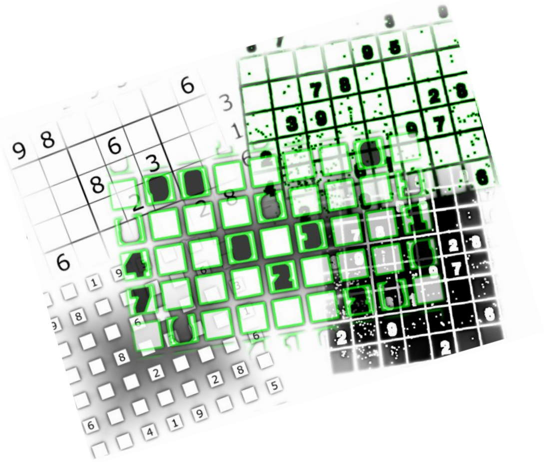
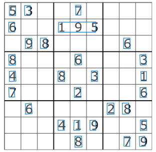


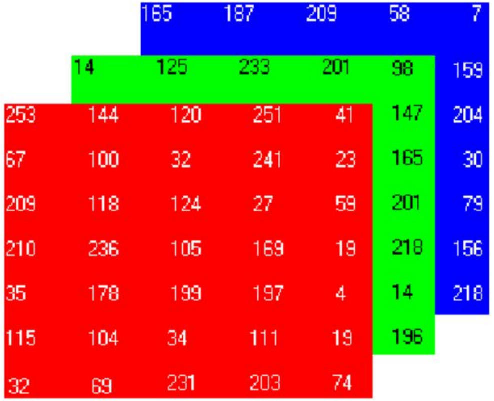
~~Sudoku and~~ Optical Character Recognition in Python

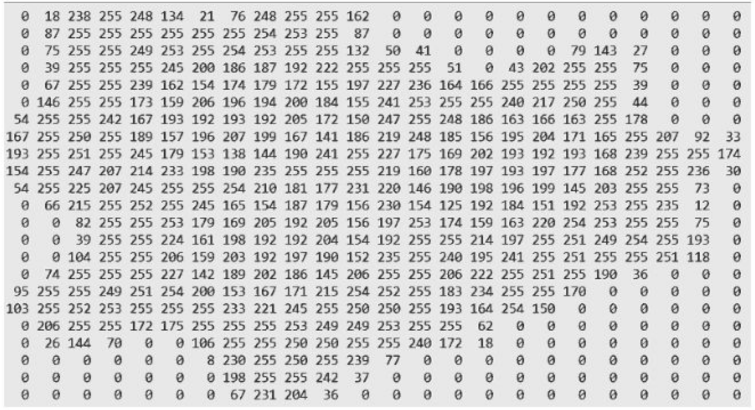
IDA Østjylland Seminar, 23/10/2023

Luminita C. Totu
Control Engineer
luminita.totu@gmail.com



OCR in Python





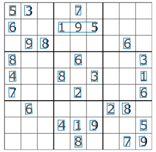
0	18	238	255	248	134	21	76	248	255	255	162	0	0	0	0	0	0	0	0	0	0	0	0
0	87	255	255	255	255	255	255	254	253	255	87	0	0	0	0	0	0	0	0	0	0	0	0
0	75	255	255	249	253	255	254	253	255	255	132	50	41	0	0	0	0	79	143	27	0	0	0
0	39	255	255	255	245	200	186	187	192	222	255	255	255	51	0	43	202	255	255	75	0	0	0
0	67	255	255	239	162	154	174	179	172	155	197	227	236	164	166	255	255	255	255	39	0	0	0
0	146	255	255	173	159	206	196	194	200	184	155	241	253	255	255	240	217	250	255	44	0	0	0
54	255	255	242	167	193	192	193	192	205	172	150	247	255	248	186	163	166	163	255	178	0	0	0
167	255	250	255	189	157	196	207	199	167	141	186	219	248	185	156	195	204	171	165	255	207	92	33
193	255	251	255	245	179	153	138	144	190	241	255	227	175	169	202	193	192	193	168	239	255	255	174
154	255	247	207	214	233	198	190	235	255	255	255	219	160	178	197	193	197	177	168	252	255	236	30
54	255	225	207	245	255	255	254	210	181	177	231	220	146	190	198	196	199	145	203	255	255	73	0
0	66	215	255	252	255	245	165	154	187	179	156	230	154	125	192	184	151	192	253	255	235	12	0
0	0	82	255	255	253	179	169	205	192	205	156	197	253	174	159	163	220	254	253	255	255	75	0
0	0	39	255	255	224	161	198	192	192	204	154	192	255	255	214	197	255	251	249	254	255	193	0
0	0	104	255	255	206	159	203	192	197	190	152	235	255	240	195	241	255	251	255	255	251	118	0
0	74	255	255	255	227	142	189	202	186	145	206	255	255	206	222	255	251	255	190	36	0	0	0
95	255	255	249	251	254	200	153	167	171	215	254	252	255	183	234	255	255	170	0	0	0	0	0
103	255	252	253	255	255	255	233	221	245	255	250	250	255	193	164	254	150	0	0	0	0	0	0
0	206	255	255	172	175	255	255	255	253	249	249	253	255	255	62	0	0	0	0	0	0	0	0
0	26	144	70	0	0	106	255	255	250	250	255	255	240	172	18	0	0	0	0	0	0	0	0
0	0	0	0	0	0	8	230	255	250	255	239	77	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	198	255	255	242	37	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	67	231	204	36	0	0	0	0	0	0	0	0	0	0	0	0	0

- A **raster** image is a matrix (with given width & height) of numbers representing the colors using one of several color systems

- A file header includes information format and mode, size, and other properties required to decode the file/content.

An OCR “pipeline” typically consists of four/five steps:

- **Image (pre)processing**
- Text box(-es) detection / **definition** in terms of image coordinates
- **Text recognition**
- Image restructuring (placing the recognized text geometrically similar to how it was in the input image)
- Result (post)processing



OCR in Python: Pipeline for Today

- ***Image Processing***
- Text Detection (bounding boxing)
- Text Recognition

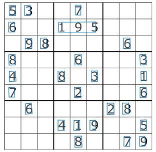


Image Processing

Opens source tools for image processing:

- Pillow (basic image processing tasks)
- Scikit-image (python based, diverse set of algorithms, good for research, not fast / real-time)
- Opencv (comprehensive library aimed at real-time computer vision, multi-language support)

Basic Image Processing functionalities:

- Reading through the file encoding format to extract the color matrix or the images “bands of data” (and conversions between color systems)
- (0,0) in the upper left corner; coordinates refer to the implied pixel corners
- Geometric transformations: rotation, ***resizing***, cropping, flip, mirror
- Enhancements: color, contrast, sharpness, brightness adjustments functions, ***grayscaling***
- Draw, write on existing images or as images
- ***Filtering & Convolution***
- ***Morphology Operations***
- ***Thresholds***

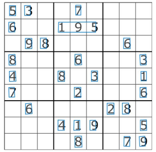


Image Processing

- Resizing
- Grayscaling
- Filtering & Convolution
- Morphology Operations
- Thresholding

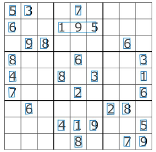


Image Processing - Resizing

- Refers to reducing its size or resolution (the width and height of the matrix)
- Multiple input pixels will be mapped to a single output pixel
- This operation can lead to a loss of information, which is why the choice of **resampling technique** is crucial to maintain as much of the original content as possible.

Different options:

- Nearest-neighbor Interpolation
- Bilinear Interpolation
- Bicubic Interpolation
- Area-based (or Pixel-averaging)
- Hamming
- Lanczos Resampling

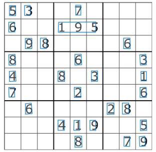


Image Processing - Grayscaling

Converting an RGB image to grayscale, some techniques:

- **Averaging Method**: takes the average of the red, green, and blue color channels.

$$Gray = (R+G+B)/3$$

- **Luminosity (or Weighted) Method**: a widely used technique as it takes into account the perceived intensity of colors to the human eye. The human eye is most sensitive to green

$$Gray = Gray = 0.299 \times R + 0.587 \times G + 0.114 \times B$$

- **Desaturation Method**: It involves taking the average of the maximum and minimum of the three color channels.

$$Gray = 0.5 * (\max(R,G,B) + \min(R,G,B))$$

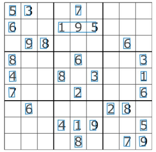


Image Processing - Thresholding/Binarization

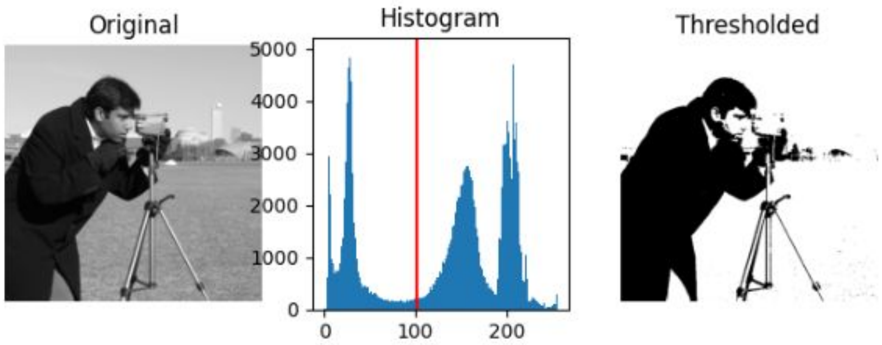
The idea is to convert a grayscale image into a binary image where the pixels are either 0 (black) or 1 (white) based on a threshold value:

- **Simple, global technique**: a single threshold value is user-chosen, and all pixels with intensities above (or below) this value are set to one level (either black or white), and all other pixels to the opposite level
- **Otsu's Thresholding**: Assumes that the image contains two classes of pixels and calculates the optimum threshold that minimizes the intraclass variance. Particularly effective for bimodal histograms.
- **Triangle Thresholding**: Draws a line from the peak of the histogram (highest frequency) to the farthest end of the histogram and then finds the point on the histogram that is farthest from this line. This point's intensity is taken as the threshold
- **Adaptive (or Local) Thresholding:** Instead of a single threshold value, different values are used for different regions of an image. Useful for images with varying light conditions. Common methods include "Mean Adaptive Thresholding" where the threshold is the mean of the neighboring area and "Gaussian Adaptive Thresholding" where the threshold is a weighted sum of the neighboring values, with weights given by a Gaussian window.

Image Processing - Thresholding

- for pictures with a bimodal histogram, more specific algorithms can be used. For instance, the minimum algorithm takes a histogram of the image and smooths it repeatedly until there are only two peaks in the histogram.

- Otsu-Thresholding:



scikit-images

- Otsu’s threshold method can be applied locally. For each pixel, an “optimal” threshold is determined by maximizing the variance between two classes of pixels of the local neighborhood (defined by block_size or a by a structuring element)

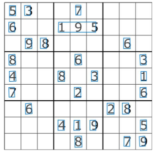
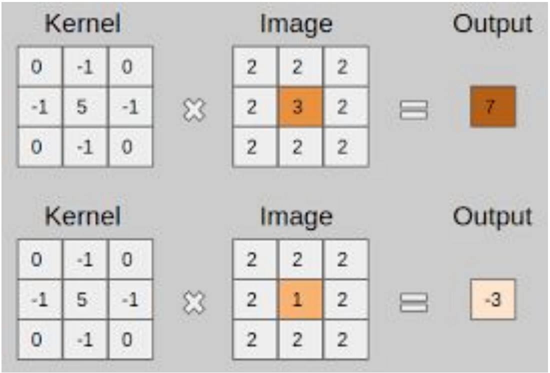
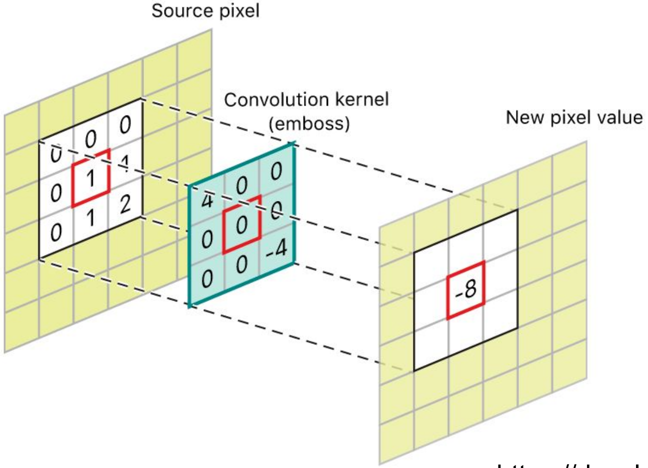
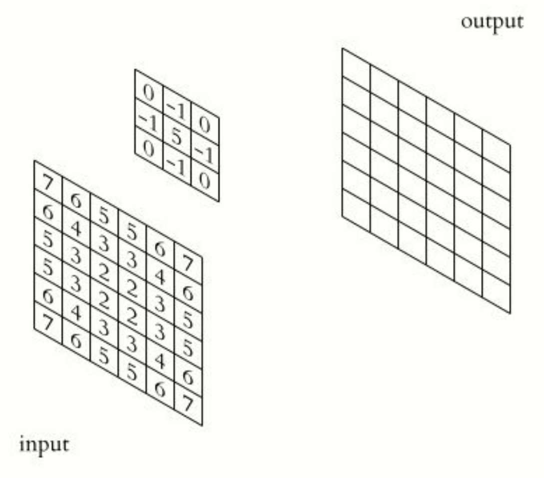


Image Processing - Convolution Kernels

Spatial Filtering with a Convolution Kernel: a small matrix used for blurring, sharpening, embossing, edge detection, and more. This is accomplished by doing a “convolution” between the kernel and an image. Each pixel in the output image is a *function* of the nearby pixels (including itself) in the input image. The kernel is that function.







https://developer.apple.com/documentation/accelerate/blurring_an_image
Prakhar Ganesh, https://towardsdatascience.com/types-of-convolution-kernels-simplified-f040cb307c37

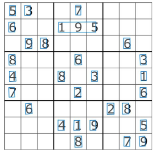
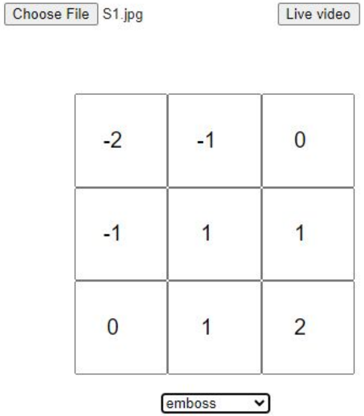
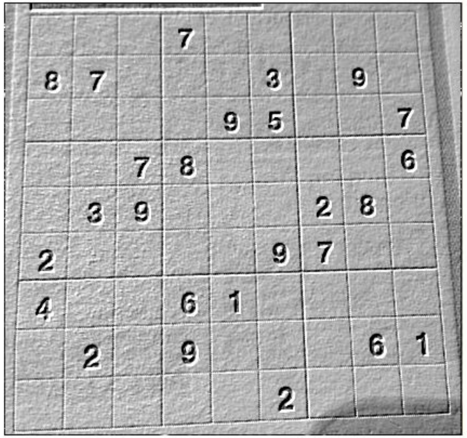


Image Processing - Convolution Kernels

- To be useful, however, a kernel should generally be small enough that the majority of the pixel accesses fall within the bounds of the target image. Performance is also a factor with large kernels.

Activity! https://setosa.io/ev/image-kernels/





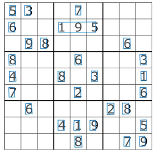


Image Processing - Convolution Kernels

- **Box Blurring Filter** is shader friendly

$$\begin{bmatrix} \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \end{bmatrix}$$

Example of a 3x3 Kernel

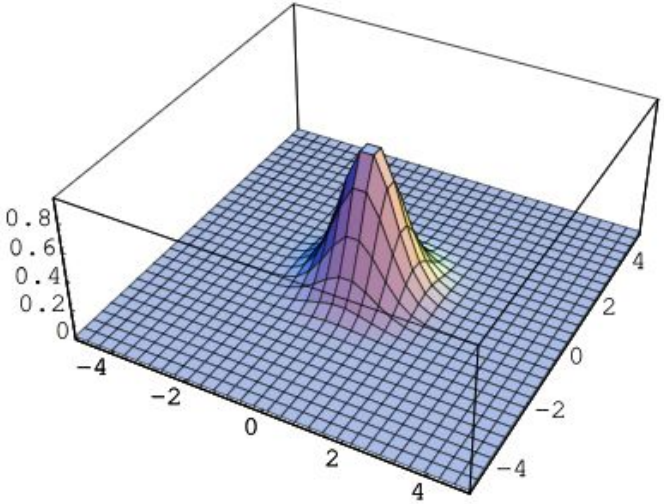
// A shader is a piece of code that is executed on the Graphics Processing Unit (GPU), usually found on a graphics card, to manipulate an image before it is drawn to the screen

Image Processing - Convolution Kernels

- **Gaussian blur**

$\frac{1}{273}$

1	4	7	4	1
4	16	26	16	4
7	26	41	26	7
4	16	26	16	4
1	4	7	4	1



Example of 2D Gaussian function with sigma = 1
Normalized; Kernel Size 5x5

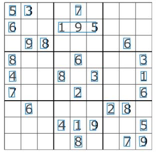


Image Processing - Convolution Kernels

Edge Detection: Basic, Sobel, Prewitt and Kirsch operators.

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

A basic 3x3 edge detector kernel

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \quad \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

The Sobel detector kernels

- Sobel, Prewitt and Kirsch operators are composed of multiple convolutions
- Sobel and Prewitt are similar: They perform a pair of horizontal and vertical convolutions, which are then used to produce a final edge value at the target pixel.
- The Kirsch edge detector performs a convolution for each of the 8 compass directions at the target pixel

$$\mathbf{g}^{(1)} = \begin{bmatrix} +5 & +5 & +5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}, \quad \mathbf{g}^{(2)} = \begin{bmatrix} +5 & +5 & -3 \\ +5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix},$$

$$\mathbf{g}^{(3)} = \begin{bmatrix} +5 & -3 & -3 \\ +5 & 0 & -3 \\ +5 & -3 & -3 \end{bmatrix}, \quad \ldots$$

https://www.taylorpetrick.com/blog/post/convolution-part1

The Kirsch detector kernels

Image Processing - Convolution Kernels

Edge Detection: Explanation of Basic Kernel

1D Black/White case:

- We need to find a way to “detect” the “01” and “10” adjacent pixels (0 black, 1 white). The edge pixel is the white one
- We consider a 3x1 kernel
- Total number of possibilities in the image are: 0**0**0, 0**0**1, 0**1**0, 0**1**1, 1**0**0, 1**0**1, 1**1**0 and 1**1**1
- The current pixel (middle one in the kernel) is an edge if the pattern is one of 0**1**0, 0**1**1, 1**1**0

$$edge(x) = -pixels[x-1] + 2 * pixels[x] - pixels[x+1]$$

\+ Clamping

pattern	*result*	*clamped*
000	0	0
001	−1	0
010	2	1
011	1	1
100	−1	0
101	−2	0
110	1	1
111	0	0

Kernel is: [-1 2 -1] + clamping

- Different options can to be considered for the boundary pixels

Image Processing - Convolution Kernels

Sharpening:

- A simple technique is to add the edge detector output to the initial image. The edges be more apparent. The sharpening effect can be controlled by introducing an amount parameter that scales the edge detector contribution, see the 3x3 example

$$K_{sharp} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} * amount$$

$$K_{sharp} = \begin{bmatrix} -0.00391 & -0.01563 & -0.02344 & -0.01563 & -0.0-391 \\ -0.01563 & -0.06250 & -0.09375 & -0.06250 & -0.01563 \\ -0.02344 & -0.09375 & 1.85980 & -0.09375 & -0.02344 \\ -0.01563 & -0.06250 & -0.09375 & -0.06250 & -0.01563 \\ -0.00391 & -0.01563 & -0.02344 & -0.01563 & -0.00391 \end{bmatrix}$$

- “Unsharp” technique - combining an edge detector and blur filter, results in a more refined sharpening effect, see the 5x5 example

https://www.taylorpetrick.com/blog/post/convolution-part3
https://www.imagemagick.org/Usage/convolve/

Image Processing - Convolution Kernels

Sharpening:

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$$K_{sharp} = \begin{bmatrix} -0.00391 & -0.01563 & -0.02344 & -0.01563 & -0.0-391 \\ -0.01563 & -0.06250 & -0.09375 & -0.06250 & -0.01563 \\ -0.02344 & -0.09375 & 1.85980 & -0.09375 & -0.02344 \\ -0.01563 & -0.06250 & -0.09375 & -0.06250 & -0.01563 \\ -0.00391 & -0.01563 & -0.02344 & -0.01563 & -0.00391 \end{bmatrix}$$

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https://www.imagemagick.org/Usage/convolve/

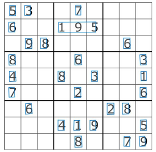


Image Processing - Morphological Operations

- Similar with the spatial filtering with a convolution kernel: it has a structuring element and a predefined calculation rule
- different from the process of convolution, the morphological operation is logical (e.g. AND, OR, NOT) rather than arithmetic
- It is applied on binary images (black & white images). Some of the techniques can be extended to grayscale images as well
- Affects the “shape” of the binary image
- See Mathematical Morphology

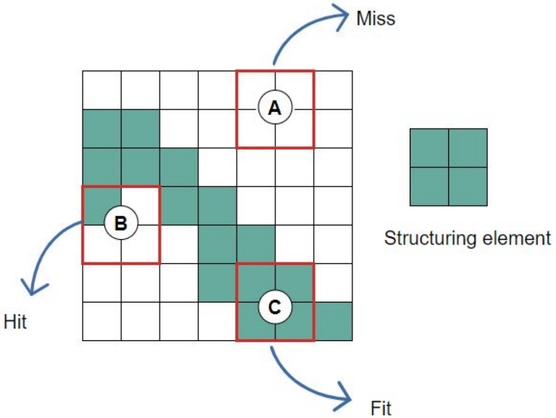
Example of Operations: Dilation (D), Erosion (E), Closing (D+E), Opening (E+D), Hit-or-Miss
Other examples: thinning, pruning, top hat

First, a **structuring element** (which is similar to the kernel in convolution, moves point-to-point across each pixel of the input image) it is a matrix or a small-sized template that is used to traverse an image. **Its pixels have values zero or one.** It also has an origin, the middle of the matrix (therefore odd size)

Image Processing - Morphological Operations

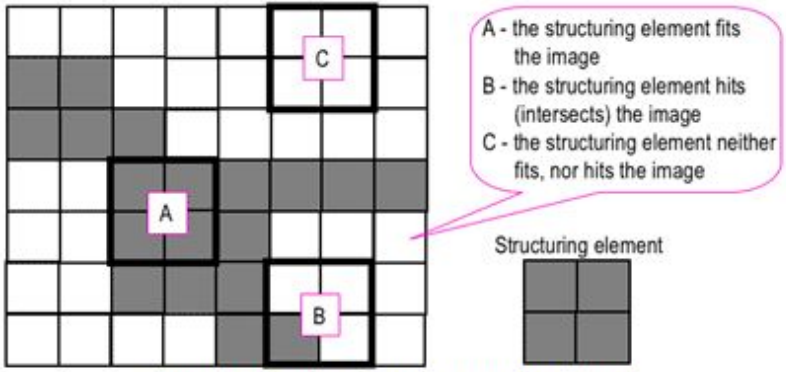
The structuring element is positioned at all possible locations in the image, and it is **compared with the overlaid pixels**.

- **Fit**: When all the pixels in the *structuring element* cover the pixels of the object,
- **Hit**: When at least one of the pixels in the *structuring element* cover the pixels of the object
- **Miss**: When no pixel in the structuring element cover the pixels of the object



Probing an image with a structuring element

https://www.educative.io/answers/what-is-morphological-image-processing



Probing of an image with a structuring element
(white and grey pixels have zero and non-zero values, respectively).

https://www.cs.auckland.ac.nz/courses/compsci773s1c/lectures/ImageProcessing-html/topic4.htm

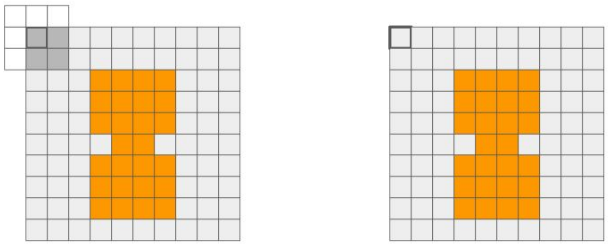
Image Processing - Morphological Operations

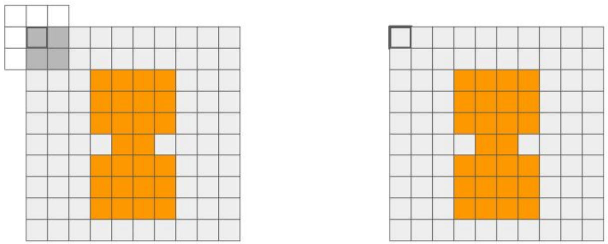
Morphological Dilation: expands the image pixels, or it adds pixels on object boundaries. Can repair breaks or intrusions. Computational rule:

- **Pixel (output) = 1 {if HIT or FIT}**
- **Pixel (output) = 0 {otherwise}**

Morphological Erosion: expands the image pixels, or it adds pixels on object boundaries
Computational rule:

- **Pixel (output) = 1 {if FIT}**
- **Pixel (output) = 0 {otherwise}**





https://penny-xu.github.io/blog/mathematical-morphology

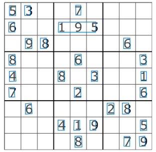
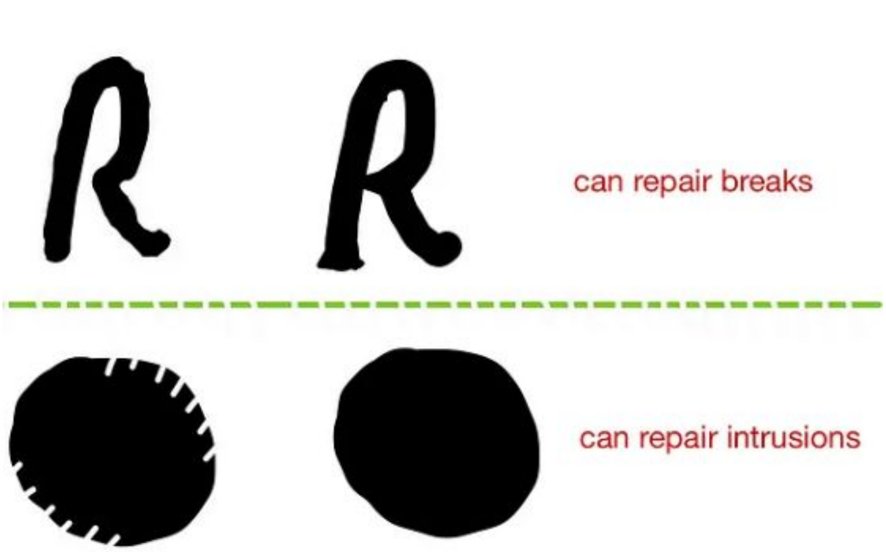


Image Processing - Morphological Operations

Examples of “purposeful” Dilation:



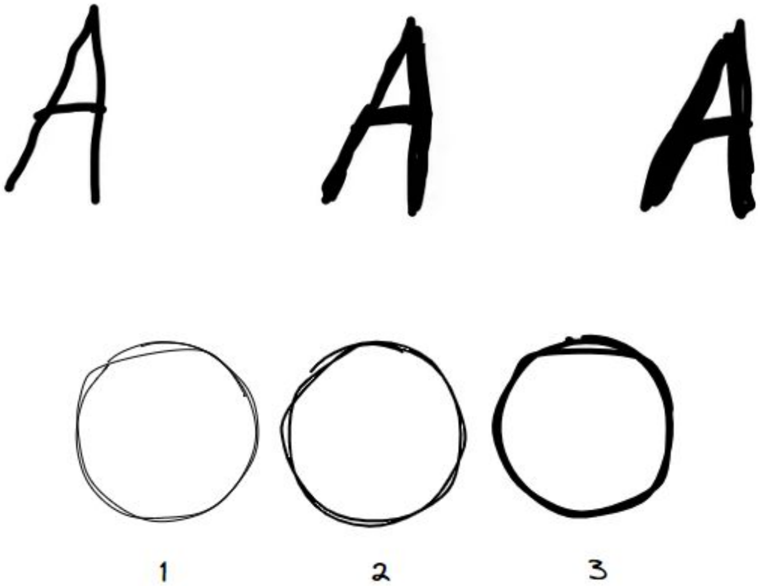
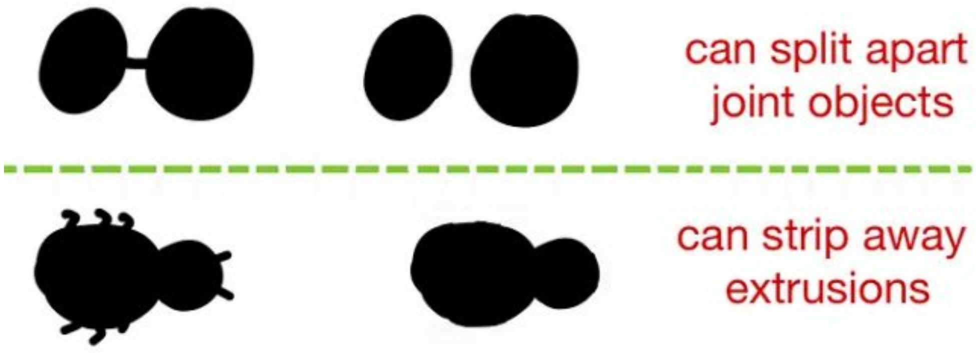
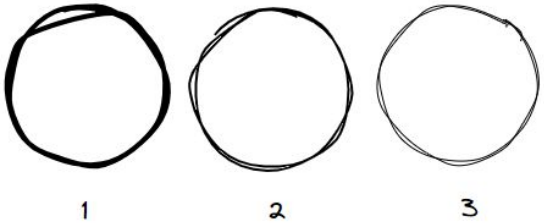


Image Processing - Morphological Operations

Examples of “purposeful” Erosion:





18876055491

kernel = np.ones((10, 1), np.uint8)

https://www.dynamsoft.com/blog/image-processing/morphological-operations/

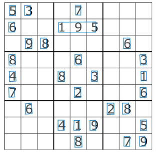
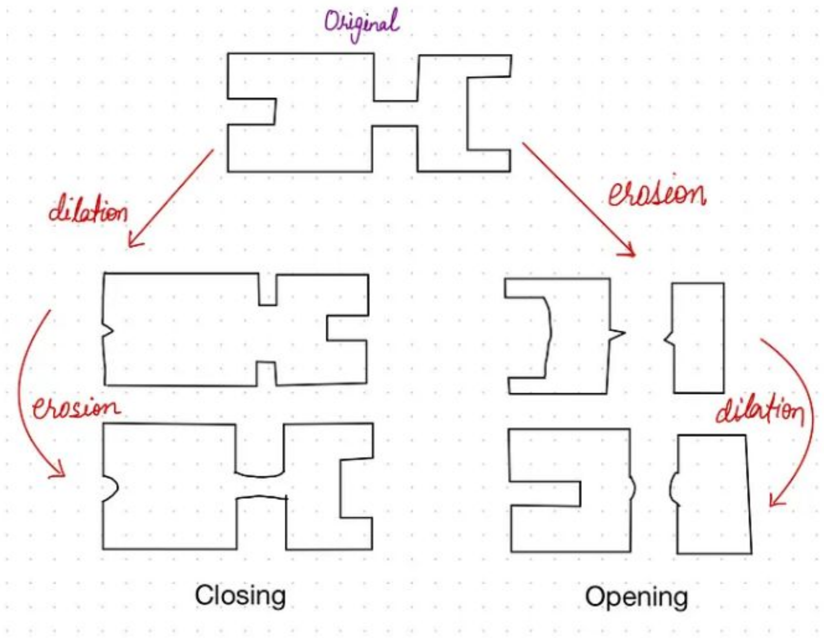


Image Processing - Morphological Operation

- **Closing** (by first performing dilation and then erosion)
- **Opening** (by first performing erosion and then dilation)

QR code after Closing

https://www.dynamsoft.com/blog/image-processing/morphological-operations/



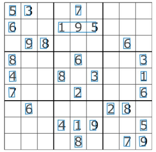


Image Processing - Morphological Operation

- **Closing** (by first performing dilation and then erosion)
- **Opening** (by first performing erosion and then dilation)

image

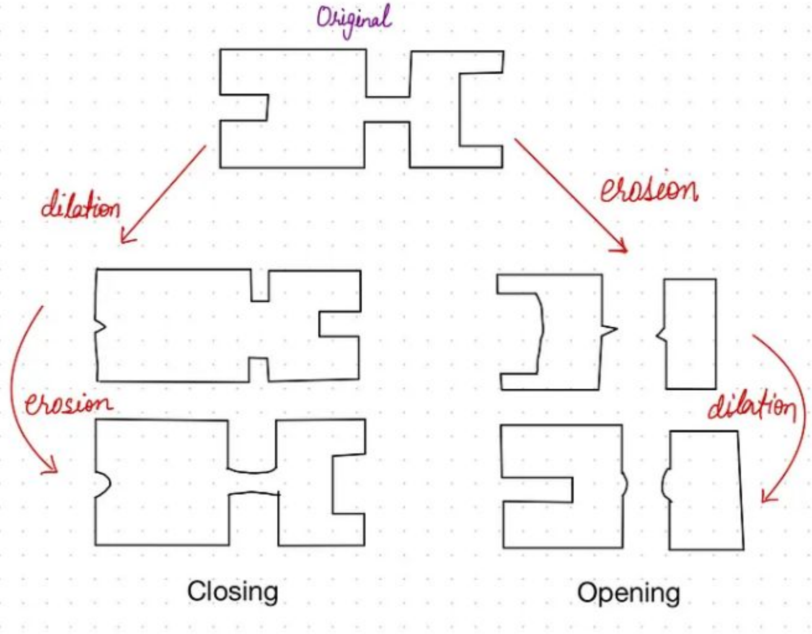
Opening to remove noise (docs opencv)

image

Closing to remove noise (docs opencv)

QR code after Closing

https://www.dynamsoft.com/blog/image-processing/morphological-operations/



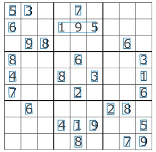


Image Processing - Morphological Operation

https://planetcalc.com/9325/

Activity !

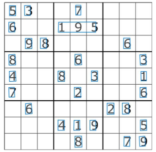


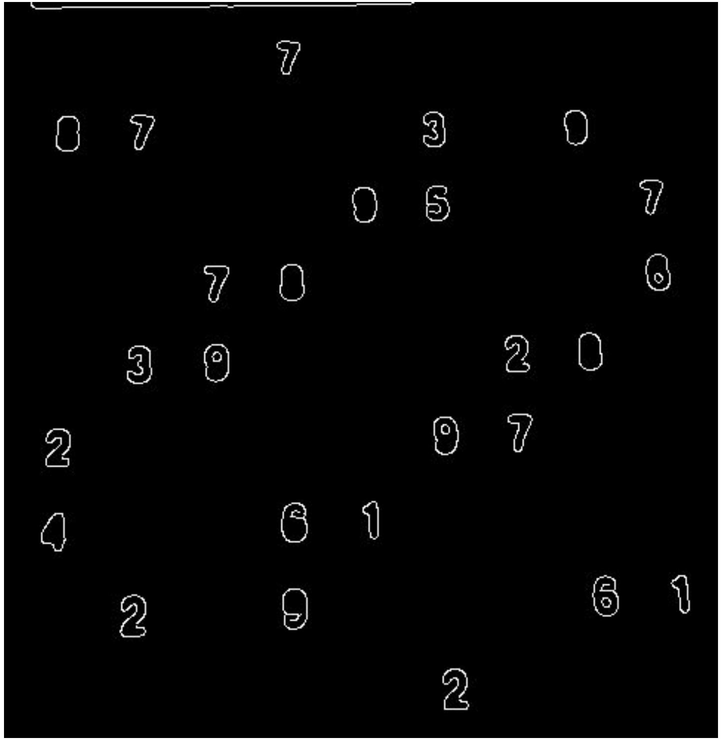
Image Processing: Other Alg

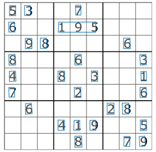
- Canny Edge Detection (John F. Canny 1986), multi-stage filter:

Noise reduction (gaussian filter 5x5), a Sobel kernel for gradients, removing everything that is not an edge based on gradient (non-maximum suppression), and an extra strep that requires two thresholds.

- Contours extraction (1985, Satoshi Suzuki and others)

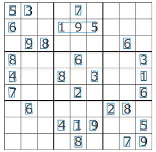
(opencv) Finding white object from black background. A curve joining all the continuous points (along the boundary), having same color or intensity.





OCR in Python: Pipeline for Today

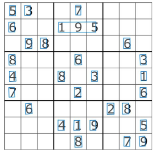
- Image Processing
- ***Text Detection (bounding boxing)***
- Text Recognition



Bounding Box Detection for Text

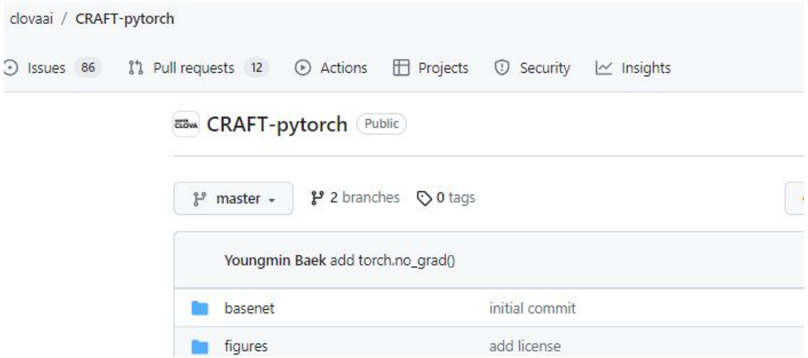
The objective is to identify and outline regions in an image that contain text. An incomplete overview of methods:

Classical Methods	NN Methods/Deep Learning
Morphological Operations are most effective for images with clear contrast between text and background (thresholding + dilation e.g)	**EAST** (Efficient and Accurate Scene Text Detector)
Connected Component Analysis (thresholding first). Suitable for simple scenarios where text regions are distinctly separate	**CRAFT** (Character-Region Awareness For Text detection)
Maximally Stable Extremal Regions: detects areas in images where pixel intensities are consistent. Suitable for scene text detection.	**SSD** (Single Shot MultiBox Detector)
	Faster R-CNN (Region-CNN, Fast R-CNN, Faster R-CNN)

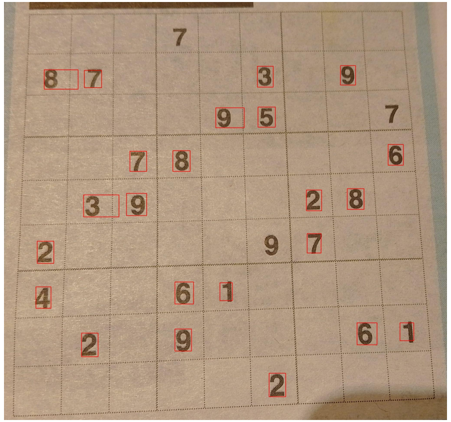


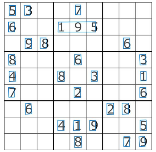
Bounding Box Detection for Text

CRAFT- pytorch:



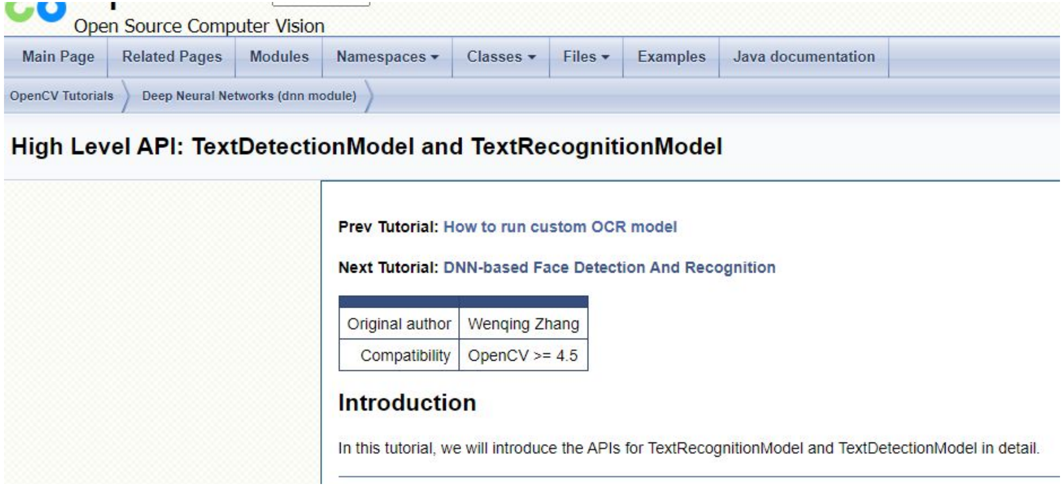
- Manually download the trained NN file
- Can run on a CPU
- **python test.py** --trained_model=dwnlds\craft_mlt_25k.pth --test_folder=...newspaper_lokalavisenfavrskov **--cuda=False**





Bounding Box Detection for Text

EAST (Efficient accurate scene text detector) is supported by OpenCV, but does not work well on my Sudoku images



Open Source Computer Vision

Main Page | Related Pages | Modules | Namespaces ▾ | Classes ▾ | Files ▾ | Examples | Java documentation

OpenCV Tutorials 〉 Deep Neural Networks (dnn module) 〉

High Level API: TextDetectionModel and TextRecognitionModel

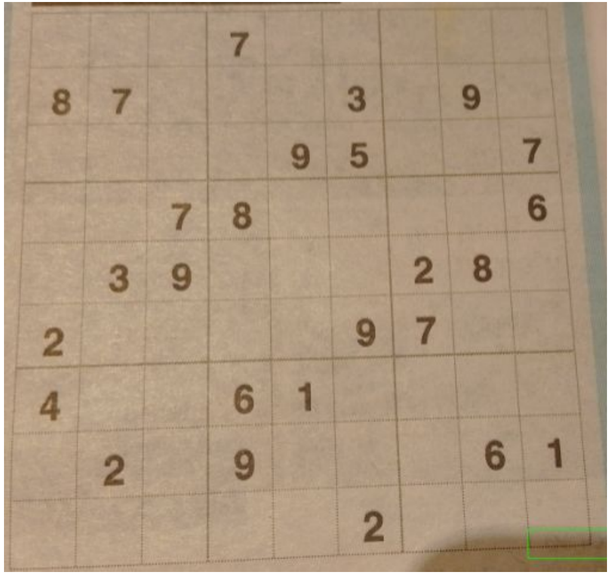
Prev Tutorial: How to run custom OCR model

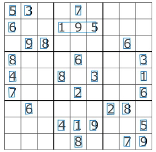
Next Tutorial: DNN-based Face Detection And Recognition

Original author	Wenqing Zhang
Compatibility	OpenCV >= 4.5

Introduction

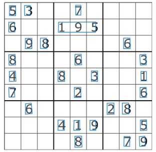
In this tutorial, we will introduce the APIs for TextRecognitionModel and TextDetectionModel in detail.





OCR in Python: Pipeline for Today

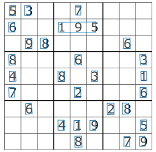
- Image Processing
- Text Detection (bounding boxing)
- ***Text Recognition***



Text Recognition

Incomplete overview of methods for text recognition, with focus on single digit recognition:

Rule based matching	Deep Learning
Template Matching - uses comparison of the image with a predefined template of each character. Works well when font and size are known and consistent, doesn't not handle well variability in fonts, sizes, and distortions.	**CNN** - LeNet-5, proposed by Yann LeCun in the late 1990s, is one of the early CNNs used for digit recognition. Modern architectures like AlexNet, VGG, and ResNet have also been adapted for OCR tasks.
Feature Extraction of like Zoning, Histograms, Profiles, and Geometrical moments, from characters and uses these features for classification. Can handle some variability in fonts and sizes, but it sensitive to distortions, noise, and requires good segmentation.	**Tesseract OCR**: An open-source OCR engine originally developed by HP and now supported by Google. Over time, its architecture has evolved, and the latest versions use LSTM-based methods. It is still continuously improved. Although powerful, it might not be the best for all specific use cases, and fine-tuning might be required
Boundary Analysis - analysis of the boundary or contour of the digit and extraction of features such as curvature, inflection points, and corners can provide clues about the digit's identity.	.**OpenCV Text Recognition** supports loading of neural networks and has a couple of options available documented https://docs.opencv.org/4.x/d4/d43/tutorial_dnn_text_spotting.html https://docs.opencv.org/4.x/d9/d1e/tutorial_dnn_OCR.html

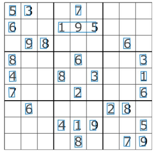


Neural Networks

```
                                                      +----------------------+
+-------------------+                                 | Input (specific      |
| Training Dataset |                                  | format e.g., image)  |
+-------------------+                                 +----------------------+
         |                                                       |
         V                                                       V
+-------------------+      +-------------------+       +---------------------+
|  Neural Network   | ==>  | Training          | ==>   | Trained Model       |
|  (Architecture)   |      | Procedure/        |       | (Stored in various  |
+-------------------+      | Algorithm         |       |  formats: pb,       |
                           | (e.g., SGD)       |       |  onnx, h5, etc.)    |
                           +-------------------+       +---------------------+
                                                                 |
                                                                 V
                                                      +----------------------+
                                                      | Output (Prediction/  |
                                                      | Classification, etc.)|
                                                      +----------------------+
```

When using a Trained Model it is first important for the final performance to know:

- input format and recommended requirements
- full output format (includes scores and details about the result)
- its own format and available run-time options (e.g. CPU/CUDA)
- know as much as possible about its pedigree (training dataset, architecture,etc)

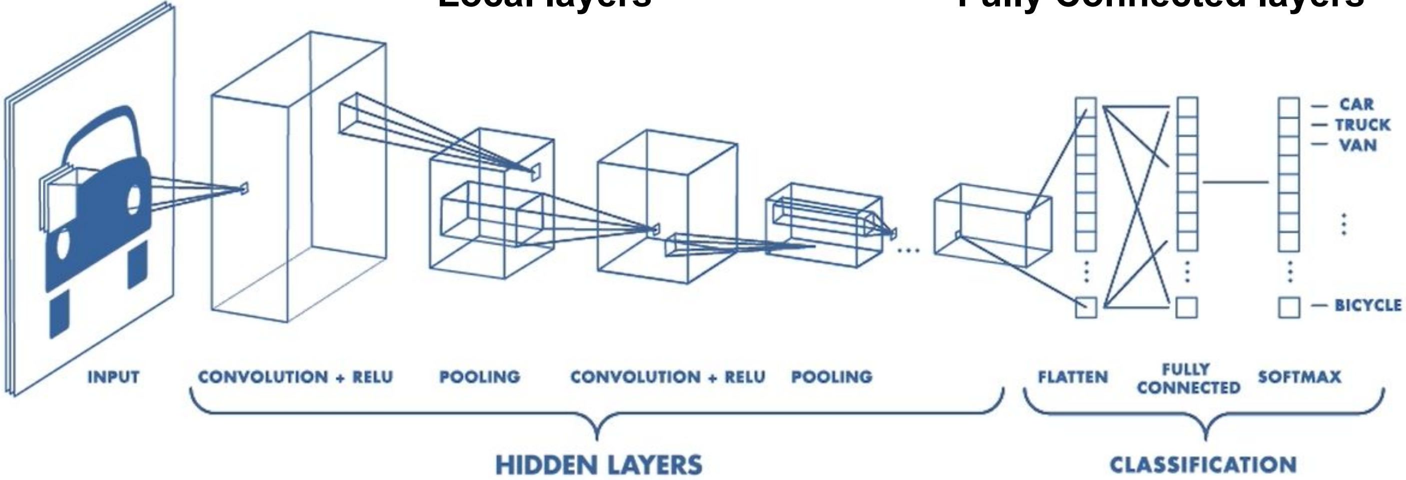


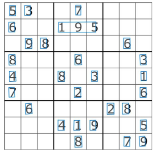
Convolutional Neural Networks

CNN are the most popular type for image processing tasks. CNNs utilize layers of convolutional filters that can learn spatial hierarchies of features. CNNs have been used extensively for tasks such as image classification, object detection, and segmentation. Examples of CNN architectures: LeNet, VGG-16, ResNet, Inception, and MobileNet.

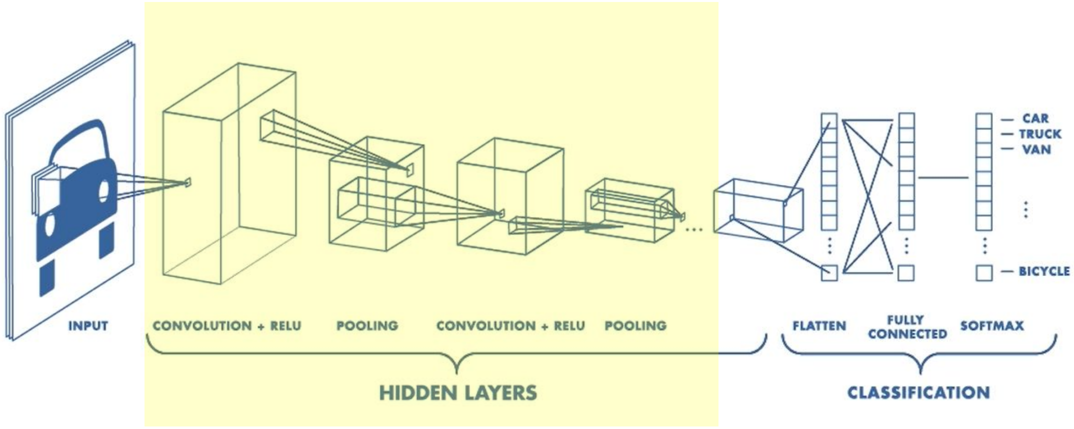
https://se.mathworks.com/videos/introduction-to-deep-learning-what-are-convolutional-neural-networks--1489512765771.html

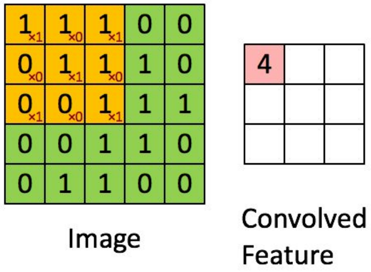
Local layers **Fully Connected layers**





Convolutional Neural Networks

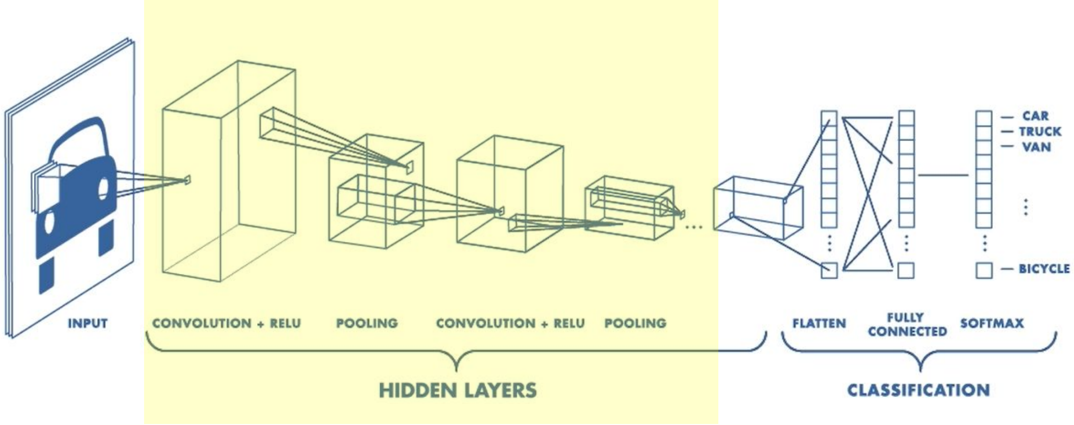




- Learnable filter/kernels are applied to each data band, just like a typical convolution operation, resulting in a stack of feature /convolution maps.
- Filters/Kernels are again typically small in width and height, and typically square
- The training will optimize the filter/kernel values
- The image is multiplied by the number of kernels/filters, the filter sliding step can reduce the size of the image slice, padding parameters, band of data depth multiplies again the number of slices

https://pyimagesearch.com/2021/05/14/convolutional-neural-networks-cnns-and-layer-types/

Convolutional Neural Networks



Input

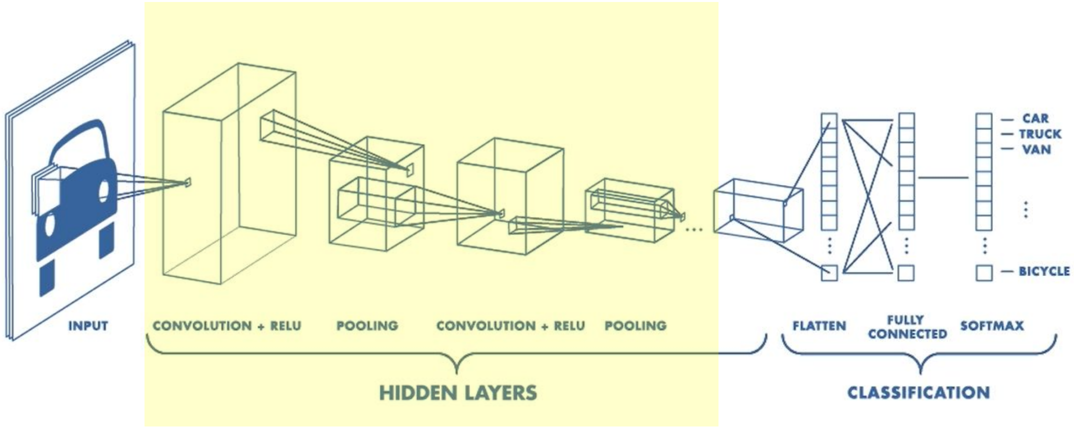
-249	-91	-37
250	-134	101
27	61	-153

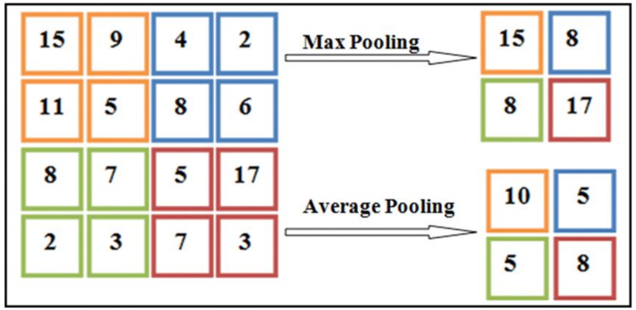
ReLU

0	0	0
250	0	101
27	61	0

- The filters/kernels weights can be both positive and negative. Depending on the region of the image and the values of the filter, the convolution can produce negative. This is perfectly normal and expected.
- By applying the ReLU activation, we effectively discard these negative activations, setting them to zero, which can simplify the learning process and lead to more robust features.
- Output is also called Activation Maps

Convolutional Neural Networks

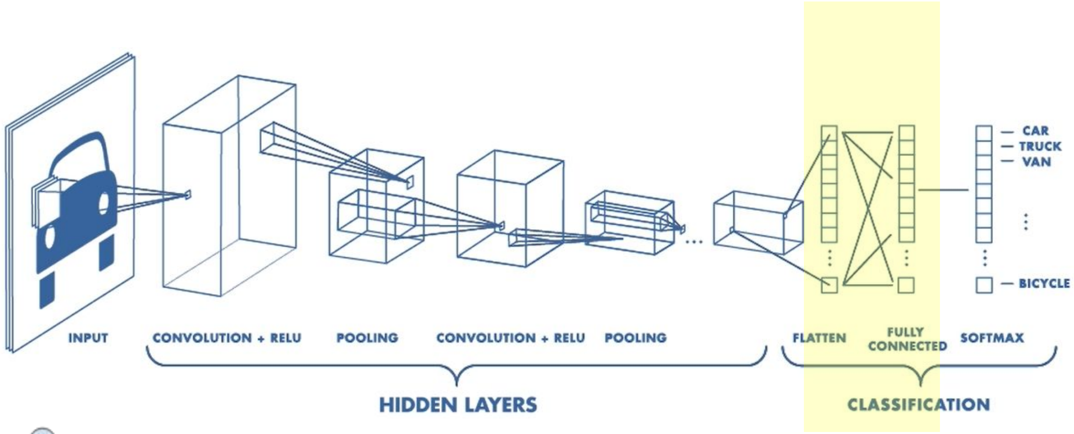


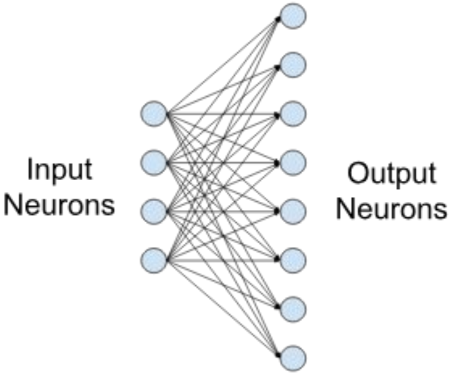


- The pooling operation involves a fixed 2D filter over each channel of feature map and summarising the features lying within the region covered by the filter in a single number

- Pooling layers are used to reduce the dimensions of the feature maps. Thus, it reduces the number of parameters to learn and the amount of computation performed in the network. The pooling layer summarises the features present in a region of the feature map generated by a convolution layer

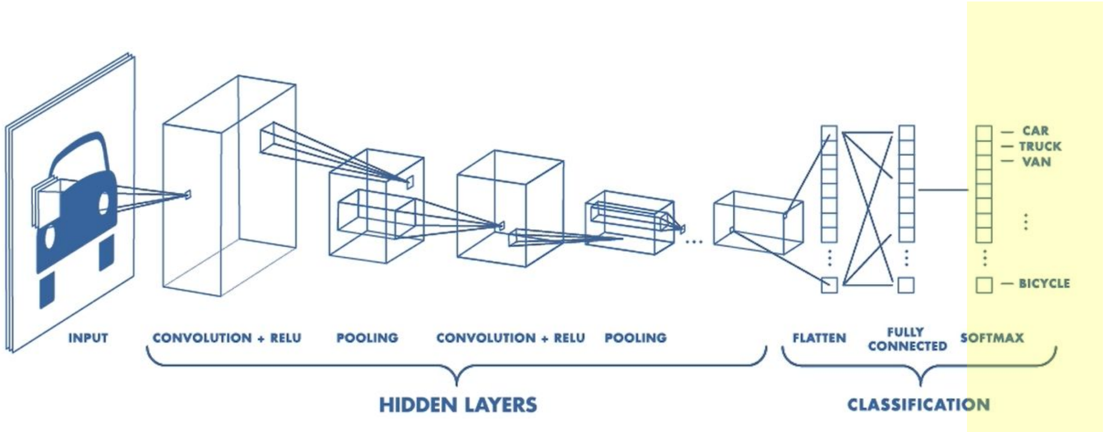
Convolutional Neural Networks

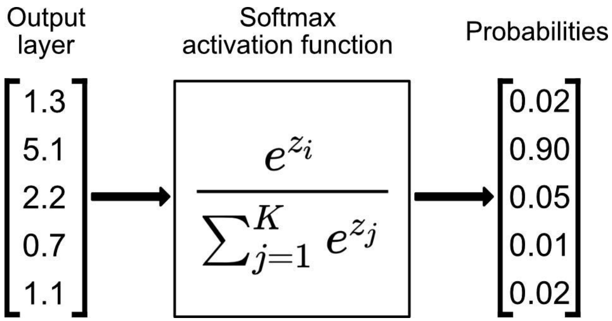




- CNN contains also at least a couple of fully connected layers, therefore “flattening” the stacking geometry of the convolutional layers
- Used to predict the class of the image based on the features extracted in previous stages

Convolutional Neural Networks



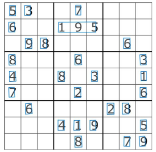


- Final classification output with a softmax function
- The softmax function is a mathematical function that maps a vector of K real numbers to a vector of K real numbers in the range (0, 1) that add up to 1. It is often used in the output layer of a neural network to produce a probability distribution over multiple classes.

Feature/ Activation Maps

https://machinelearningmastery.com/how-to-visualize-filters-and-feature-maps-in-convolutional-neural-networks/

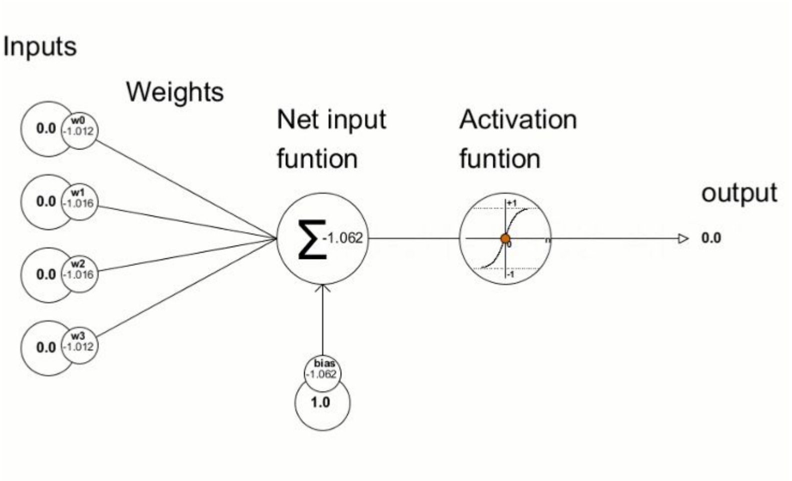
- The obtained feature maps and activation maps of the convolution layers are not usually/easily directly interpretable for humans

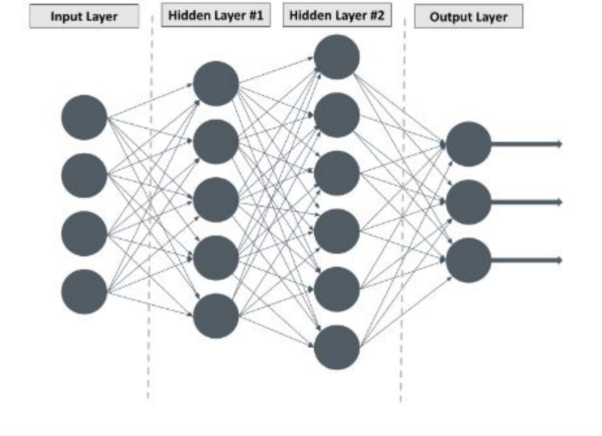


Convolutional Neural Networks

There is a full equivalence between a Classical NN layer and Conv layer: (https://www.arxiv-vanity.com/papers/1712.01252/)

- A classical NN layer consists of (fully connected) neurons (which are a inputs, a set of weights, and an activation function)
- The convolutional layers have **sparse connectivity** for the filter/kernel (which is a set of weights) - there is a **shared weights aspect** - and an activation function (e.g. RELU) and intrinsic 2D/3D geometric structure
- Convolutional operation can be converted to matrix multiplication, which has the same calculation way with fully connected layer.





The skeleton of a neural network