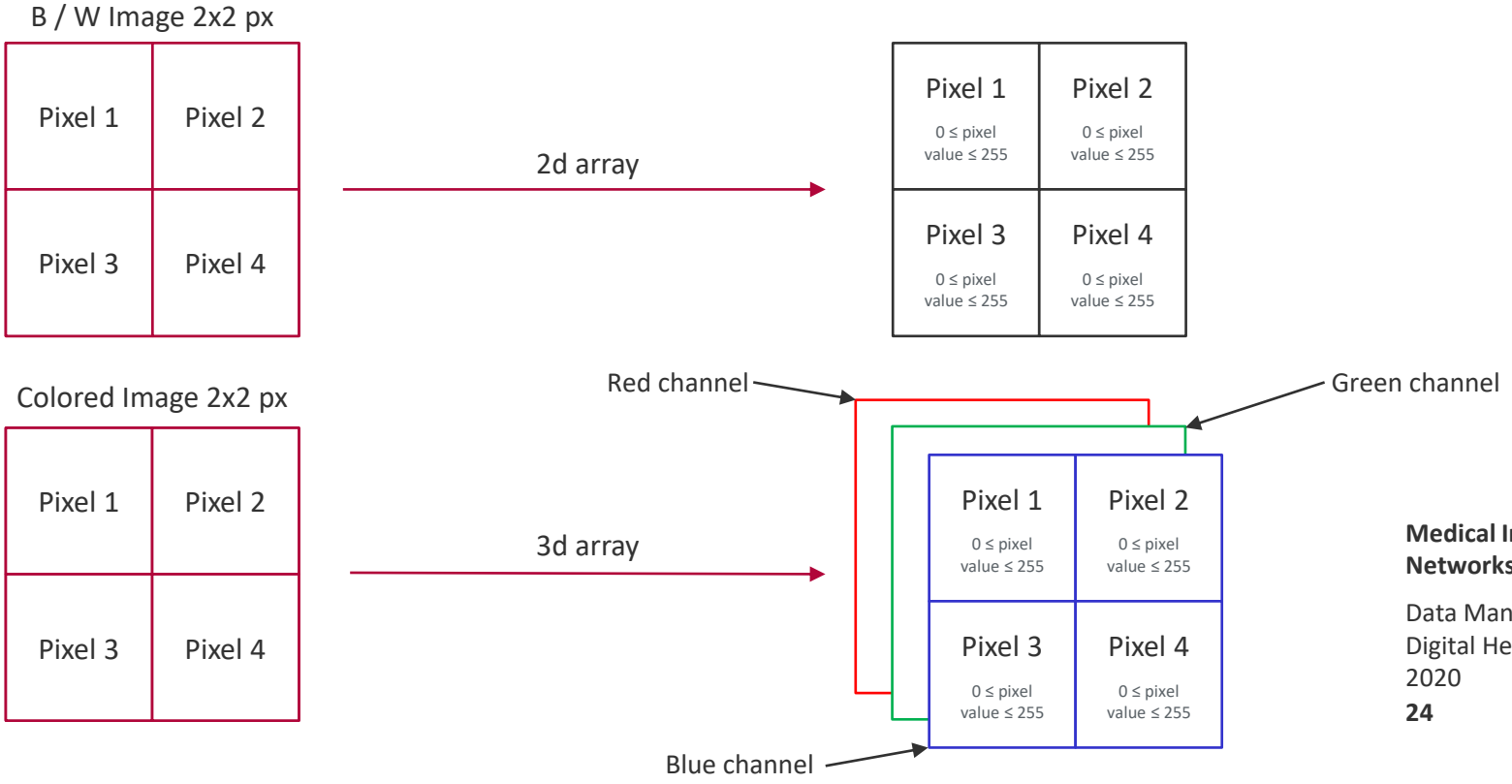
CNN
Classification



CNN Classification
Goal Is to Understand This Image at the End of the Lecture

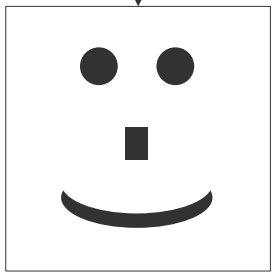


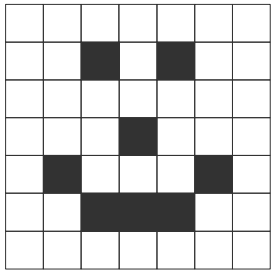
CNN


B / W Image 2x2 px
Pixel 1
Pixel 2
Pixel 3
Pixel 4
2d array
Pixel 1
0 ≤ pixel value ≤ 255
Pixel 2
0 ≤ pixel value ≤ 255
Pixel 3
0 ≤ pixel value ≤ 255
Pixel 4
0 ≤ pixel value ≤ 255
Colored Image 2x2 px
Pixel 1
Pixel 2
Pixel 3
Pixel 4
3d array
Red channel
Green channel
Blue channel
Pixel 1
0 ≤ pixel value ≤ 255
Pixel 2
0 ≤ pixel value ≤ 255
Pixel 3
0 ≤ pixel value ≤ 255
Pixel 4
0 ≤ pixel value ≤ 255

CNN
What We See Vs. What Computers See

What we see





255	255	255	255	255	255	255
255	255	0	255	0	255	255
255	255	255	255	255	255	255
255	255	255	0	255	255	255
255	0	255	255	255	0	255
255	255	0	0	0	255	255
255	255	255	255	255	255	255

What the computer sees

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- Diagnostic Radiology & Computer-aided Diagnosis
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- **Convolutional Neural Network (CNN)**
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CNN
Convolution Layer

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau) g(t - \tau) dx$$

- Process of adding each element of the image to its local neighbors, weighted by the kernel
- The matrix operation being performed—convolution—is not traditional matrix multiplication, despite being similarly denoted by
- Example, two three-by-three matrices, the first a **kernel**, and the second an **image piece** → Result is a three-by-three matrix
- Convolution is the process of flipping both the rows and columns of the kernel and multiplying locally similar entries and summing
- For example, A (part of the image matrix) = [2 5 17] and B (part of the filter matrix) = [1 0 1]. Then the answer of A *(convolve) B = [2*1 + 5*0 + 17*1] = [2 + 0 + 17] = [19]

Convolution Layer

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

Input Image

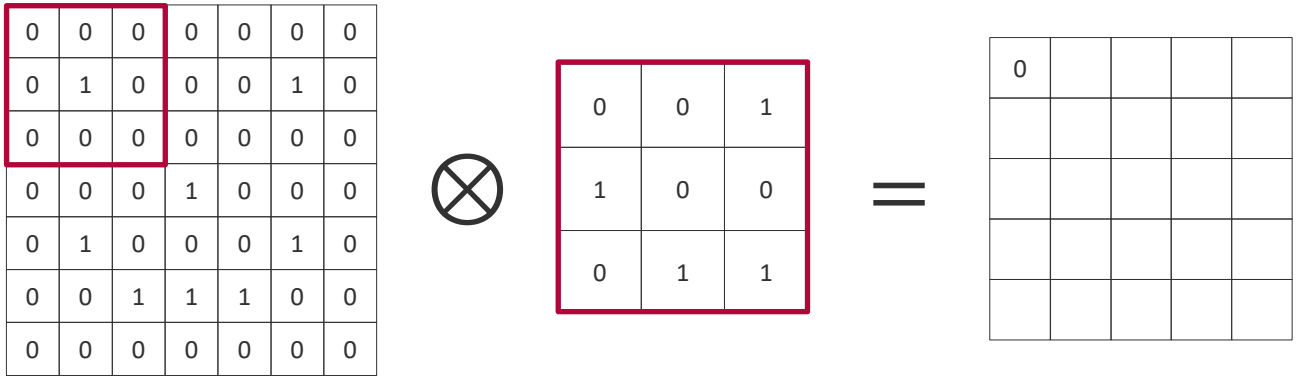
Also called ‘filter’ or ‘kernel’

0	0	1
1	0	0
0	1	1

Feature Detector

Convolution Layer

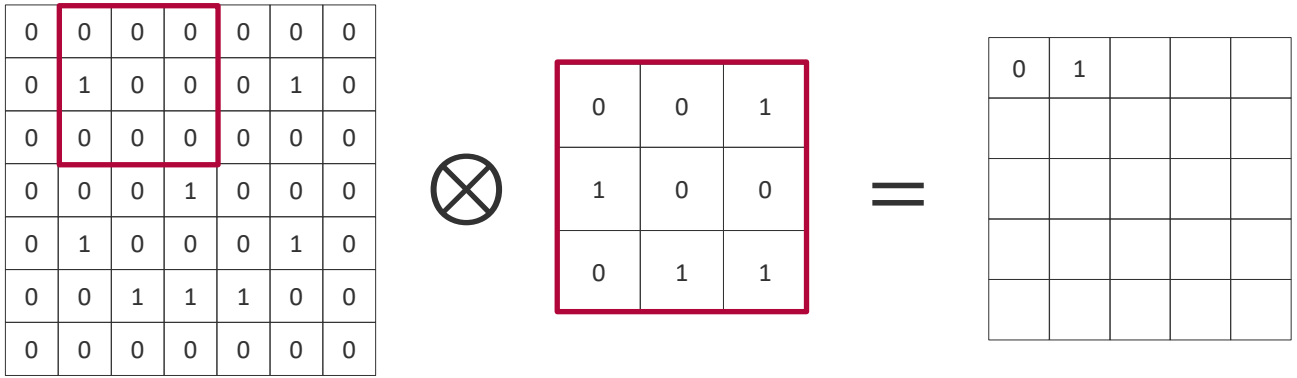
$$(I * K)_{xy} = \sum_{i=1}^{h} \sum_{j=1}^{w} K_{ij} \cdot I_{x+i-1,y-j-1}$$



Input Image (I) Feature Detector (K) Feature Map

[0*0 + 0*0 + 0*1 + 0*1 + 1*0 + 0*0 + 0*0 + 0*1 + 0*1] = [0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0] = [0]

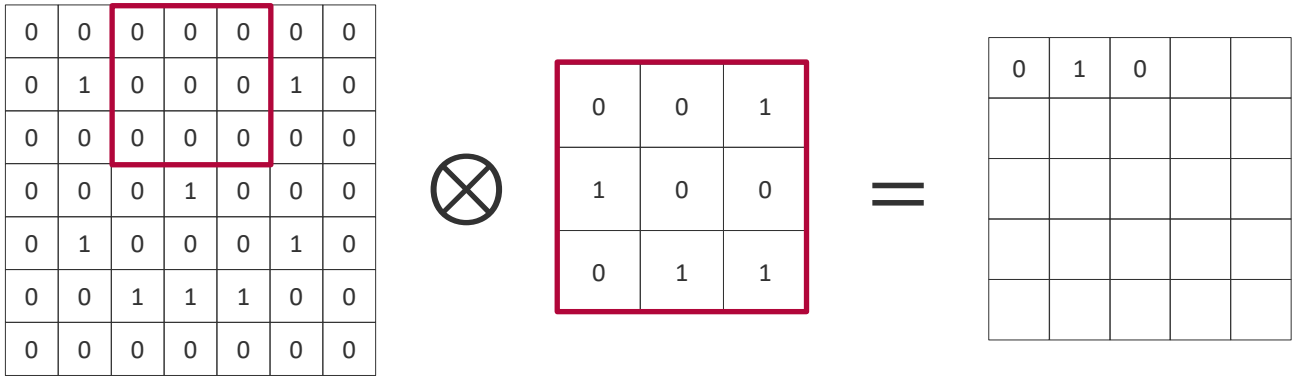
Convolution Layer



Input Image | Feature Detector | Feature Map

$$[0*0 + 0*0 + 0*1 + 1*1 + 0*0 + 0*0 + 0*0 + 0*1 + 0*1] = [0 + 0 + 0 + 1 + 0 + 0 + 0 + 0 + 0] = [1]$$

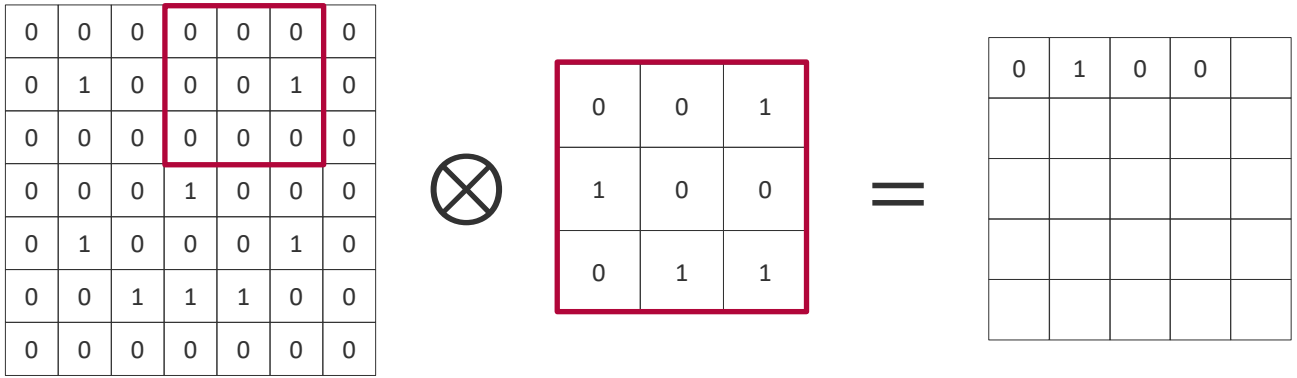
Convolution Layer



Input Image | Feature Detector | Feature Map

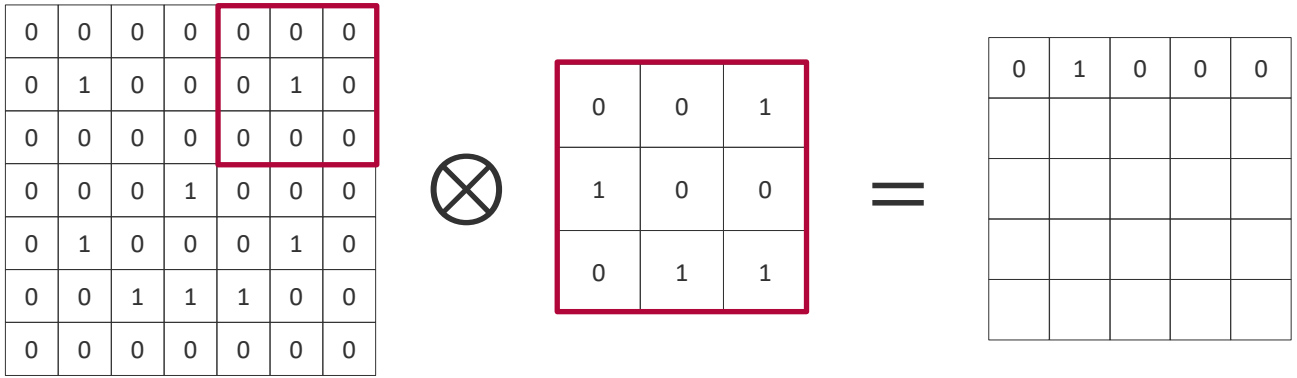
[0*0 + 0*0 + 0*1 + 0*1 + 0*0 + 0*0 + 0*0 + 0*1 + 0*1] = [0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0] = [0]

Convolution Layer



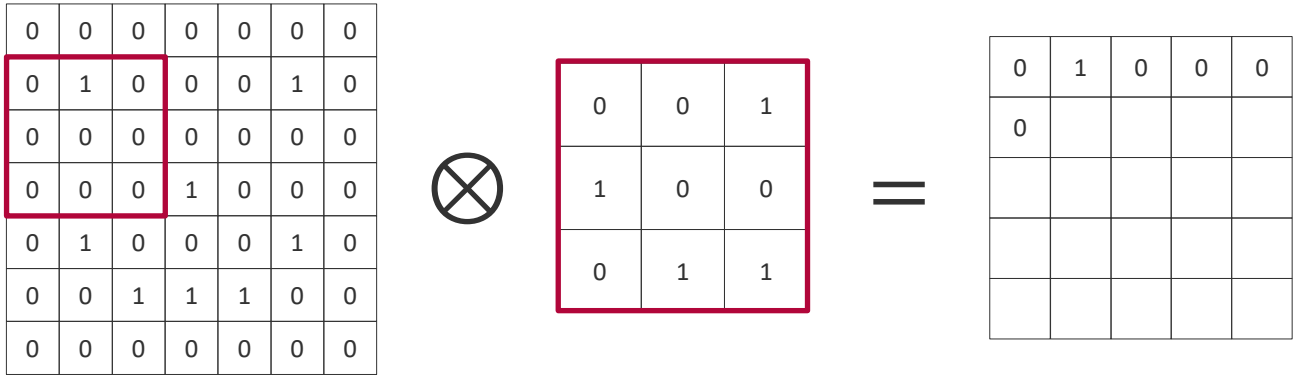
Input Image | Feature Detector | Feature Map

Convolution Layer



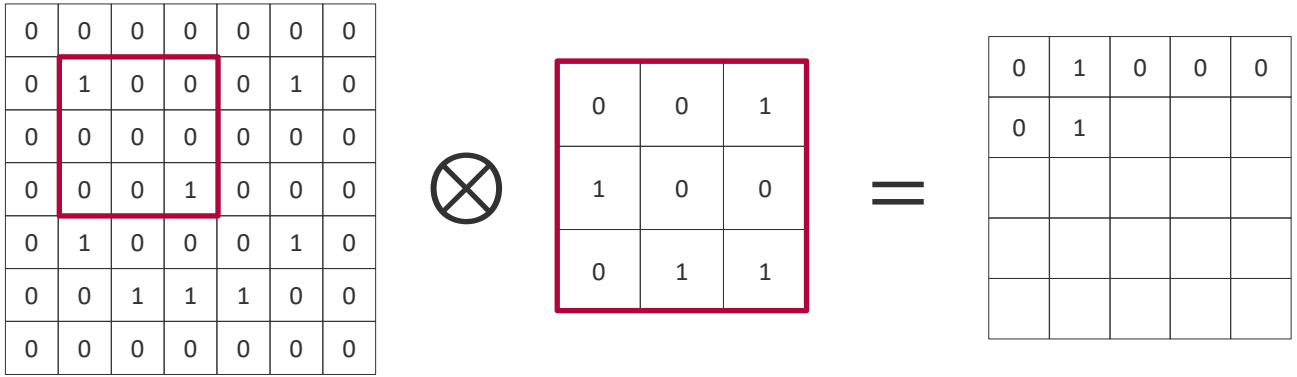
Input Image | Feature Detector | Feature Map

Convolution Layer



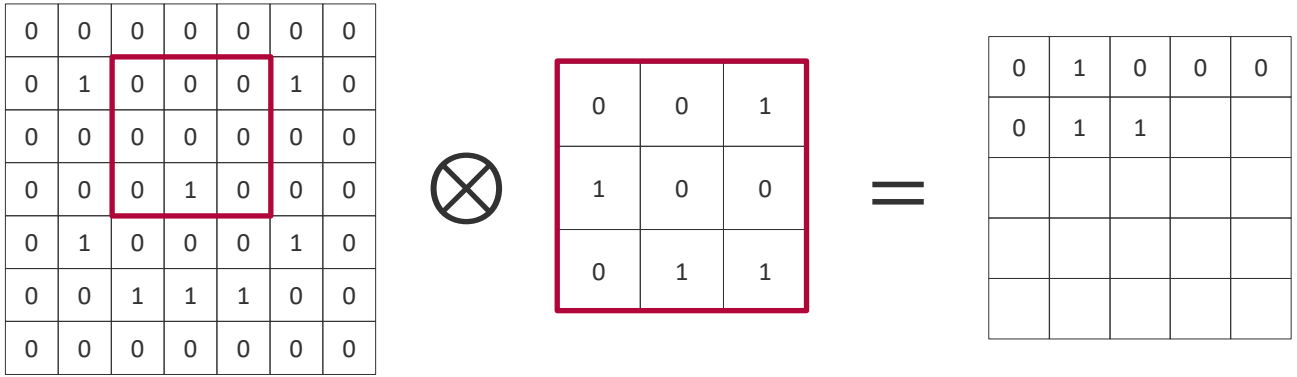
Input Image | Feature Detector | Feature Map

Convolution Layer



Input Image | Feature Detector | Feature Map

Convolution Layer

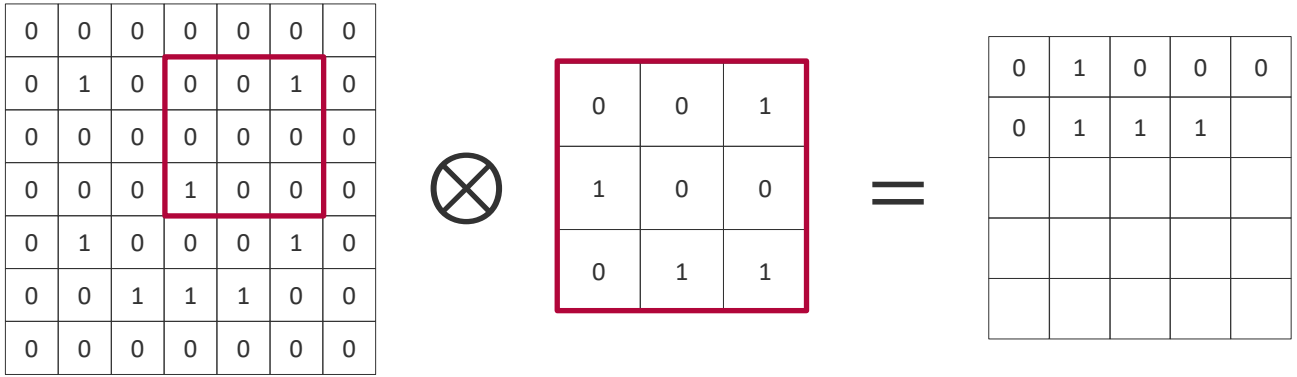


Input Image

Feature Detector

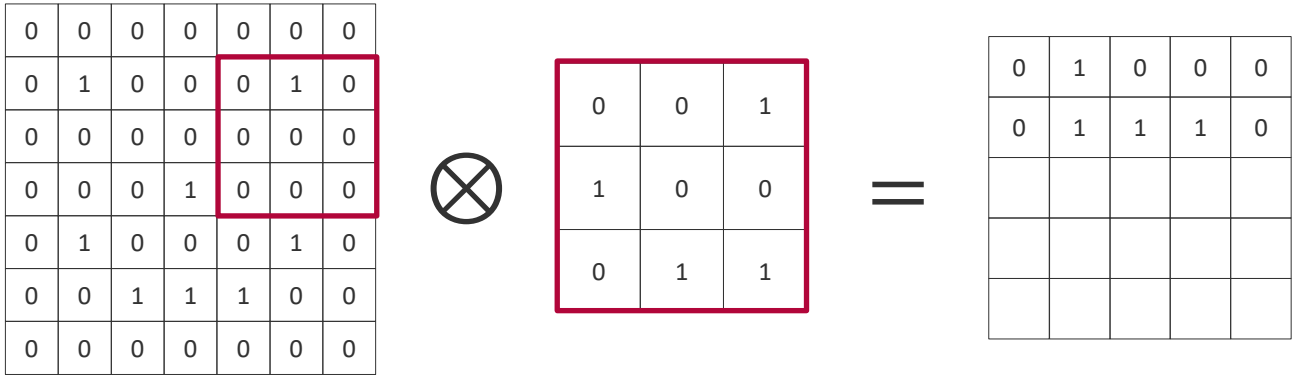
Feature Map

Convolution Layer



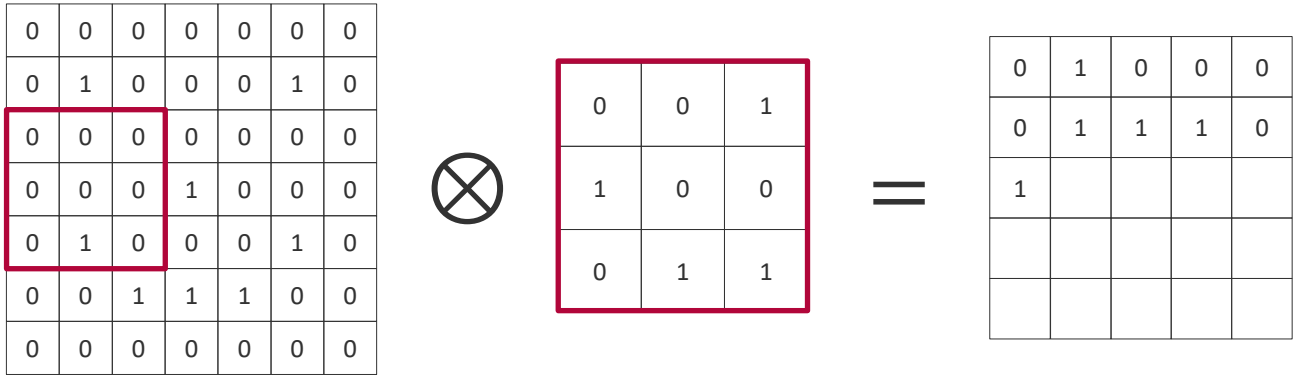
Input Image | Feature Detector | Feature Map

Convolution Layer



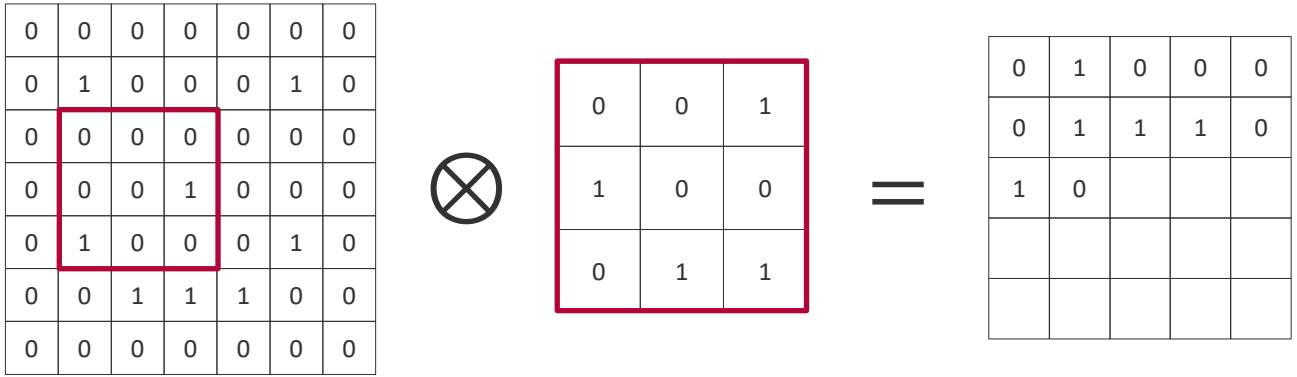
Input Image | Feature Detector | Feature Map

Convolution Layer



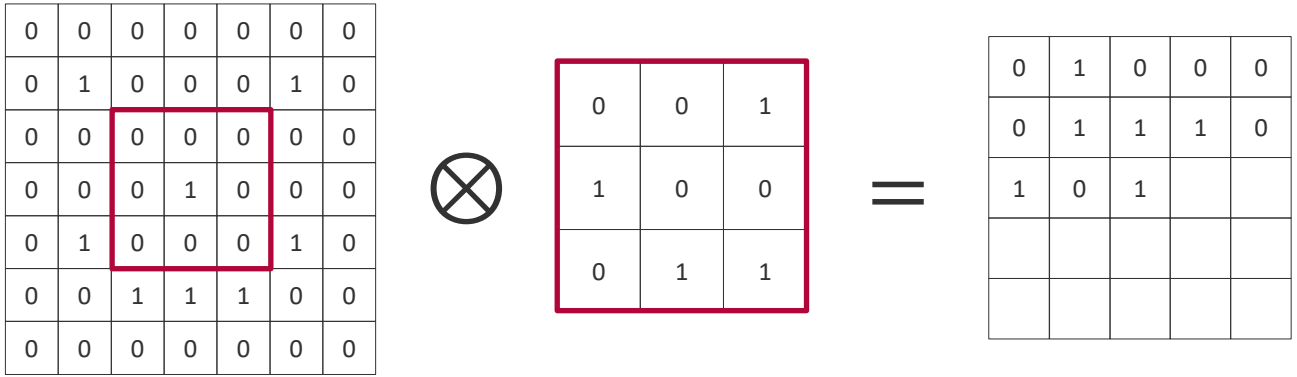
Input Image | Feature Detector | Feature Map

Convolution Layer



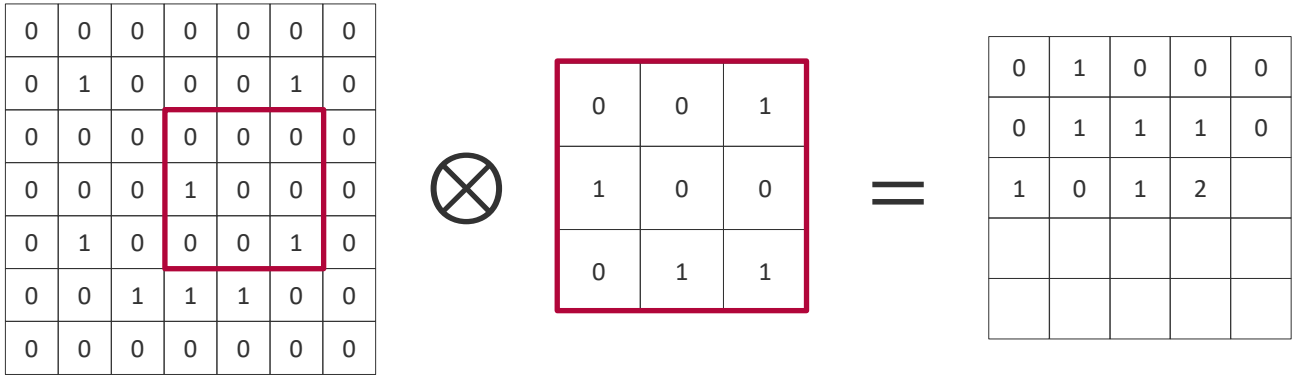
Input Image | Feature Detector | Feature Map

Convolution Layer



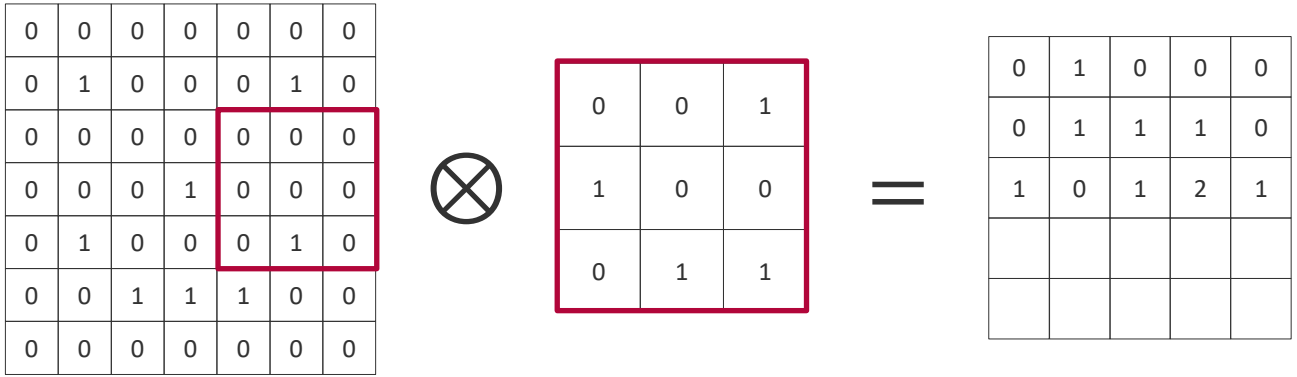
Input Image | Feature Detector | Feature Map

Convolution Layer



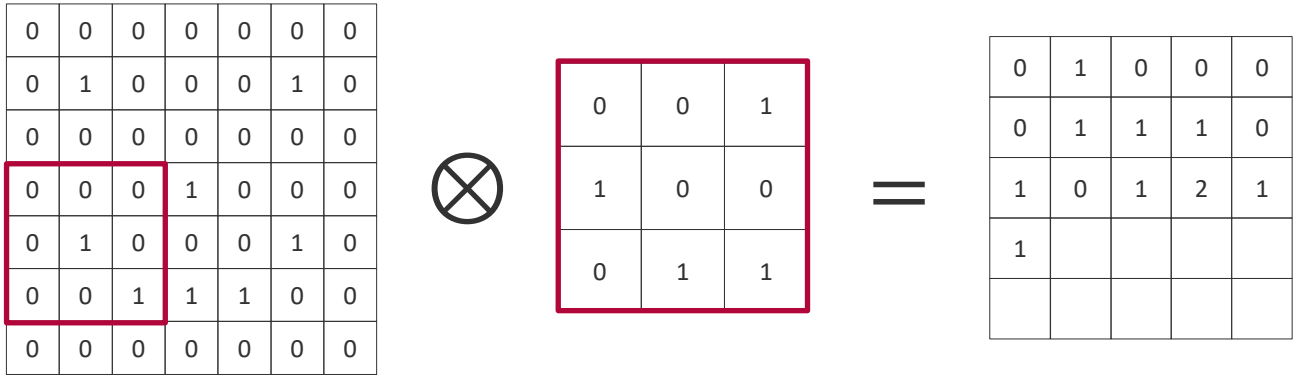
Input Image | Feature Detector | Feature Map

Convolution Layer



Input Image | Feature Detector | Feature Map

Convolution Layer

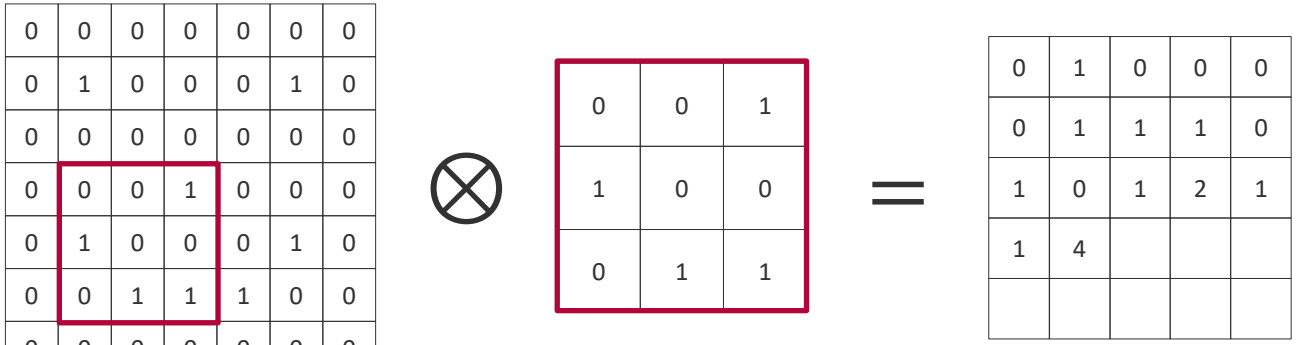


Input Image

Feature Detector

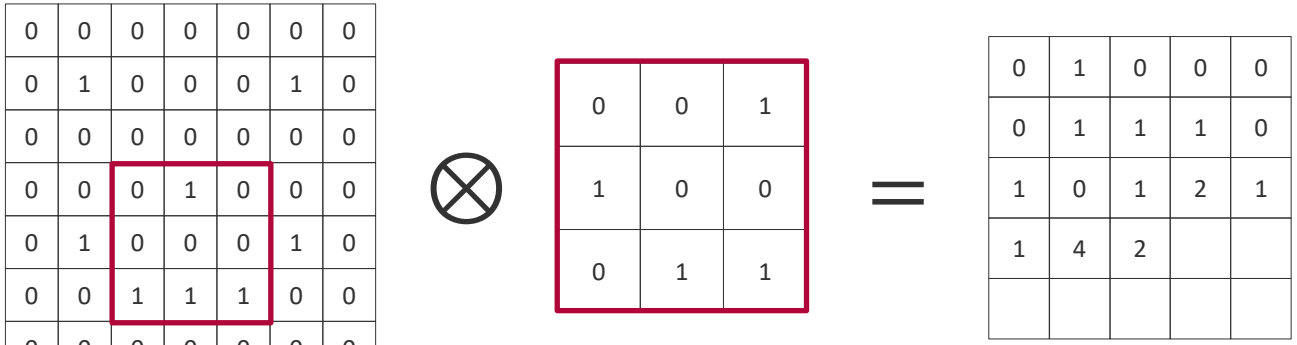
Feature Map

Convolution Layer



Input Image | Feature Detector | Feature Map

Convolution Layer

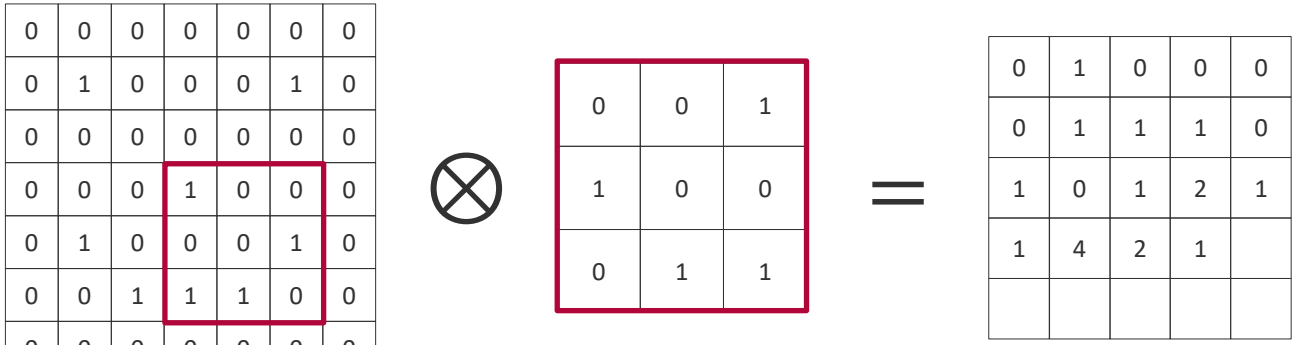


Input Image

Feature Detector

Feature Map

Convolution Layer

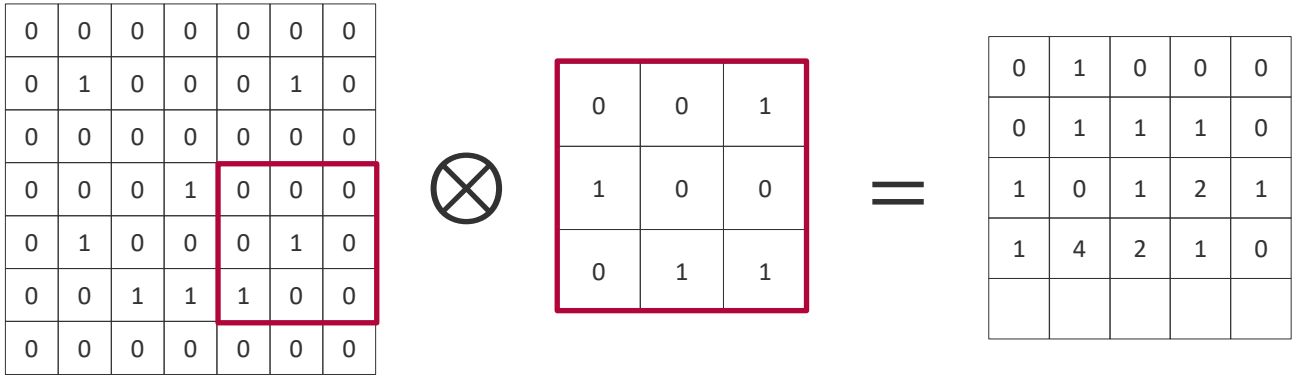


Input Image

Feature Detector

Feature Map

Convolution Layer

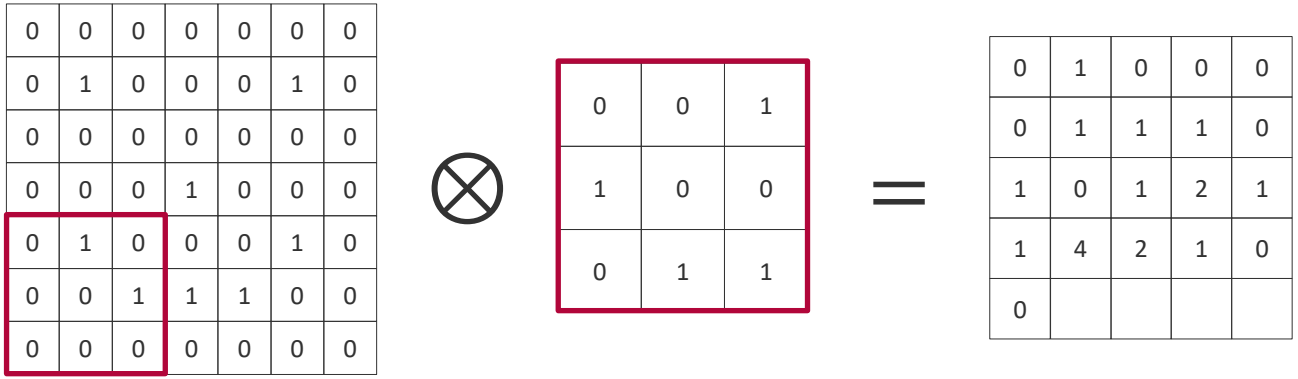


Input Image

Feature Detector

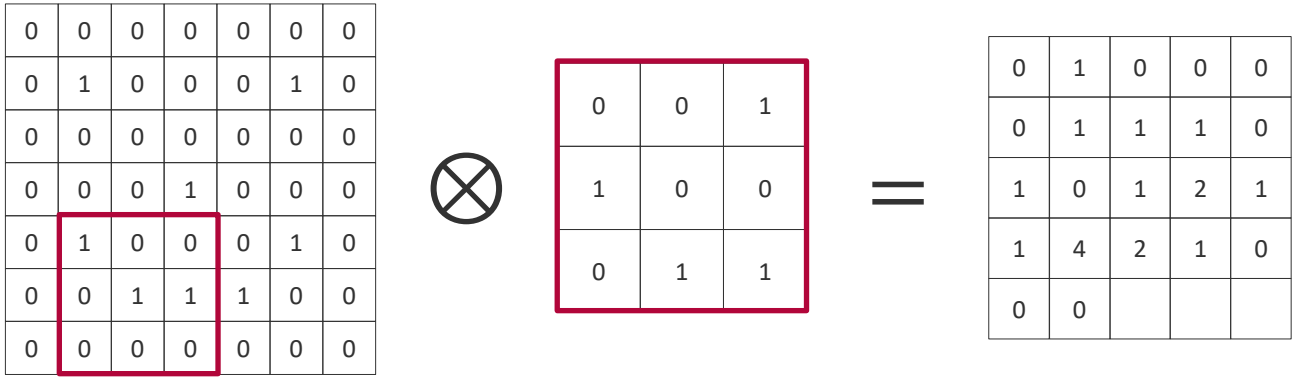
Feature Map

Convolution Layer



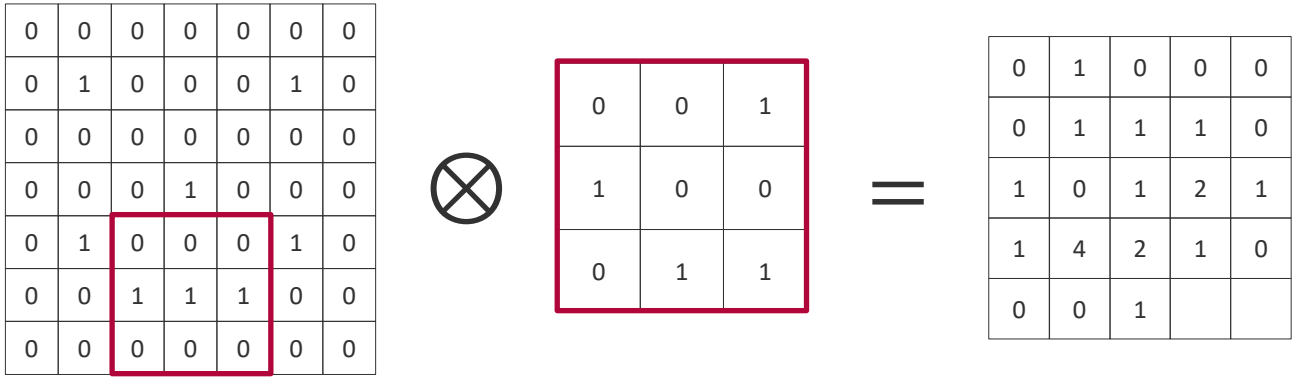
Input Image | Feature Detector | Feature Map

Convolution Layer



Input Image | Feature Detector | Feature Map

Convolution Layer

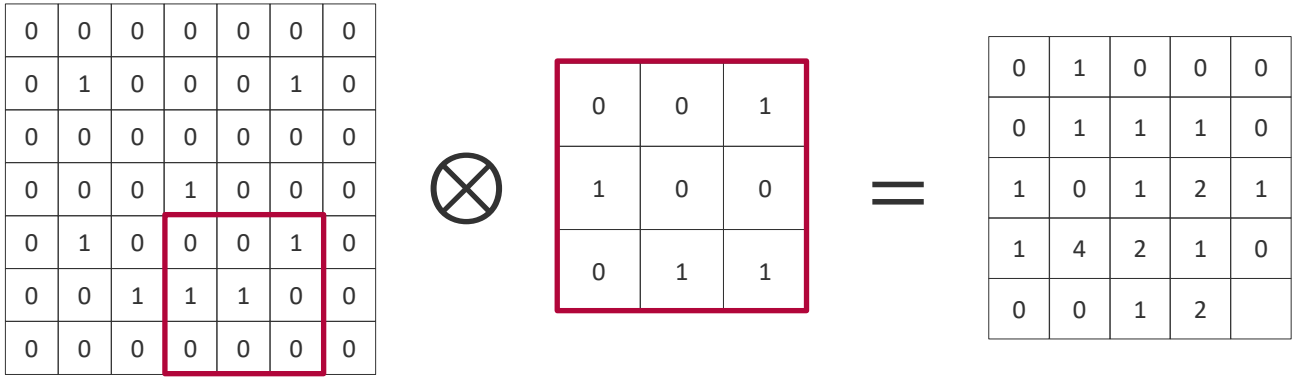


Input Image

Feature Detector

Feature Map

Convolution Layer

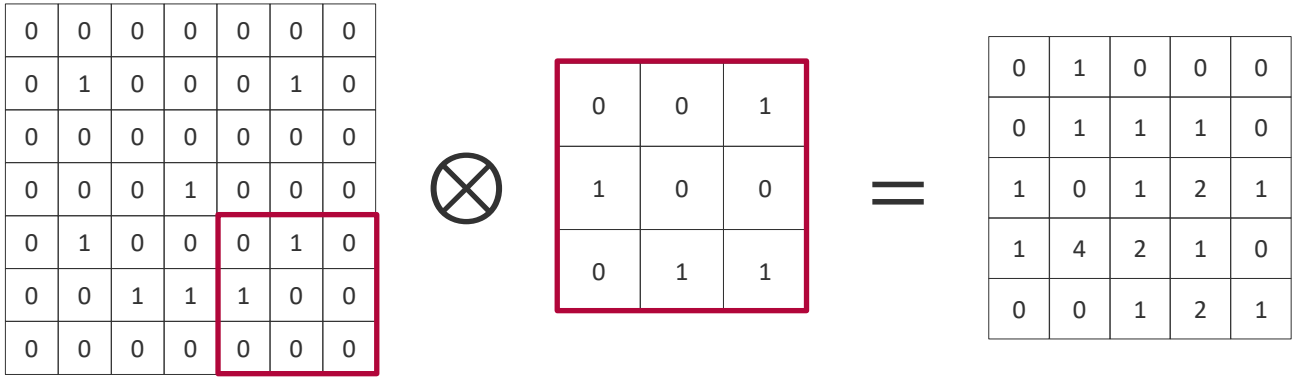


Input Image

Feature Detector

Feature Map

Convolution Layer

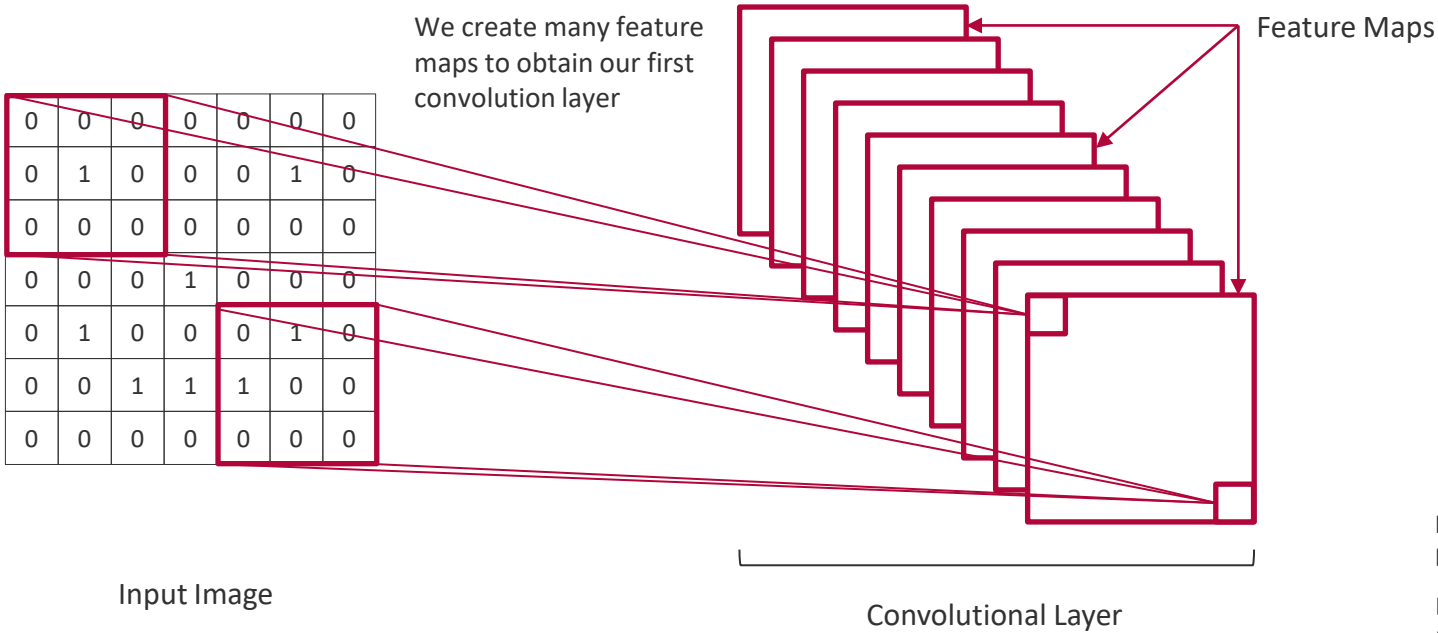


Input Image

Feature Detector

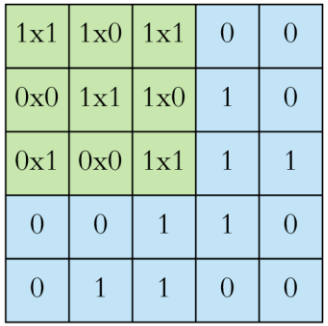
Feature Map

Convolution Layer

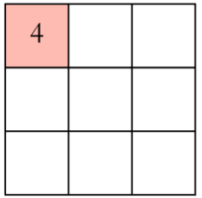


Convolution Layer
Why Feature Maps

- Recognize features like edges, … automatically
- Image Classification (previous Deep Learning)
  - Hand-Craft Features
    - **Texture Features**: Histogram based, Entropy, Haralick features (Cooccurrence matrix), Gray-level run length metrics, Local Binary Pattern, Fractal, etc.
    - **Morphological Features**: Hu's moments, Shape features, Granulometry, Bending Energy, Roundness ratio, etc.



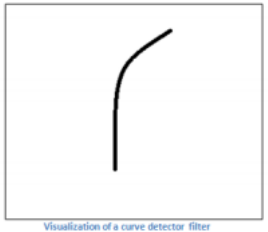
Input x Filter



Feature Map

https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

Convolution Layer
Why Feature Maps

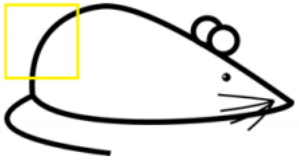


Visualization of a curve detector filter

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Original image



Visualization of the filter on the image

Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

*

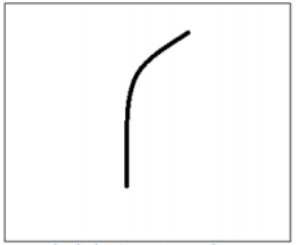
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = (50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600 (A large number!)

https://lipyeow.github.io/ics491f17/morea/deepnn/ImageClassification-CNN.pdf

Convolution Layer
Why Feature Maps



Visualization of a curve detector filter

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Visualization of the filter on the image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = 0

https://lipyeow.github.io/ics491f17/morea/deepnn/ImageClassification-CNN.pdf

Convolution Layer
Convolutional Operator

Different filters will produce different Feature Maps for the same input image. Examples:

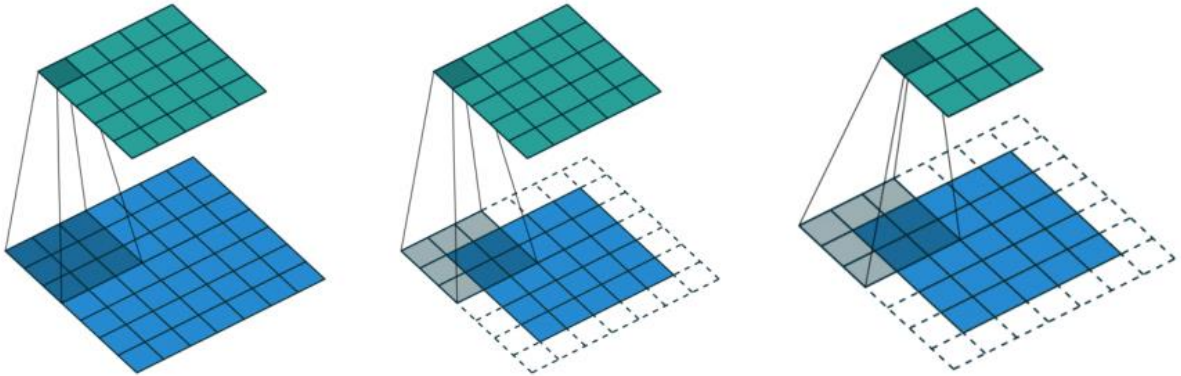
Operation	Kernel ω	Image result g(x,y)
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	

Gaussian blur 3 × 3 (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	
Gaussian blur 5 × 5 (approximation)	$\frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	
Unsharp masking 5 × 5 Based on Gaussian blur with amount as 1 and threshold as 0 (with no image mask)	$\frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & -476 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	

https://en.wikipedia.org/wiki/Kernel_(image_processing)

CNN
Convolution Layer

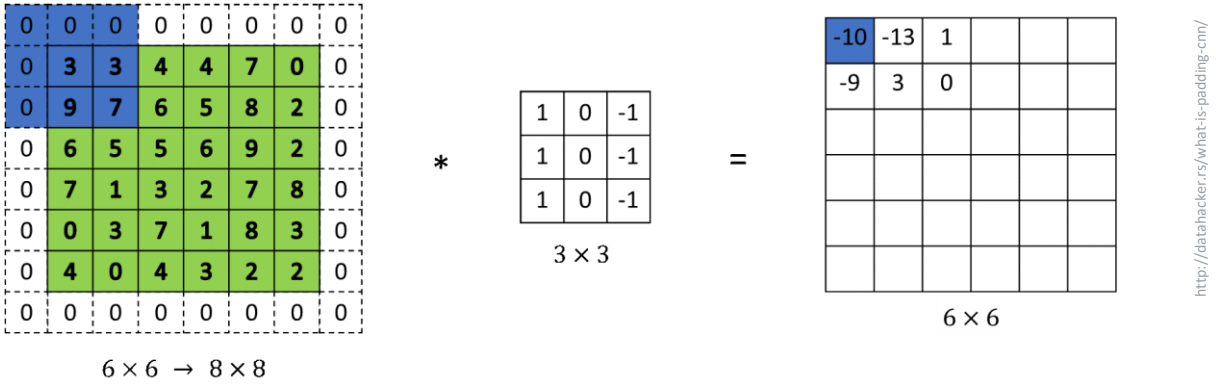
- In practice, a CNN learns the values of these filters on its own during the training process
- Although we still need to specify parameters such as number of filters, filter size, padding, and stride before the training process



https://lipyeow.github.io/ics491f17/morea/deepnn/ImageClassification-CNN.pdf

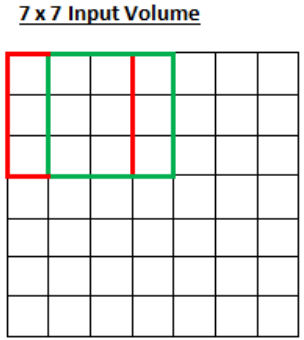
Convolution Layer
Padding

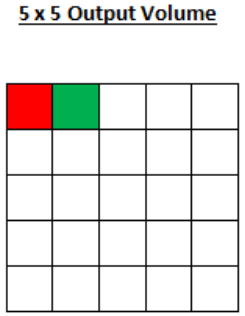
- Adding extra pixels of filler around the boundary of input image → Increasing the effective size of the image
- Typically, set values of the extra pixels to zero
- **Valid convolutions** ↔ no padding
- **Same convolution** ↔ pad so that output size is the same as the input size

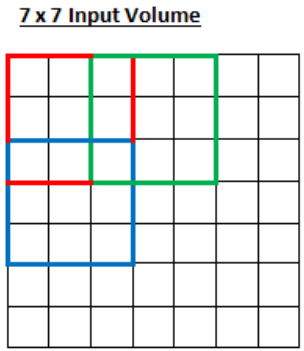


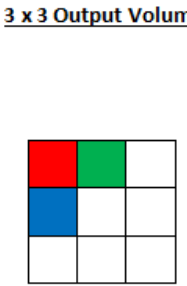
Convolution Layer
Striding

- Stride controls how the filter convolves around the input
- In the example we had, the filter convolves around the input by shifting one unit at a time
- The amount by which the filter shifts is the stride
- Stride is normally set in a way so that the output volume is an integer and not a fraction









O – Output height/length

I – Input height/length

K – Filter size

P – Padding

S – Stride

$$O = \frac{(I - K + 2P)}{S} + 1$$

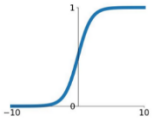
https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks-Part-2/

Convolution Layer
Activation (ReLU)

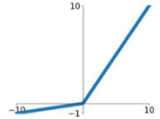
- An additional operation called Rectified Linear Unit (ReLU) has been used after every Convolution operation
- Basically, ReLU is an element wise operation (applied per pixel) and replaces all negative pixel values in the feature map by zero
- The purpose of ReLU is to introduce non-linearity to the network
- Other nonlinear functions such as tanh or sigmoid can also be used instead of ReLU, but ReLU has been found to perform better in most situations

Activation Functions

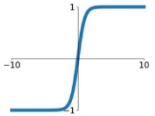
Sigmoid
$\sigma(x) = \frac{1}{1+e^{-x}}$



Leaky ReLU
$\max(0.1x, x)$

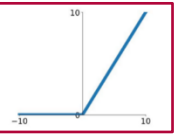


tanh
$\tanh(x)$

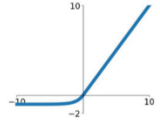


Maxout
$\max(w_1^T x + b_1, w_2^T x + b_2)$

ReLU
$\max(0, x)$



ELU
$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$



Bias term

$$(I * K)_{xy} = \sigma\left(b + \sum_{i=1}^{h}\sum_{j=1}^{w} K_{ij} \cdot I_{x+i-1,y-j-1}\right)$$

https://medium.com/dataseries/basic-overview-of-convolutional-neural-network-cnn-4fcc7dbb4f17

Convolution Layer
<< QUIZ >>

- Which matrix represents vertical edge detection?

A

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

B

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

Convolution Layer
<< QUIZ >>

- Which matrix represents vertical edge detection?

A

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

✓

B

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

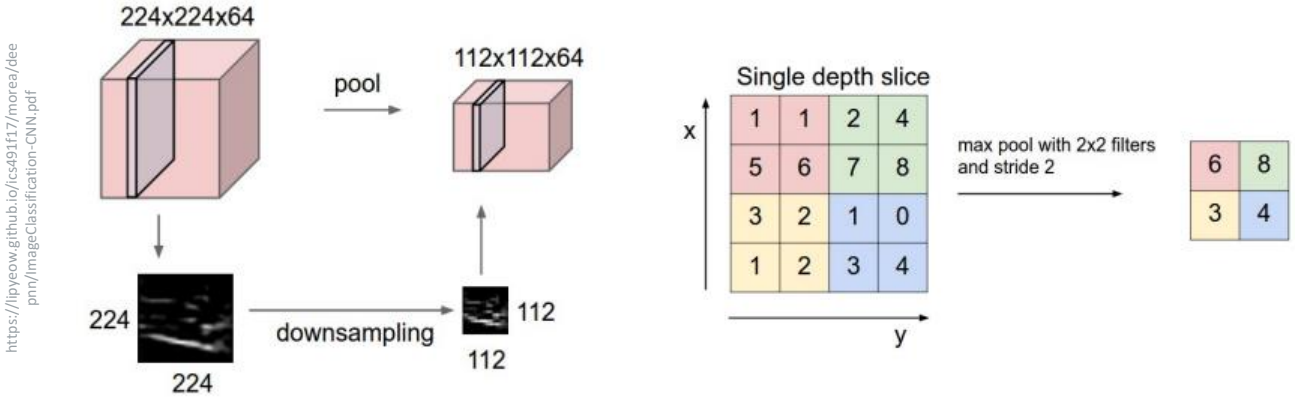
✗

Agenda

- Diagnostic Radiology & Computer-aided Diagnosis
- Computer Vision
- **Convolutional Neural Network (CNN)**
  - Convolution Layer
  - **Pooling Layer**
  - Fully Connected Layer
  - Backpropagation

CNN
Pooling Layer

- Pooling layer downsamples the volume spatially, independently in each depth slice of the input



https://lipyeow.github.io/ics491f17/morea/deepnn/ImageClassification-CNN.pdf

- The most common downsampling operation is **max**, giving rise to **max pooling**, here shown with a stride of 2

CNN
Pooling Layer

CNN
Pooling Layer

Feature Map

Pooled Feature Map

CNN
Pooling Layer

CNN
Pooling Layer

CNN
Pooling Layer

CNN
Pooling Layer

CNN
Pooling Layer

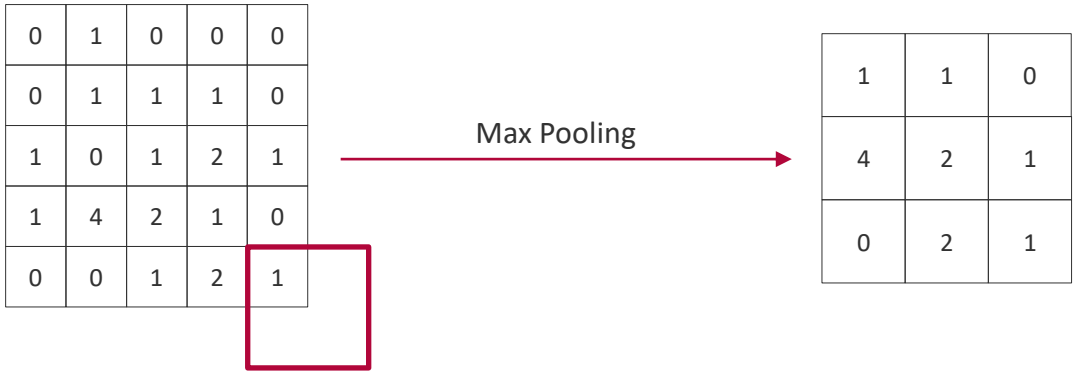
CNN
Pooling Layer

CNN
Pooling Layer

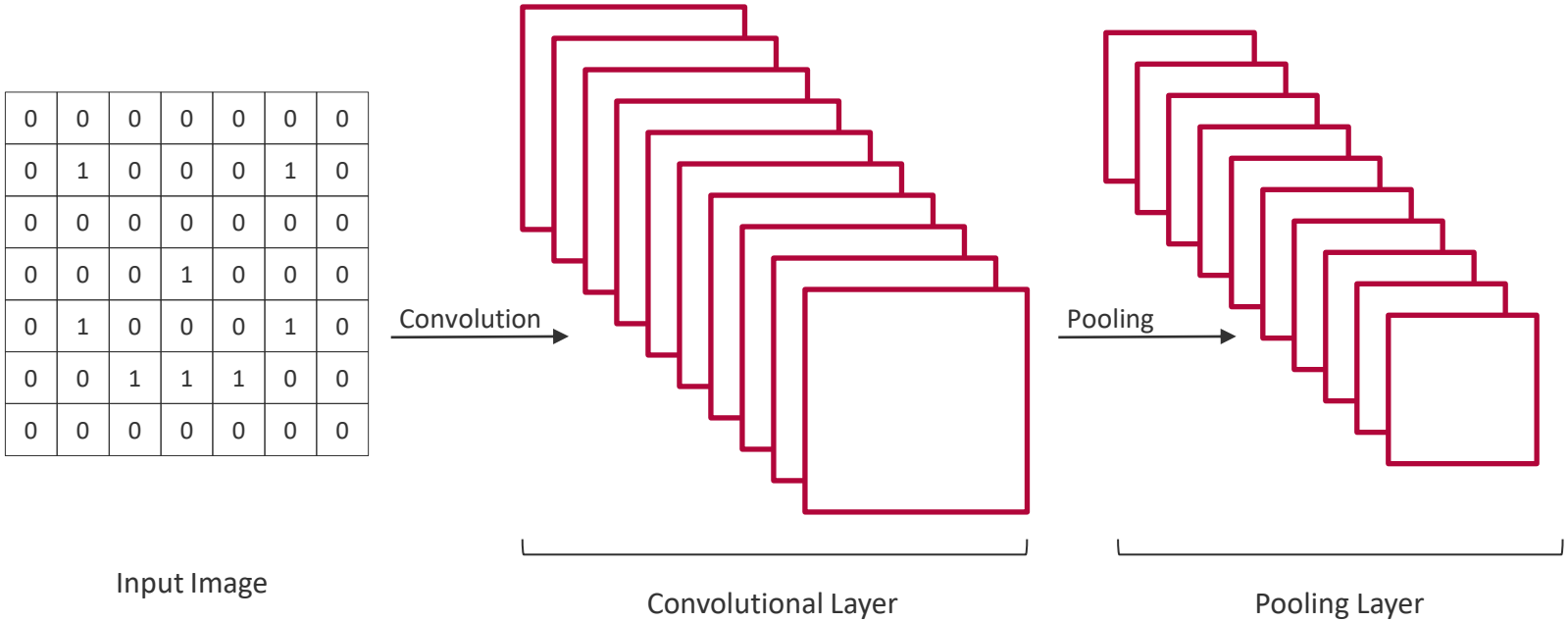
Feature Map

Pooled Feature Map

CNN
Pooling Layer



CNN
Pooling Layer

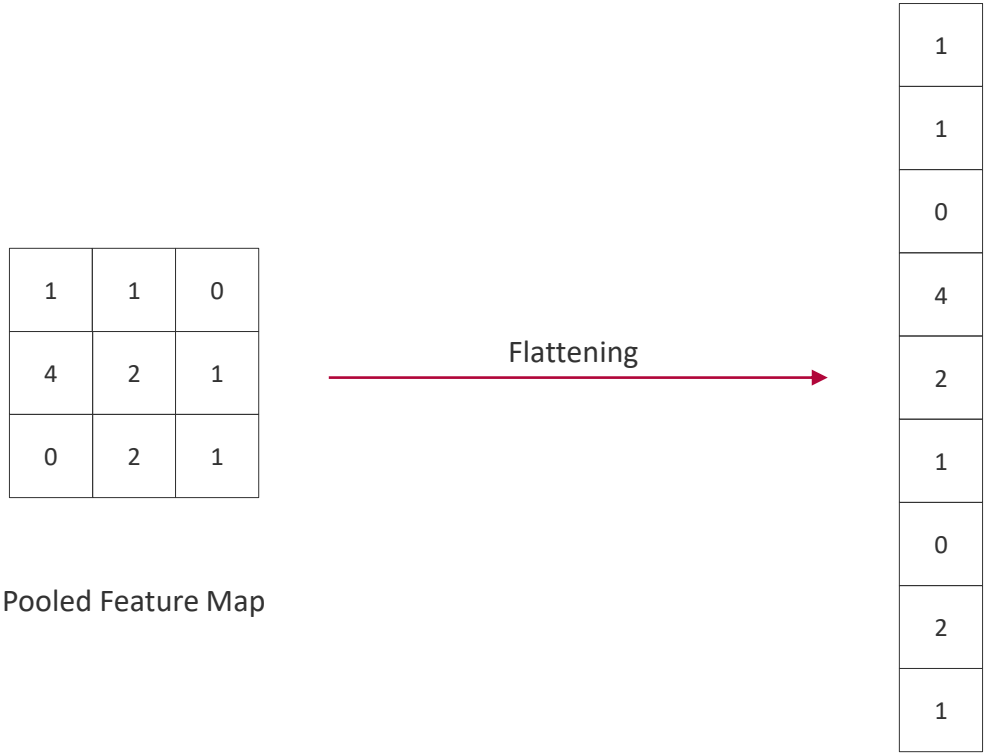


CNN
Flattening

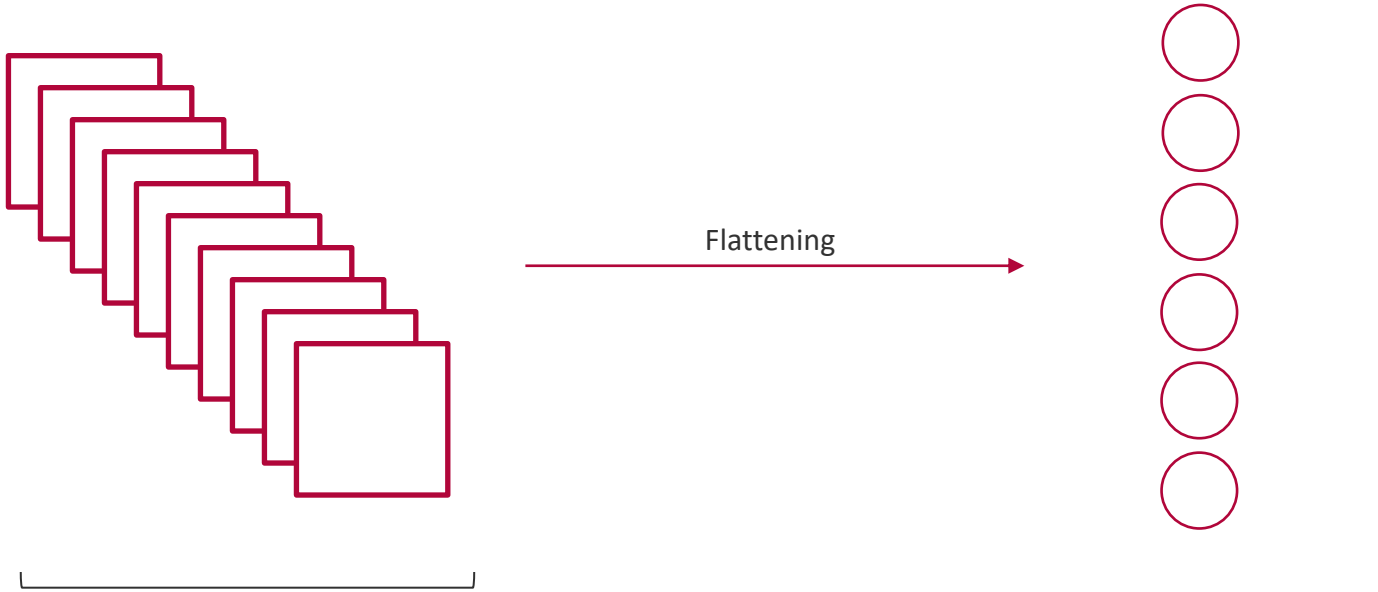
1	1	0
4	2	1
0	2	1

Pooled Feature Map

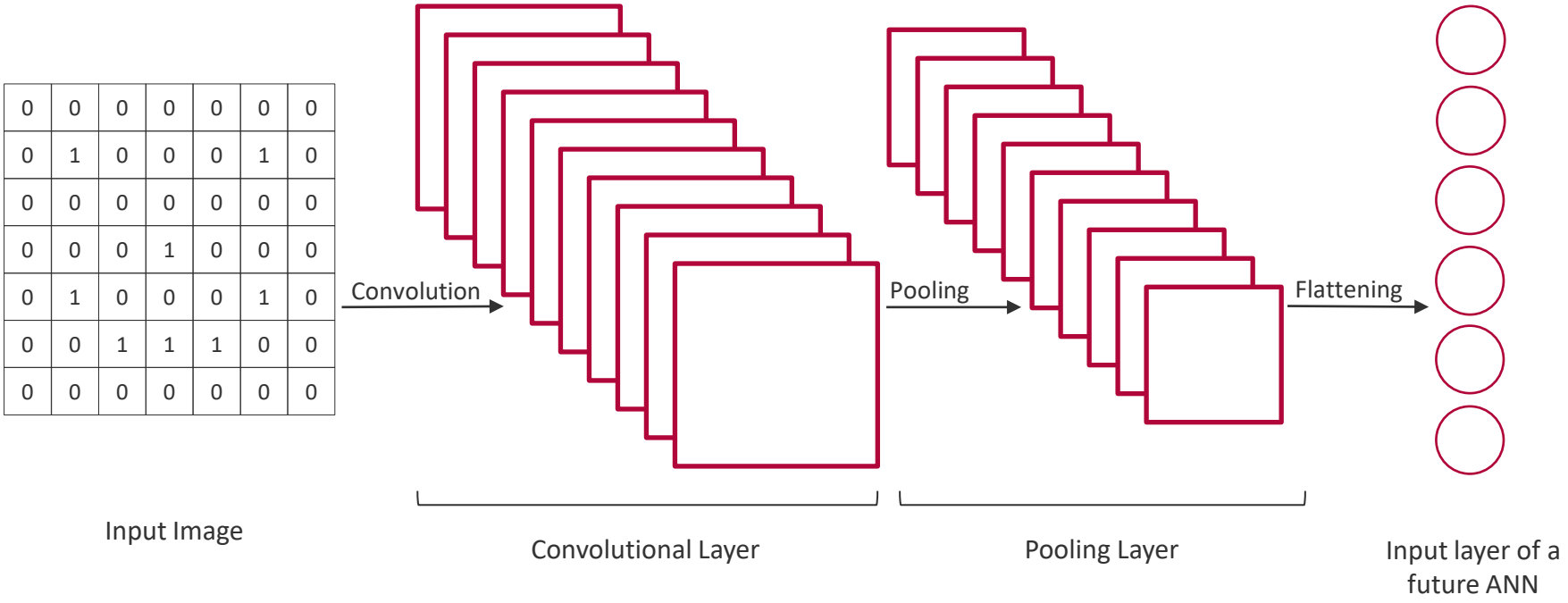
CNN
Flattening



CNN
Flattening



CNN
Flattening

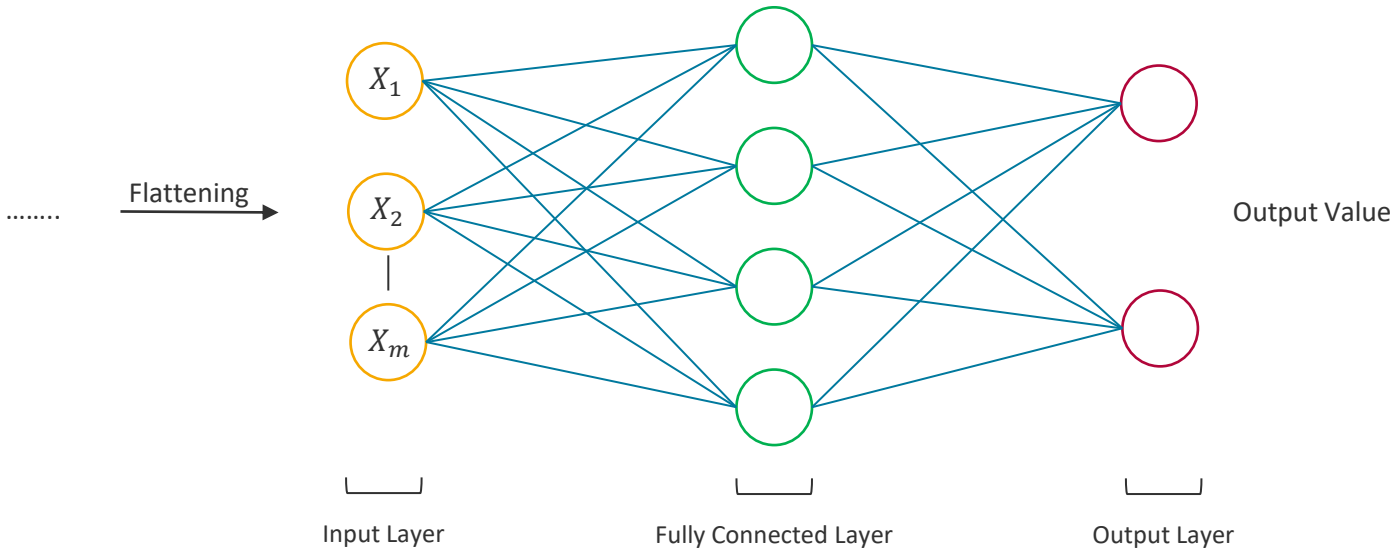


Agenda

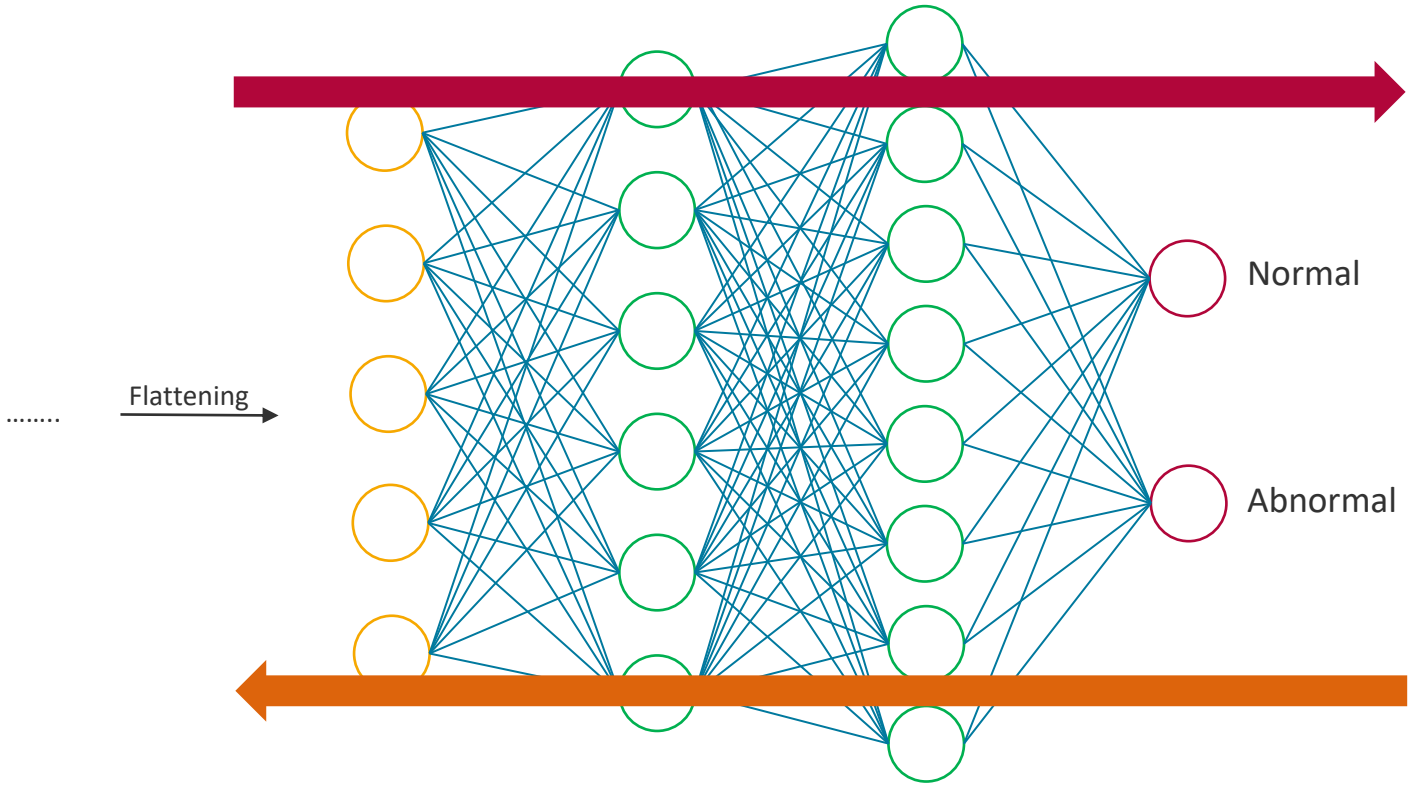
- Diagnostic Radiology & Computer-aided Diagnosis
- Computer Vision
- **Convolutional Neural Network (CNN)**
  - Convolution Layer
  - Pooling Layer
  - **Fully Connected Layer**
  - Backpropagation

CNN
Fully Connected Layer

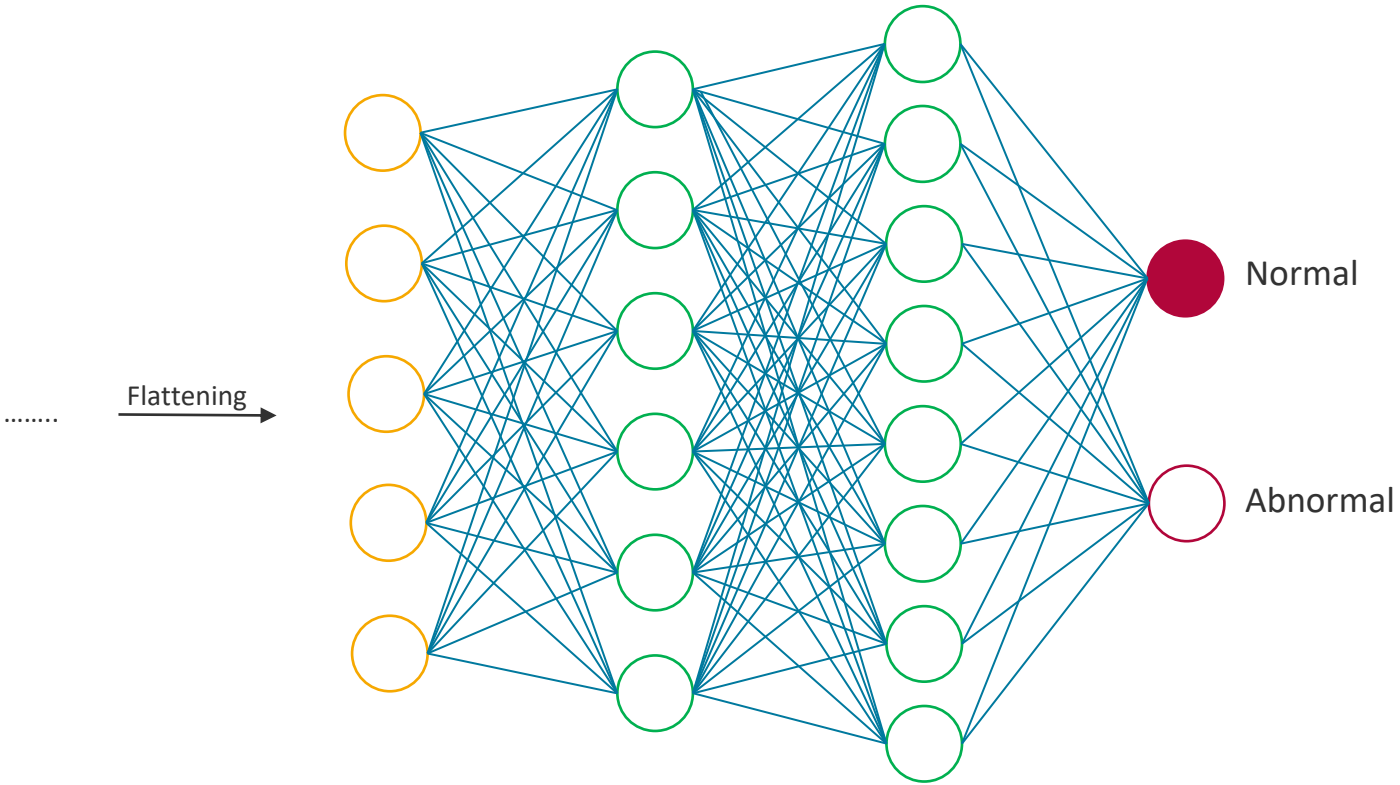
- Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular neural networks



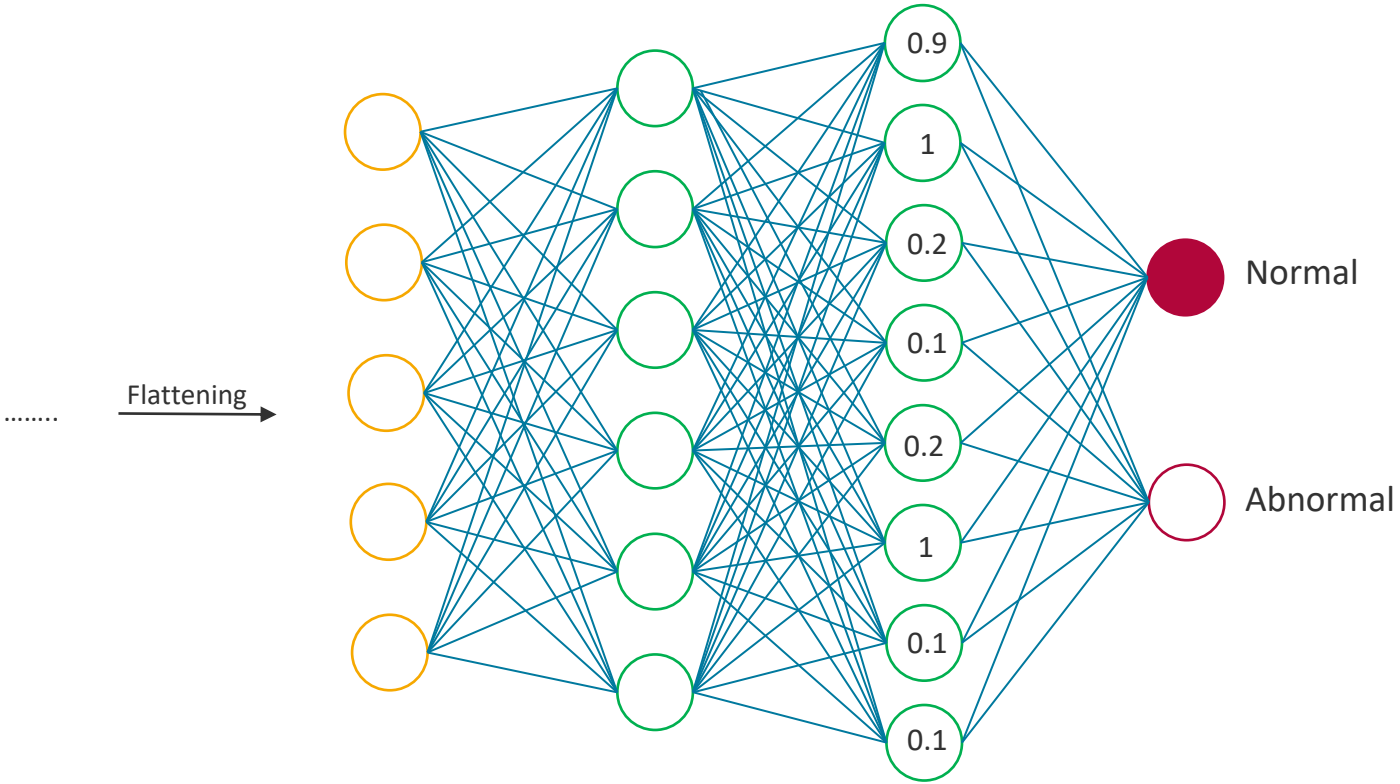
CNN
Fully Connected Layer



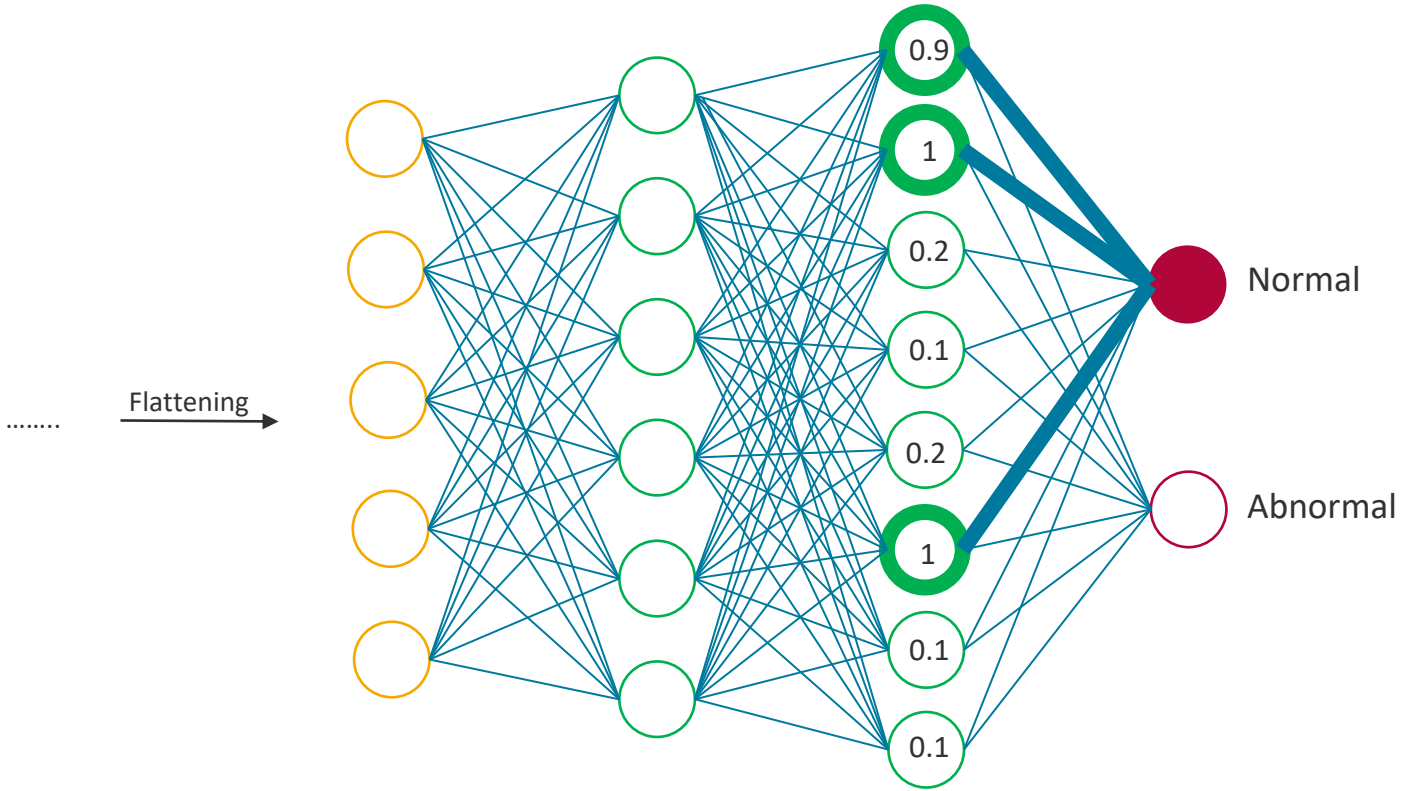
CNN
Fully Connected Layer



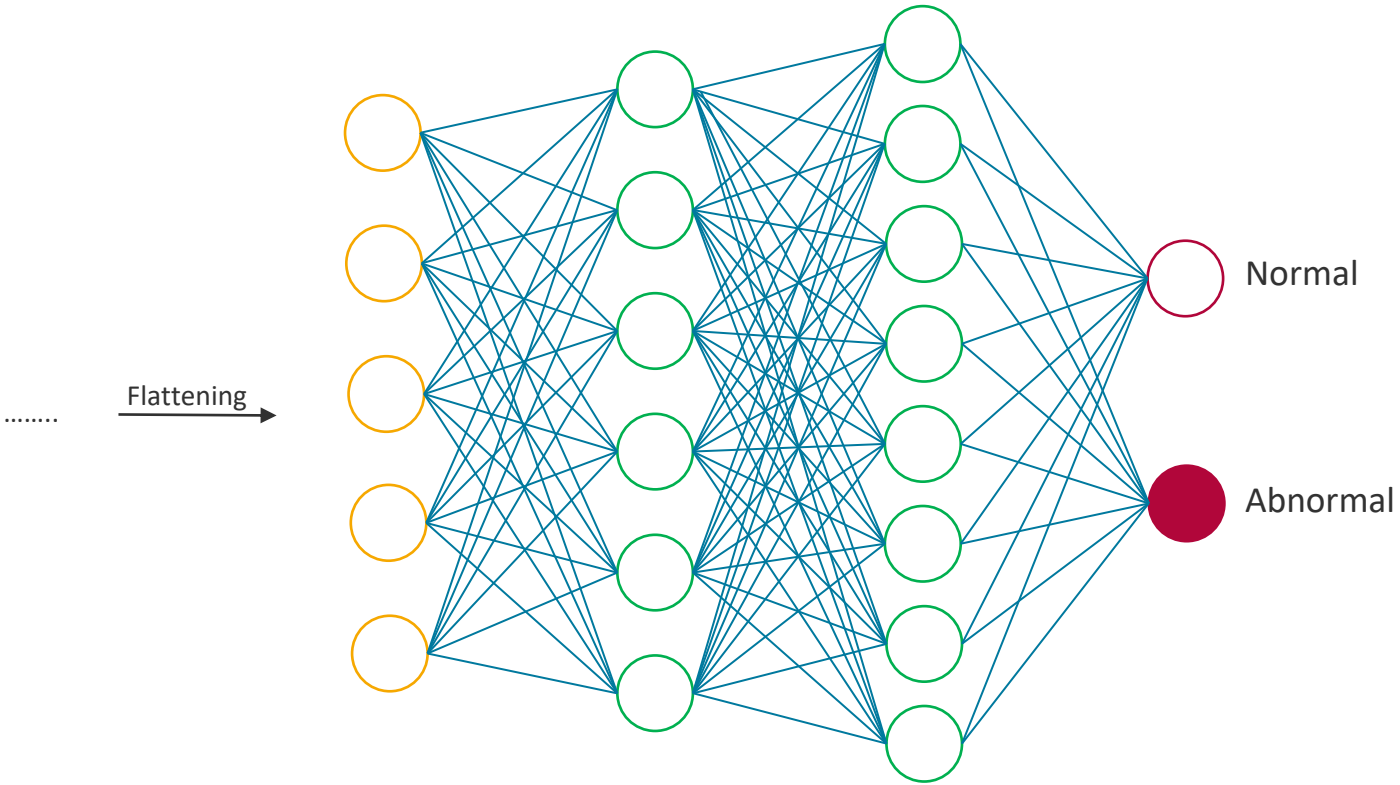
CNN
Fully Connected Layer



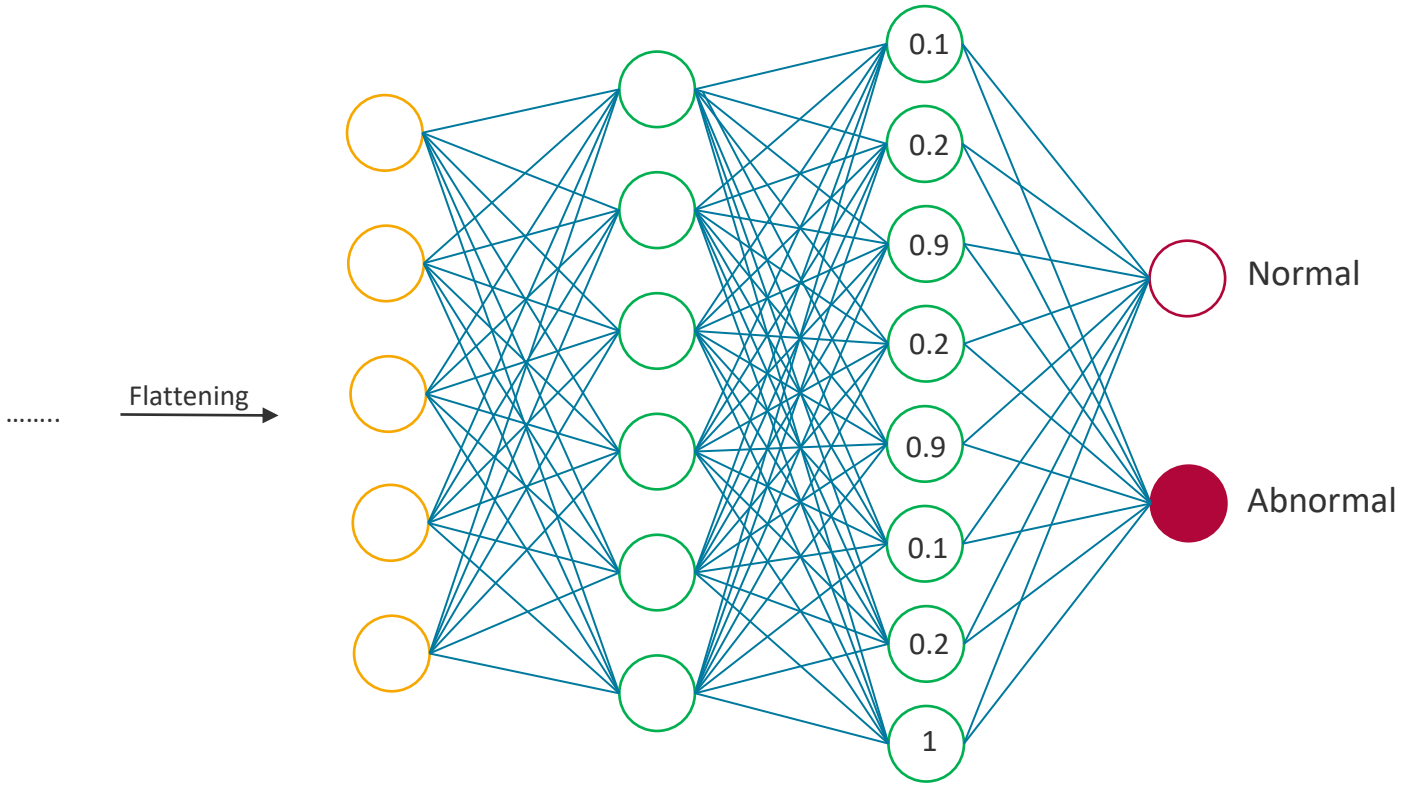
CNN
Fully Connected Layer



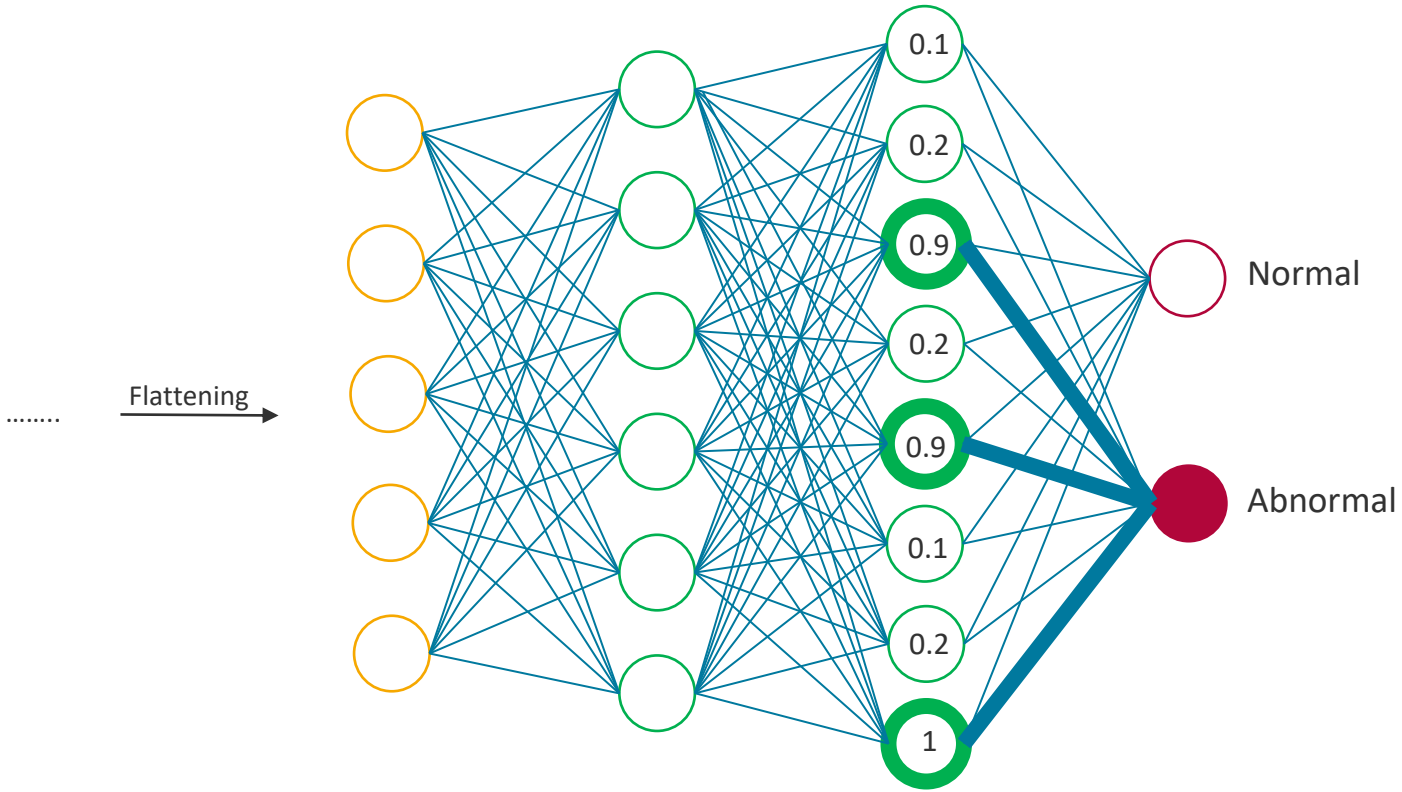
CNN
Fully Connected Layer



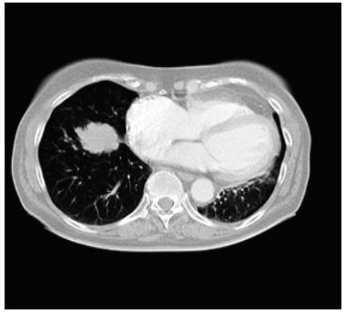
CNN
Fully Connected Layer



CNN
Fully Connected Layer



CNN
Fully Connected Layer



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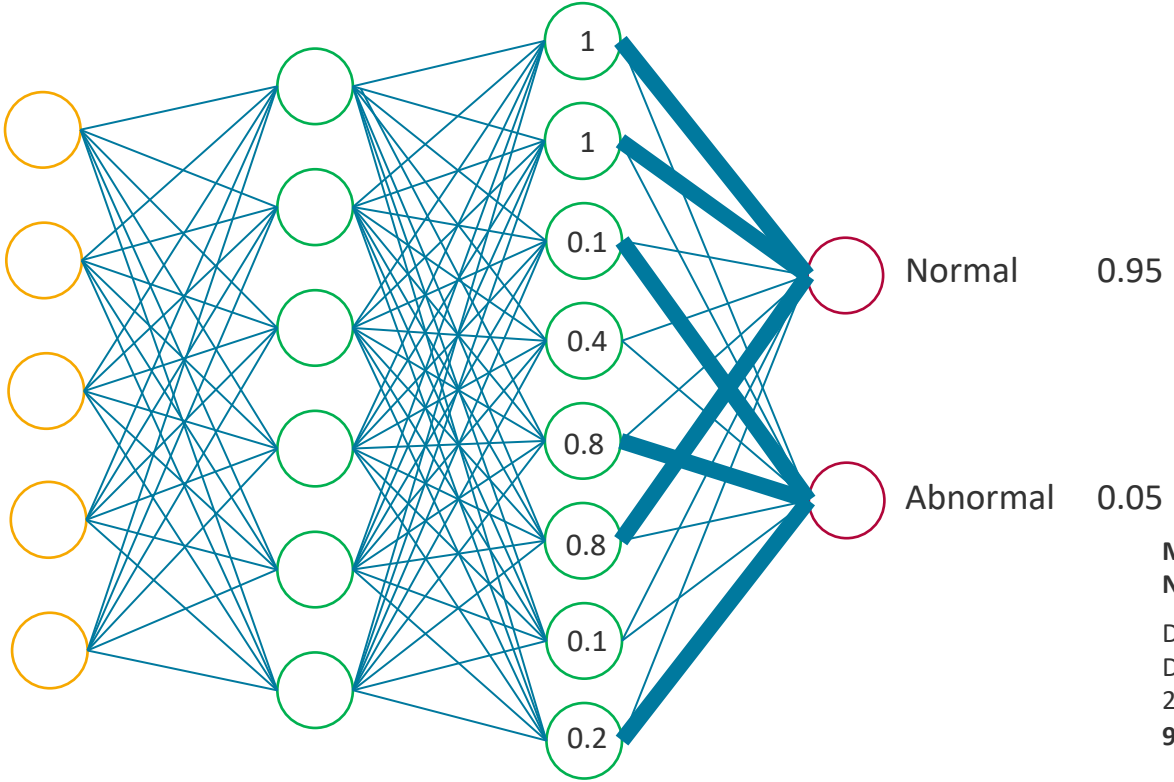
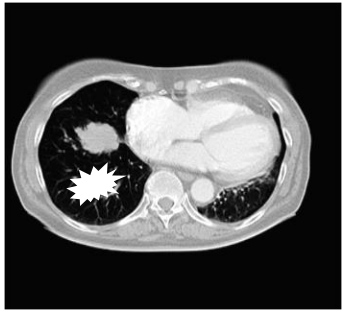
Flattening



Medical Images: Neural Networks

Data Management for Digital Health, Winter 2020

CNN
Fully Connected Layer



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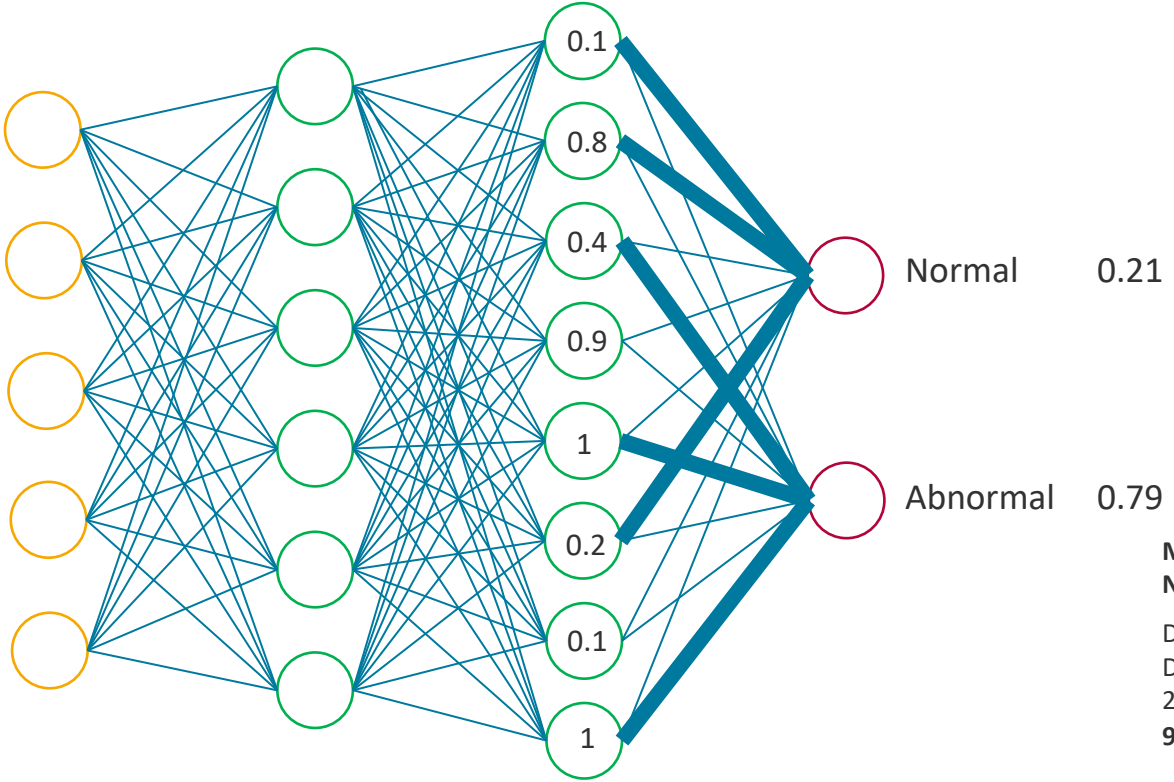
Flattening



Medical Images: Neural Networks

Data Management for Digital Health, Winter 2020

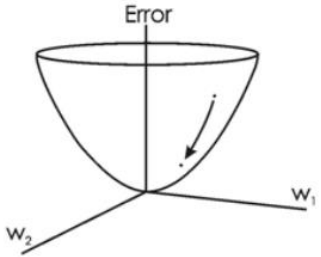
Agenda

- Diagnostic Radiology & Computer-aided Diagnosis
- Computer Vision
- **Convolutional Neural Network (CNN)**
  - Convolution Layer
  - Pooling Layer
  - Fully Connected Layer
  - **Backpropagation**

CNN
Backpropagation

- Algorithm to calculate all weights and biases
- Cost Function

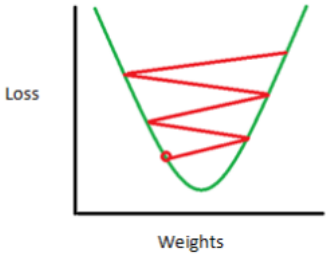
$$L_{total} = \sum \frac{1}{2}(target - output)^2$$



- Minimize gradient of the cost function
  - This is the mathematical equivalent of dL/dW where W are the weights at a particular layer
- Weight updates $w = w_i - \eta \frac{dL}{dW}$

w = Weight
w_i = Initial Weight
η = Learning Rate

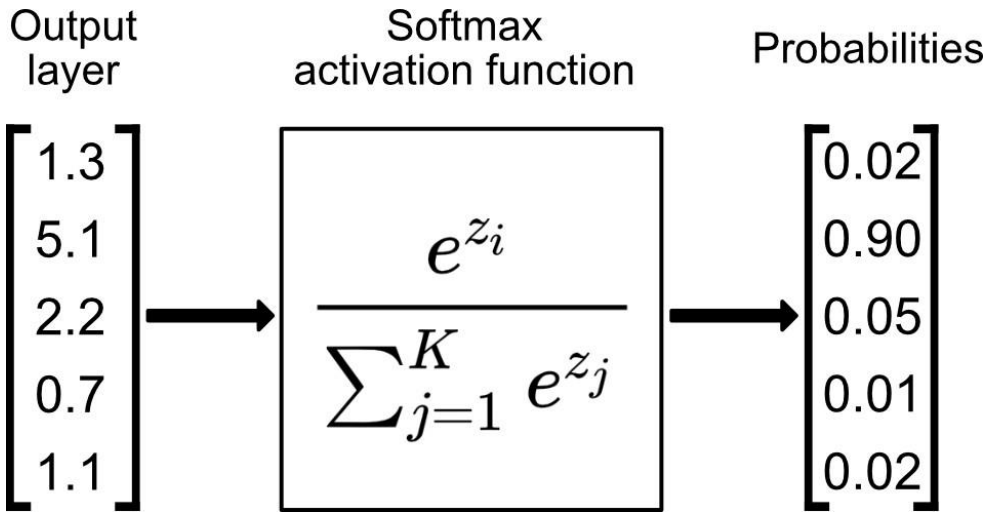
- Learning Rate
  - Parameter chosen by the programmer
  - High learning rate means bigger steps in the weight updates
  - Too high learning rate could result in jumps and not precise to reach optimum



https://lipyeow.github.io/ics491f17/morea/deepnn/ImageClassification-CNN.pdf

CNN
Softmax

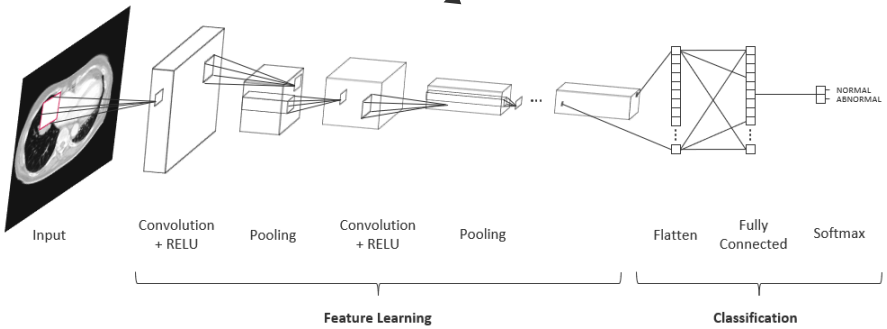
- Used as the last activation function of a neural network to normalize the output of a network to a probability distribution over predicted output classes



What to Take Home?

- Diagnostic Radiology & Computer-aided Diagnosis
- Computer Vision
- Convolutional Neural Network (CNN)
  - Convolution Layer (feature extraction)
    - Filters or ‘kernels’
    - Convolution (Padding, Striding, Activation)
  - Pooling Layer
  - Fully Connected Layer
  - Backpropagation

Do you understand this now?



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Questions?