CPE 352 Data Science

6 – Signal and Image Data

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Topics

- Signal data
- Image data

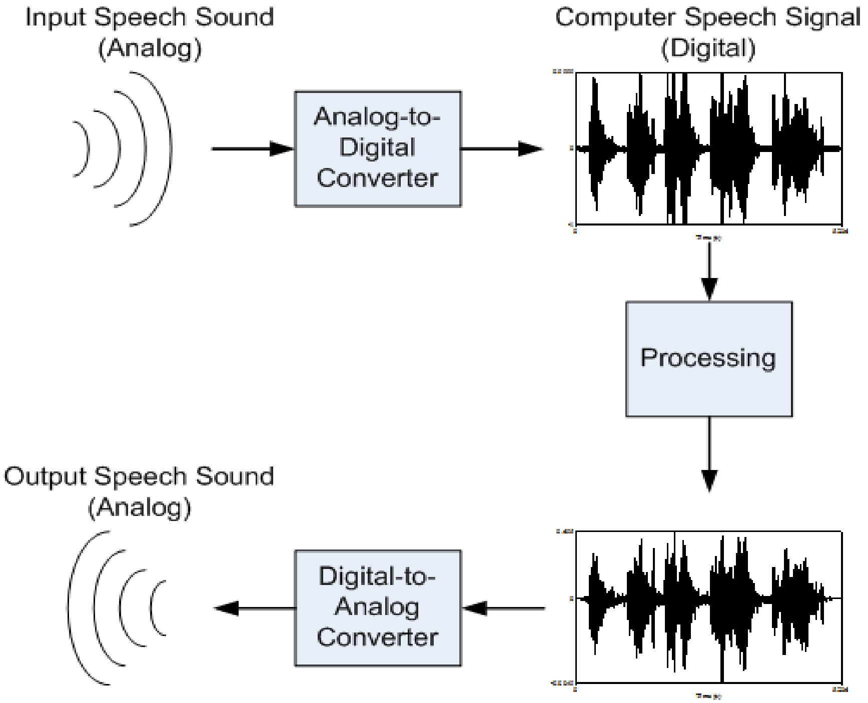
https://drive.google.com/file/d/1uo6d4JP8Fck_4UfDEqc0hKDsmzjh8mSN/view?usp=sharing

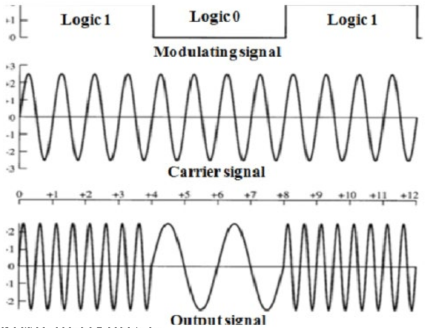
Signal Data

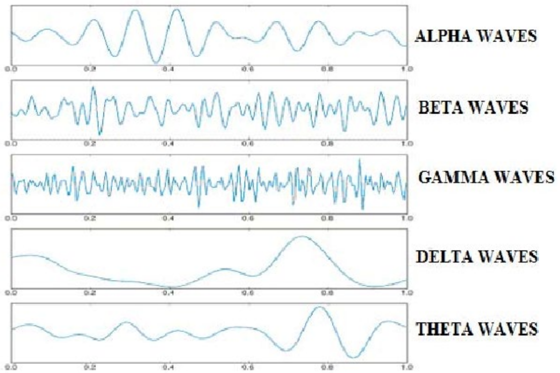
Part 1

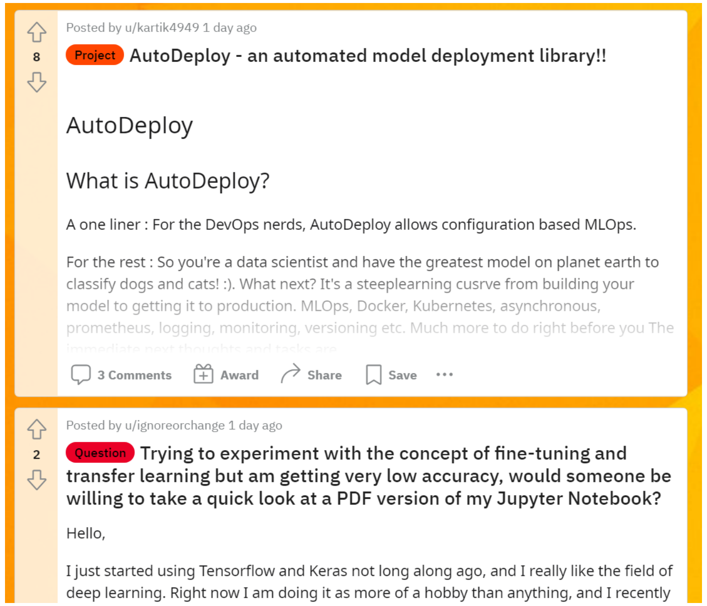
Signal Processing

- What are signals?
- A function or measurement that convey information



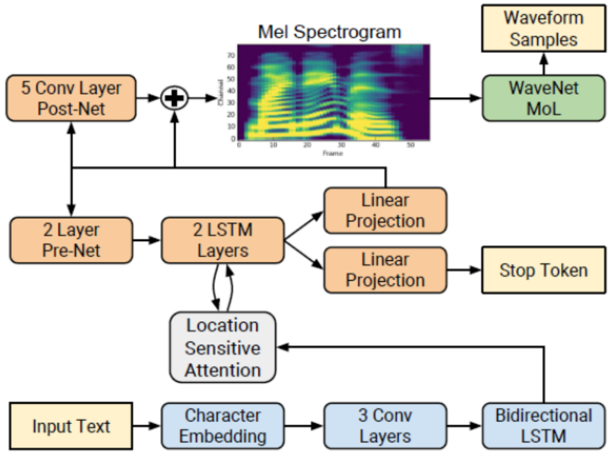




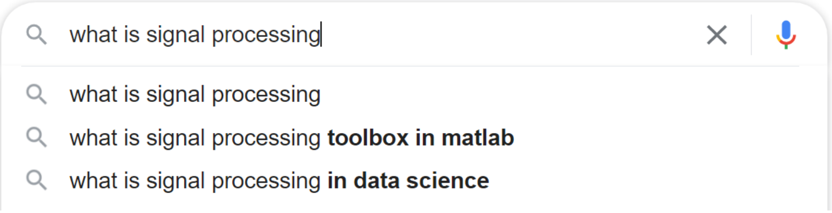


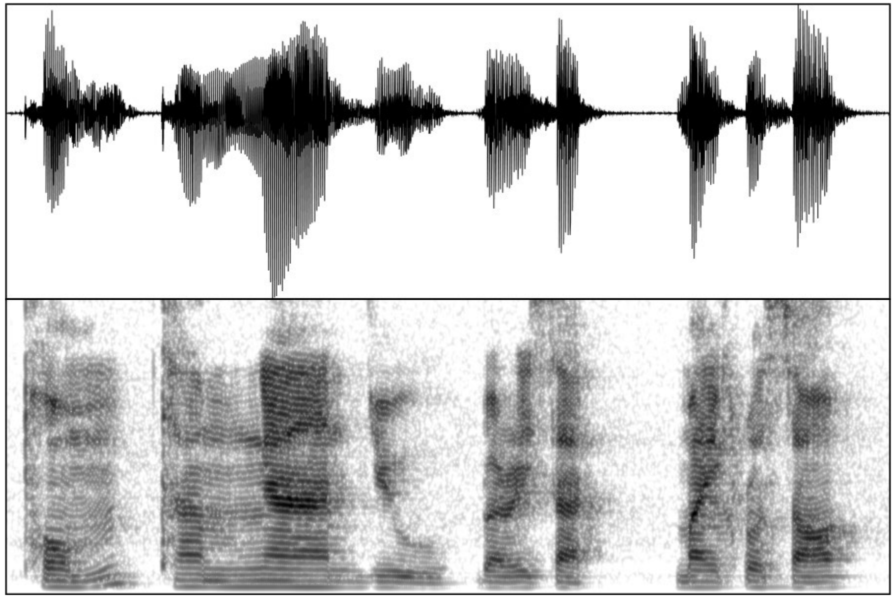
Signal Processing

- What is signal processing?



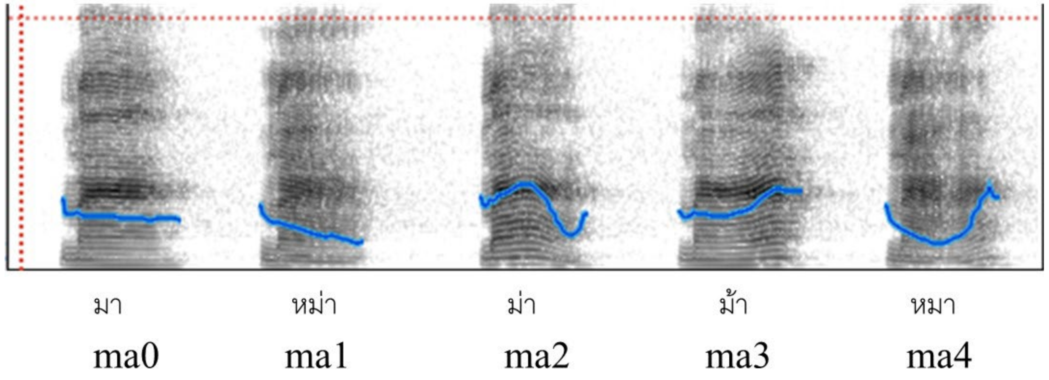
Google





Signal Processing

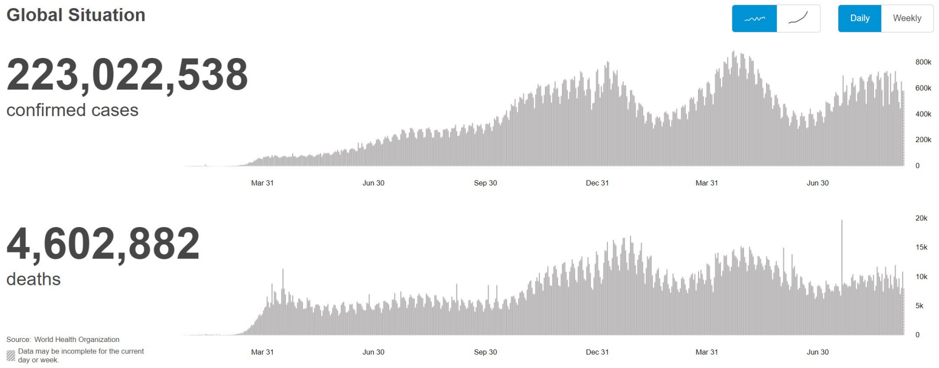
- Speech recognition with linguistic rules

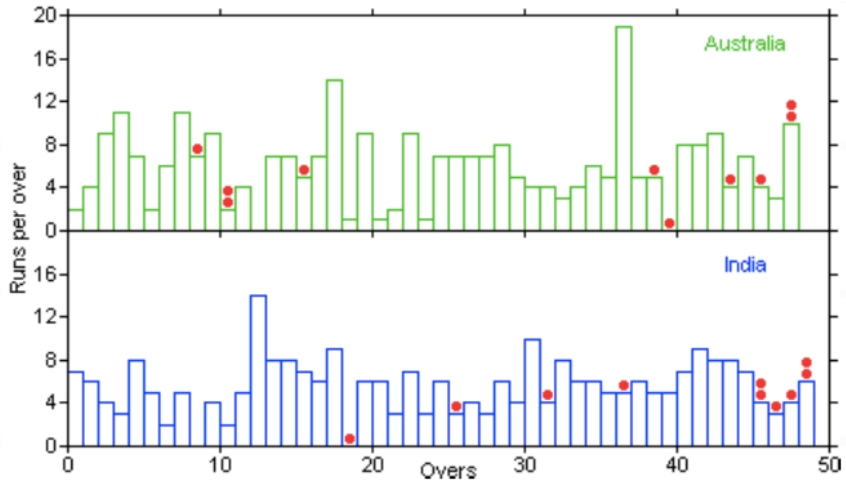


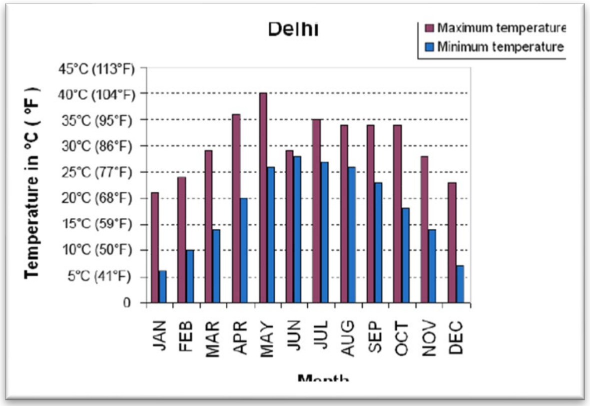
- Image segmentation / recognition

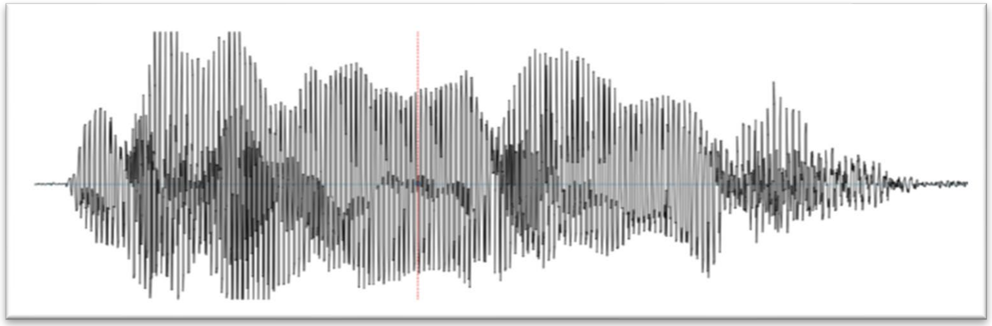
Time Series

- An ordered collection of numbers









Signals – Definition

- Signals are measurable quantities that convey information about phenomena and vary with independent variables (such as time)
- The term signal includes, among others,
  - Electrical – e.g. voltage/current measurements
  - Acoustical – e.g. speech from microphone
  - Visual – e.g. digital camera photo
  - Radio – e.g. WiFi
  - Geophysical – e.g. GPS measurement
  - Biological– e.g protein, genome, blood sugar
  - Etc.

Signal Representation

- Signals are represented as functions of one or more independent variables
- The independent variable can be continuous time, discrete time index, x-y location, etc.
- This course will focus mostly on signals with time (t, n) as independent variables.
- Mathematically, we denote a signal using a symbol and a parenthesis with an independent variable inside

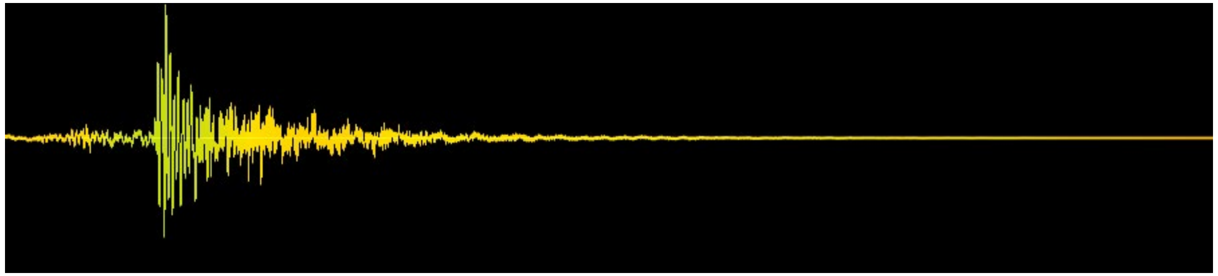
Continuous Time – CT $x(t)$ $y[n]$ Discrete Time – DT

Acoustical

Acoustical Signal
Quantity: Pressure
Information: Sound

Pressure
/Intensit
y

$x(t)$



Time

Geophysical

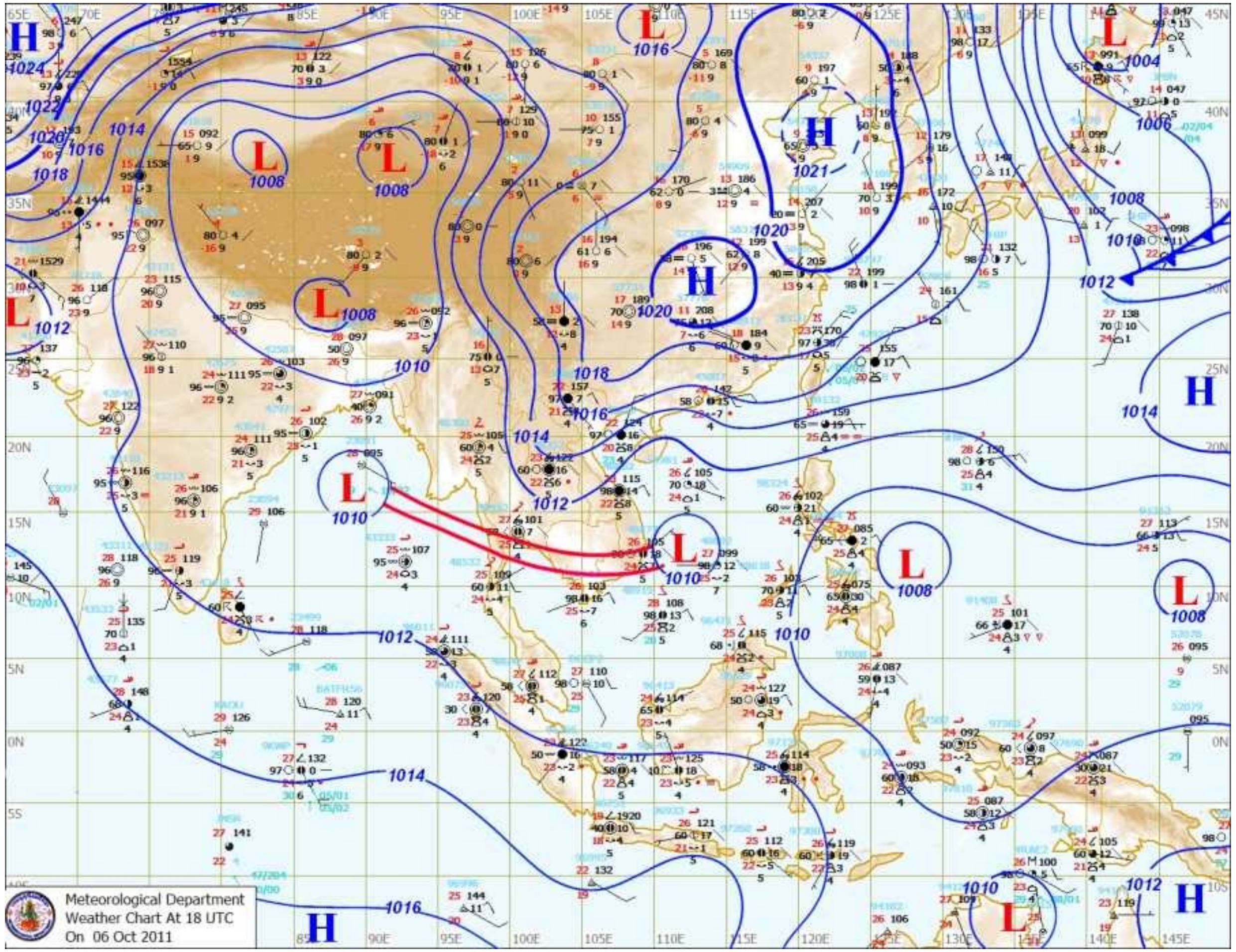
Atmospheric Pressure Signal

Quantity: Atmospheric Pressure

Information: Weather

Latitude

$p(x,y)$



Longitude

Thailand 2011 Devastating Flood

Visual

Visual Signal (Image)

Quantity:
Intensity (Light)

Information: Scenery,
Objects

y-coordinate

$I(x,y)$

x-coordinate

Finance

Finance Signal

Quantity: Stock value

Information: Company value

Price, $f(t)$

Time (t)

Facebook Stock Price

Signal Representation

We can describe signals using

- Functions
  - e.g. $x(t) = \sin(t)$
- Value (only for a discrete-time signal)
  - e.g. $x[n] = \{\ldots, 0, 0, \underset{\substack{\uparrow \\ n=0}}{1}, 4, 6, 0, 0, \ldots\}$
- Graph

Understanding graph of signals

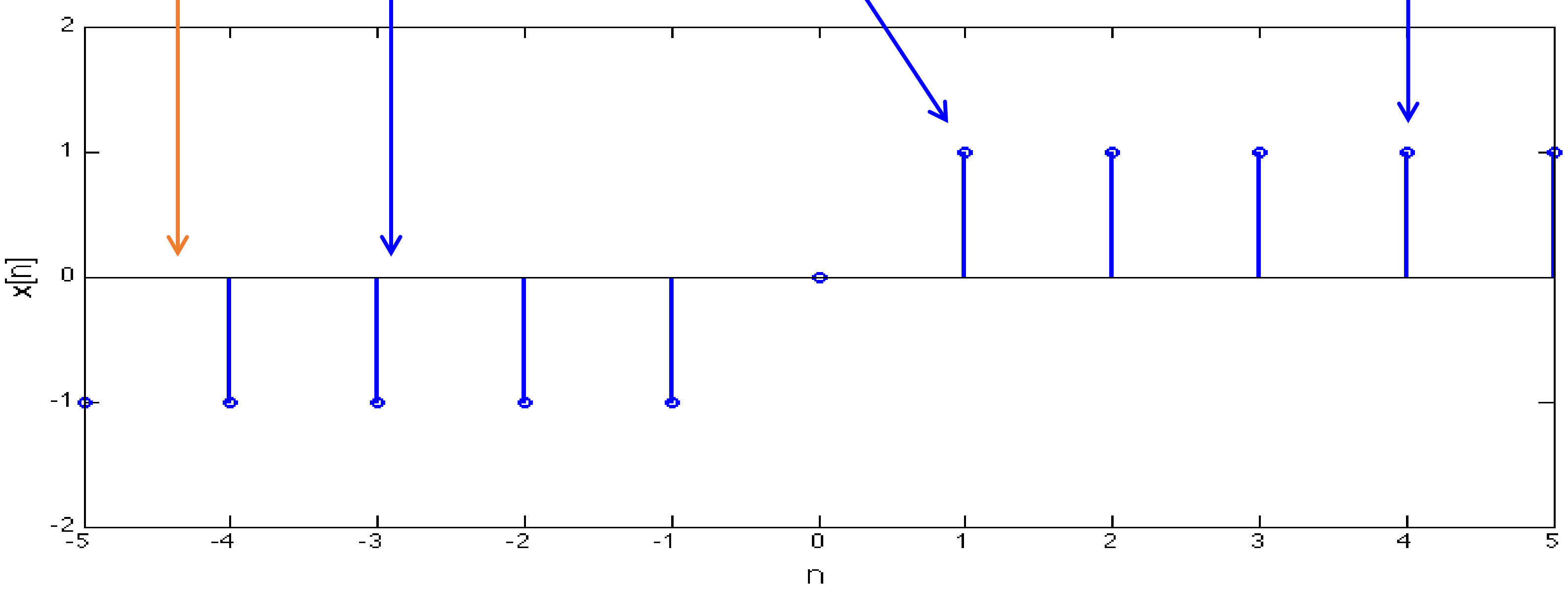
X-axis at x[n] = 0

Stem: signal values at each time points

x[-3]

x[1]

x[4]



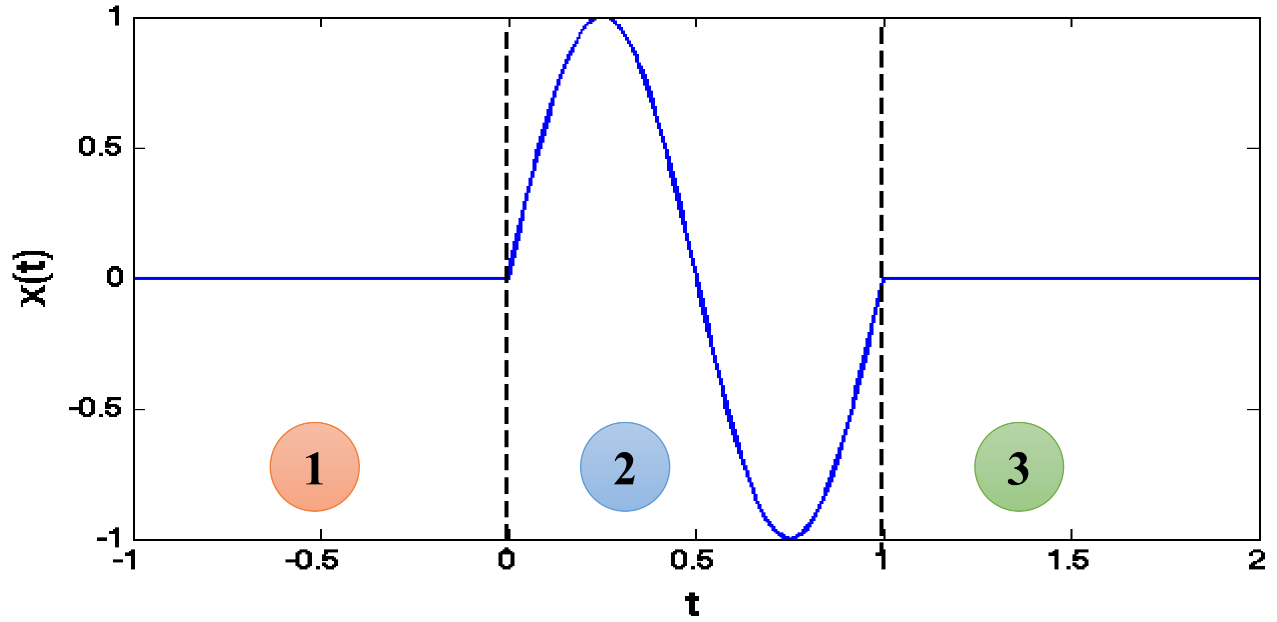
Y-axis: signal (x[n]) value axis

X-axis: time (independent variable) value axis

Signal as functions

$$x(t) = \begin{cases} 0, & t < 0 \\ \sin(2\pi t), & 0 < t < 1 \\ 0, & t > 1 \end{cases}$$

1
2
3



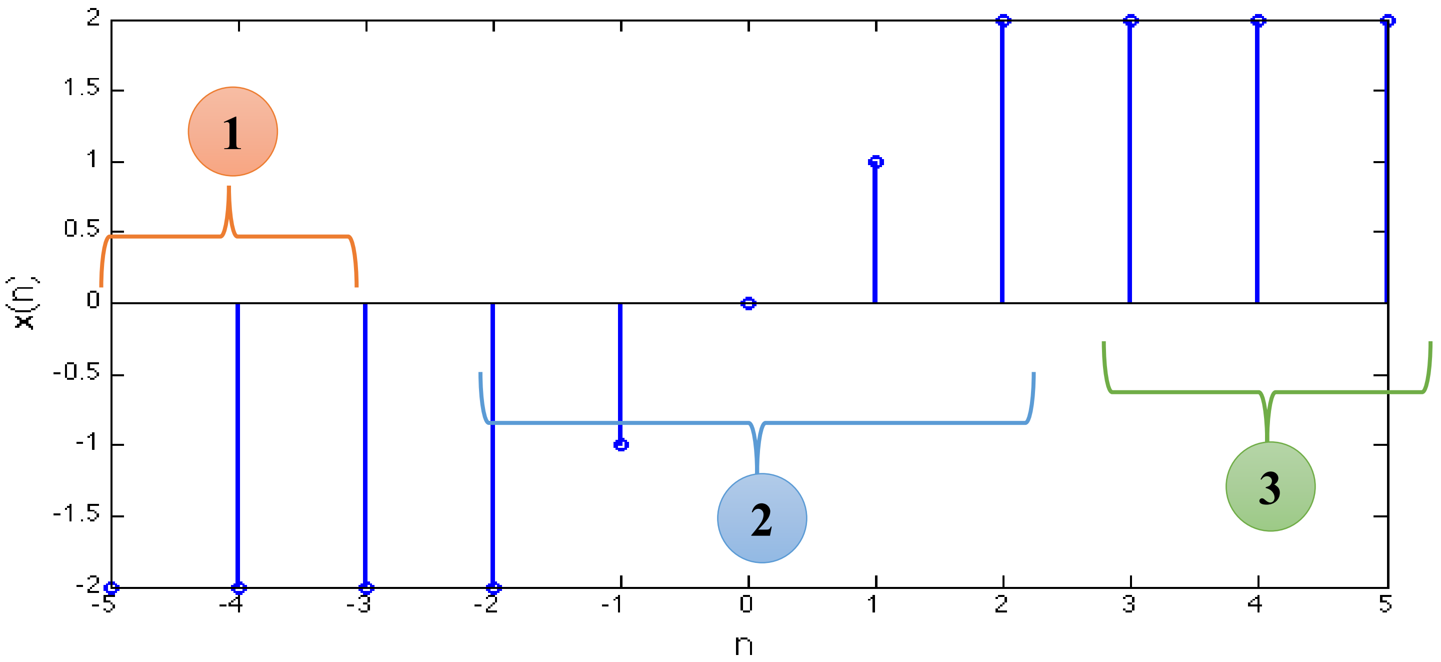
Signal as functions

$$x[n] = \begin{cases} -2, & n < -2 \\ n, & -2 \le n < 3 \\ 2, & n \ge 3 \end{cases}$$

1

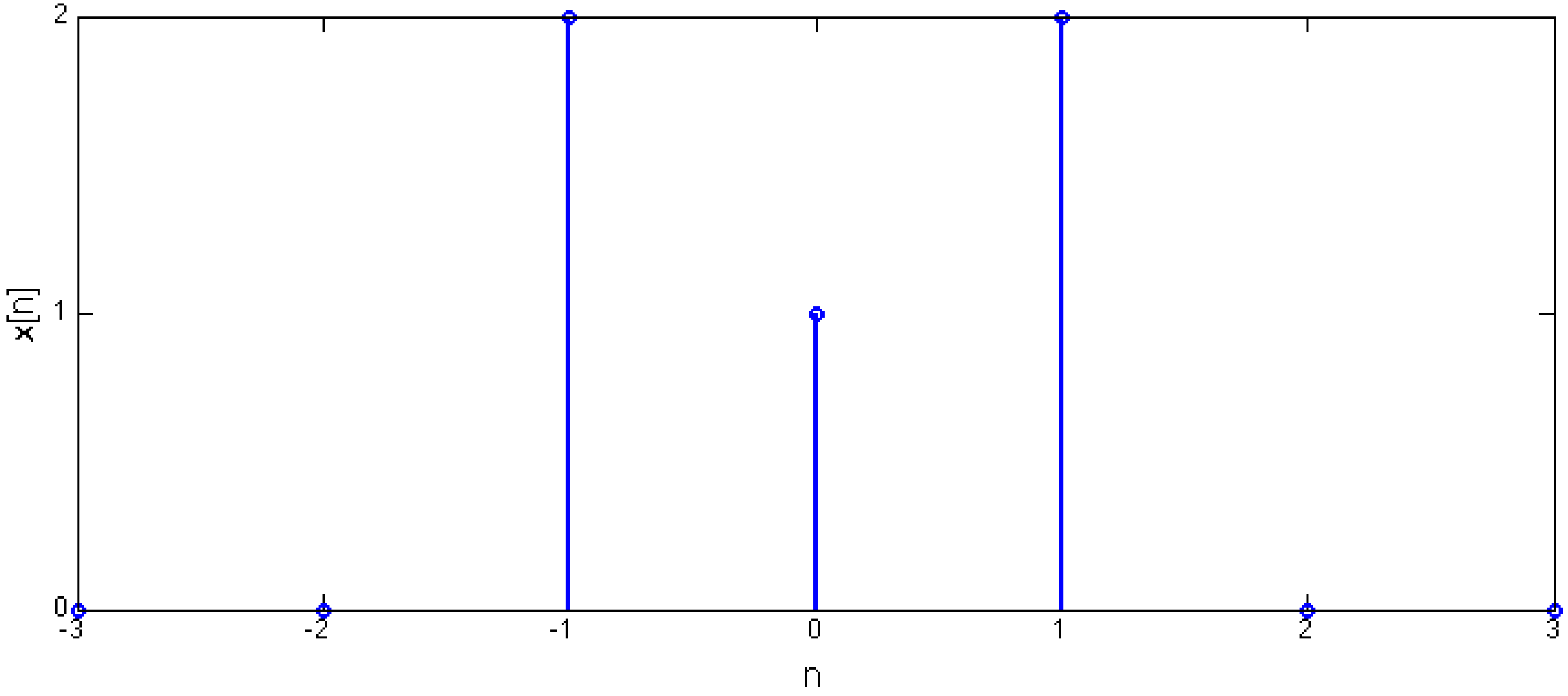
2

3



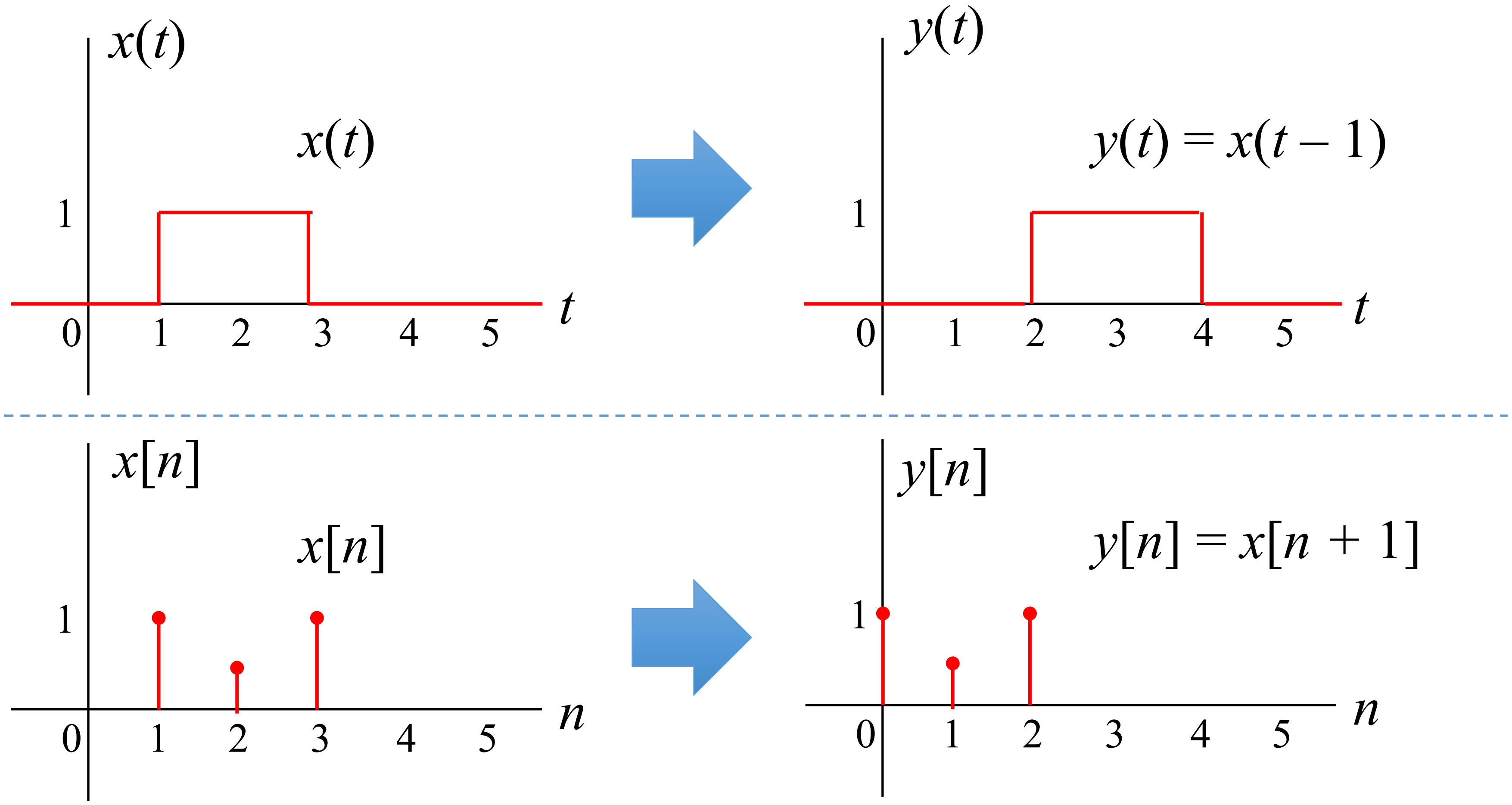
Signal as a sequence of values

$$x[n] = \{\ldots, 0, 2, \underset{\substack{\uparrow \\ n=0}}{1}, 2, 0, \ldots\}$$



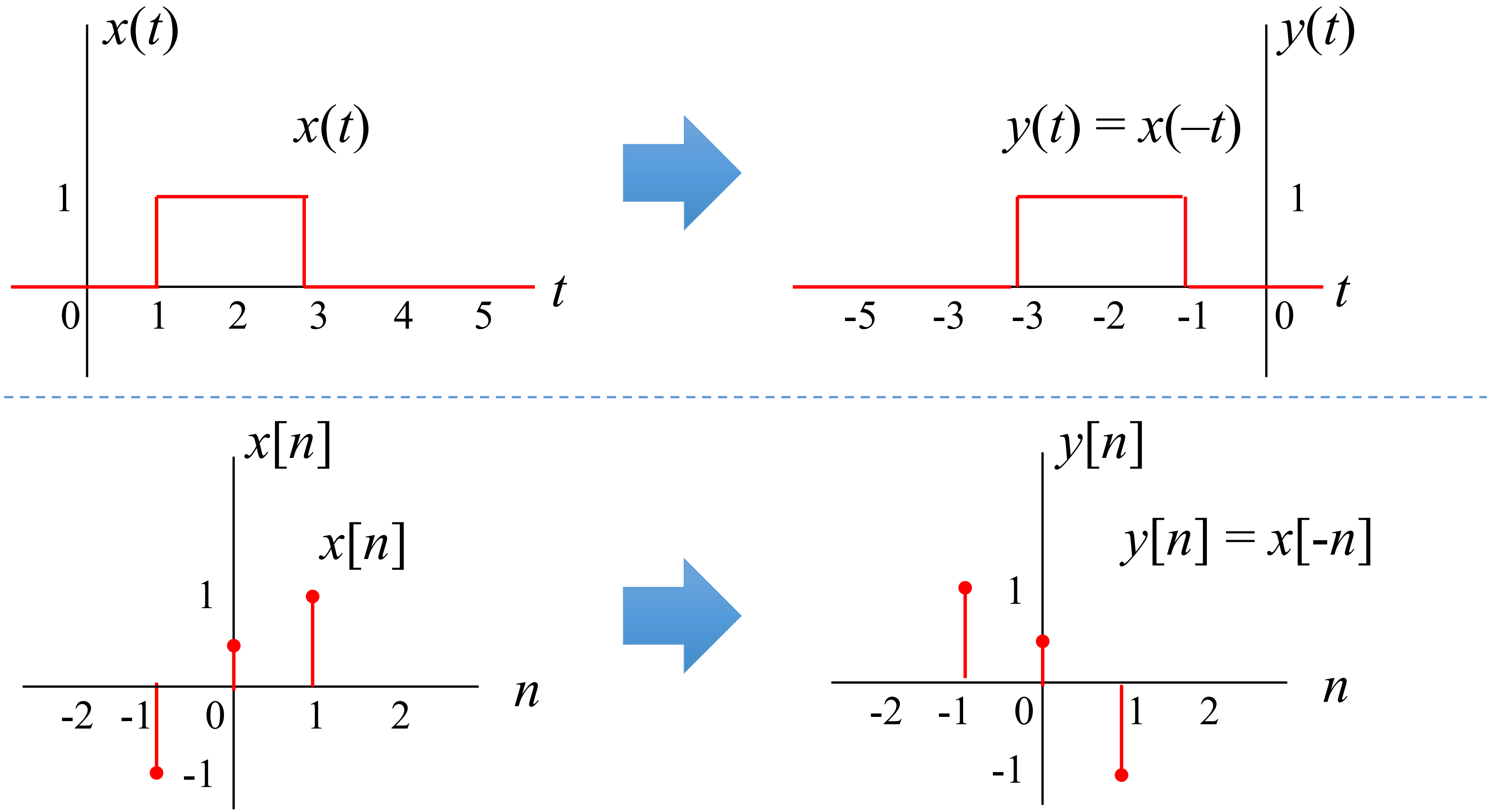
Transformation of the independent variable

Time Shift



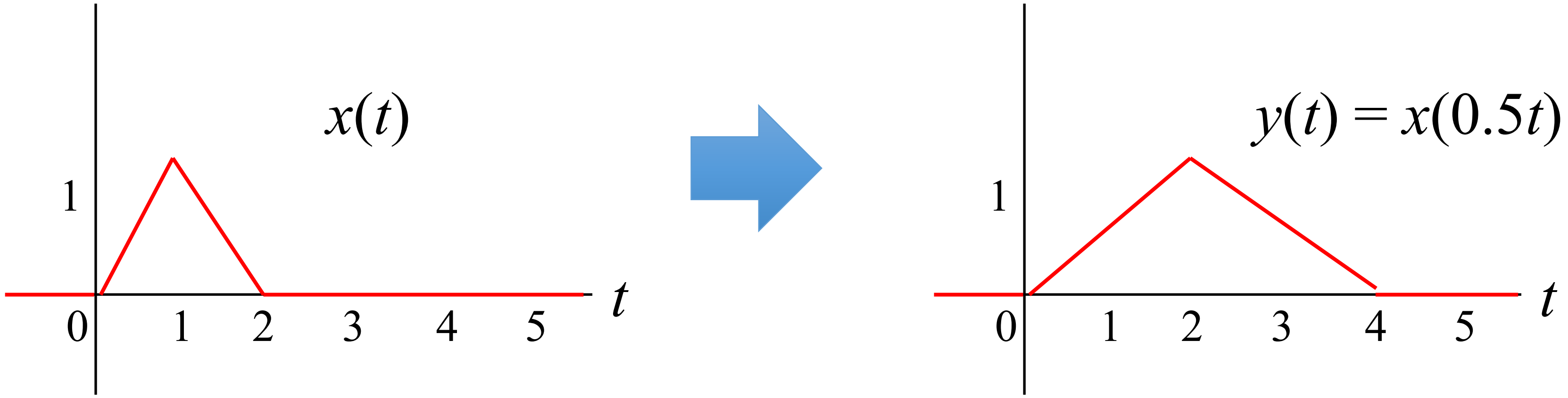
Transformation of the independent variable

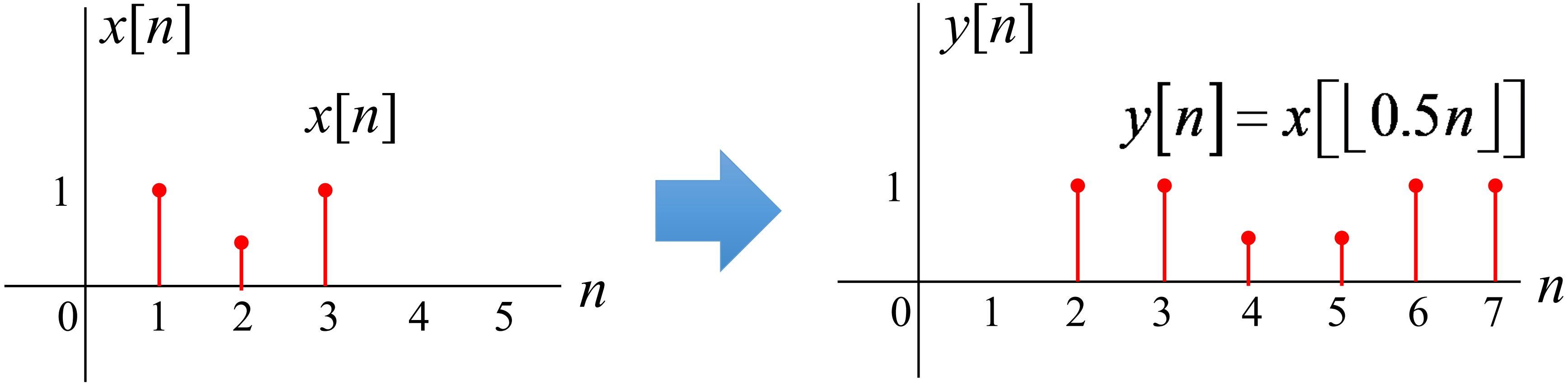
Time Reversal



Transformation of the independent variable

Time Scaling



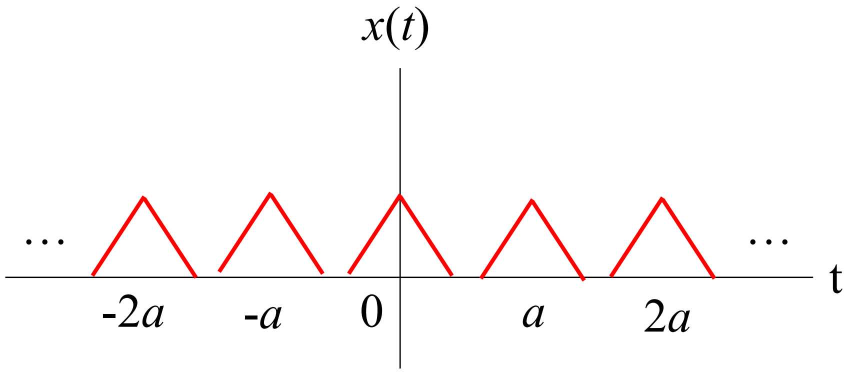


Transformation of the independent variable

Periodic Signals

CT: $x(t) = x(t+T)$

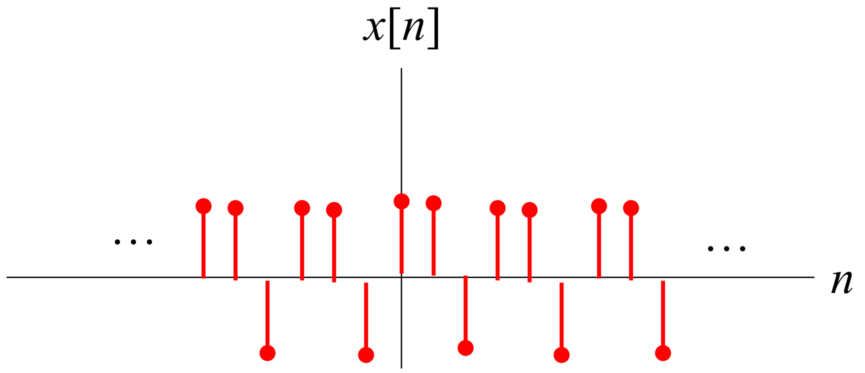
T_0 (fundamental period) is the smallest positive value of T that the above equation hold



$T_0 = a$

DT: $x[n] = x[n+N]$

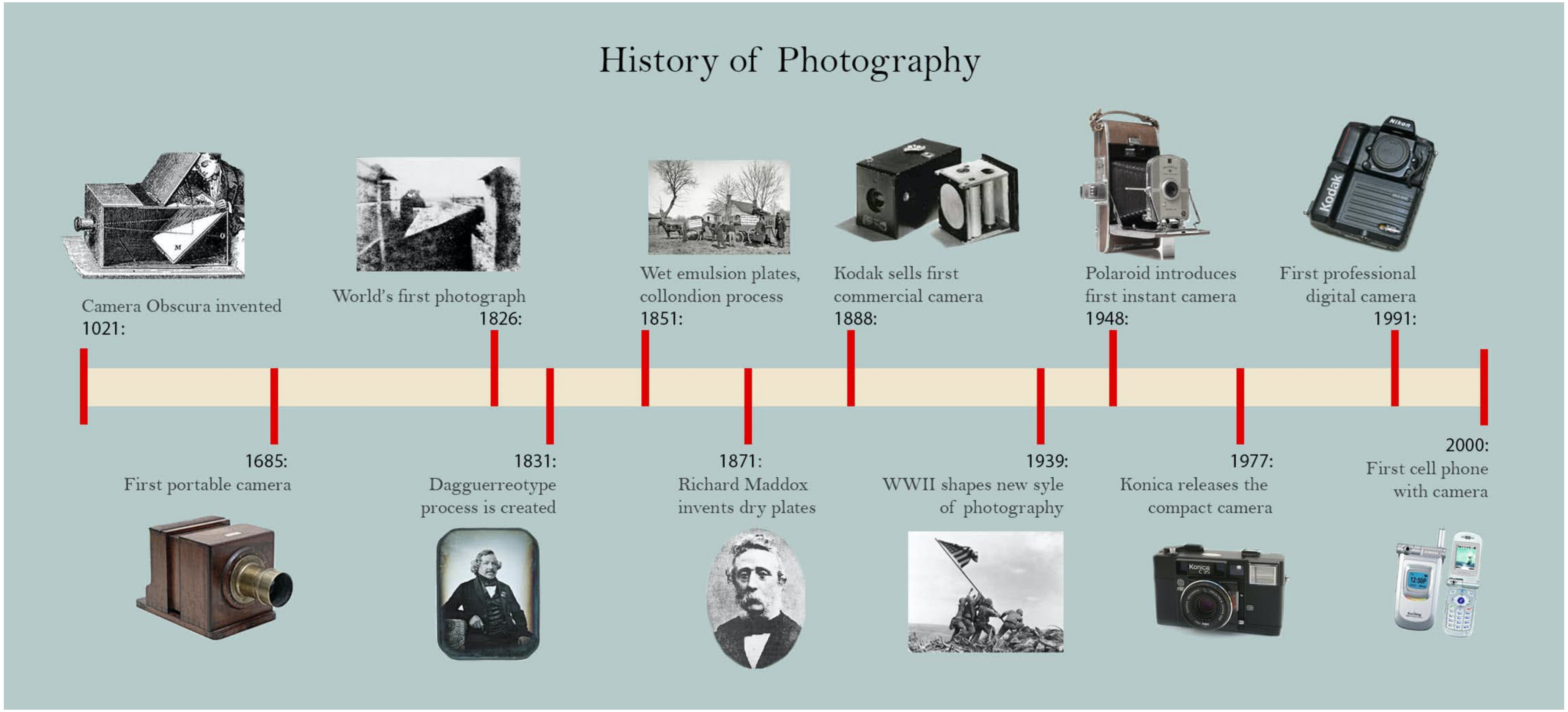
N_0 (fundamental period) is the smallest positive value of N that the above equation hold



$N_0 = 3$

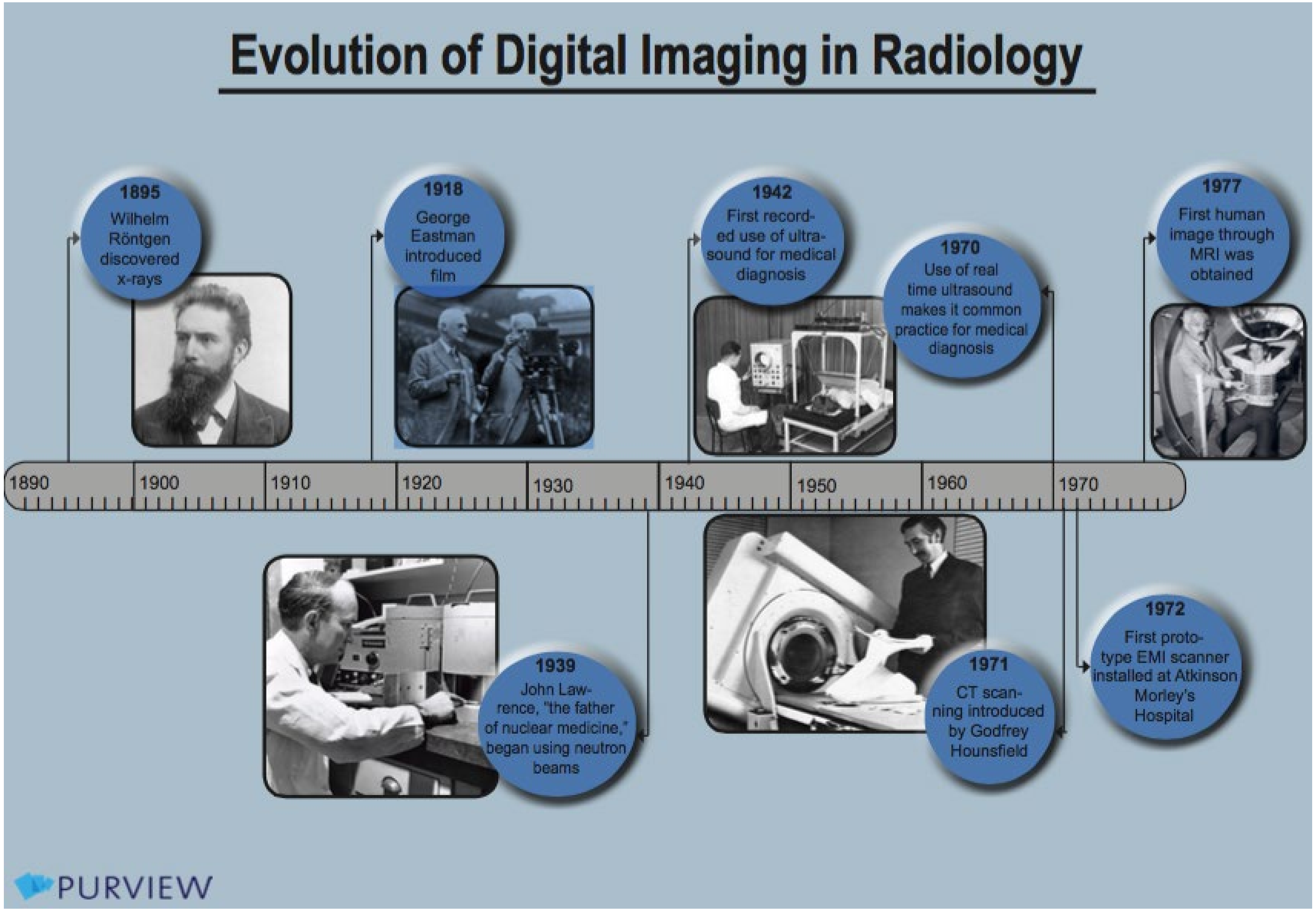
Image Data

Part 2



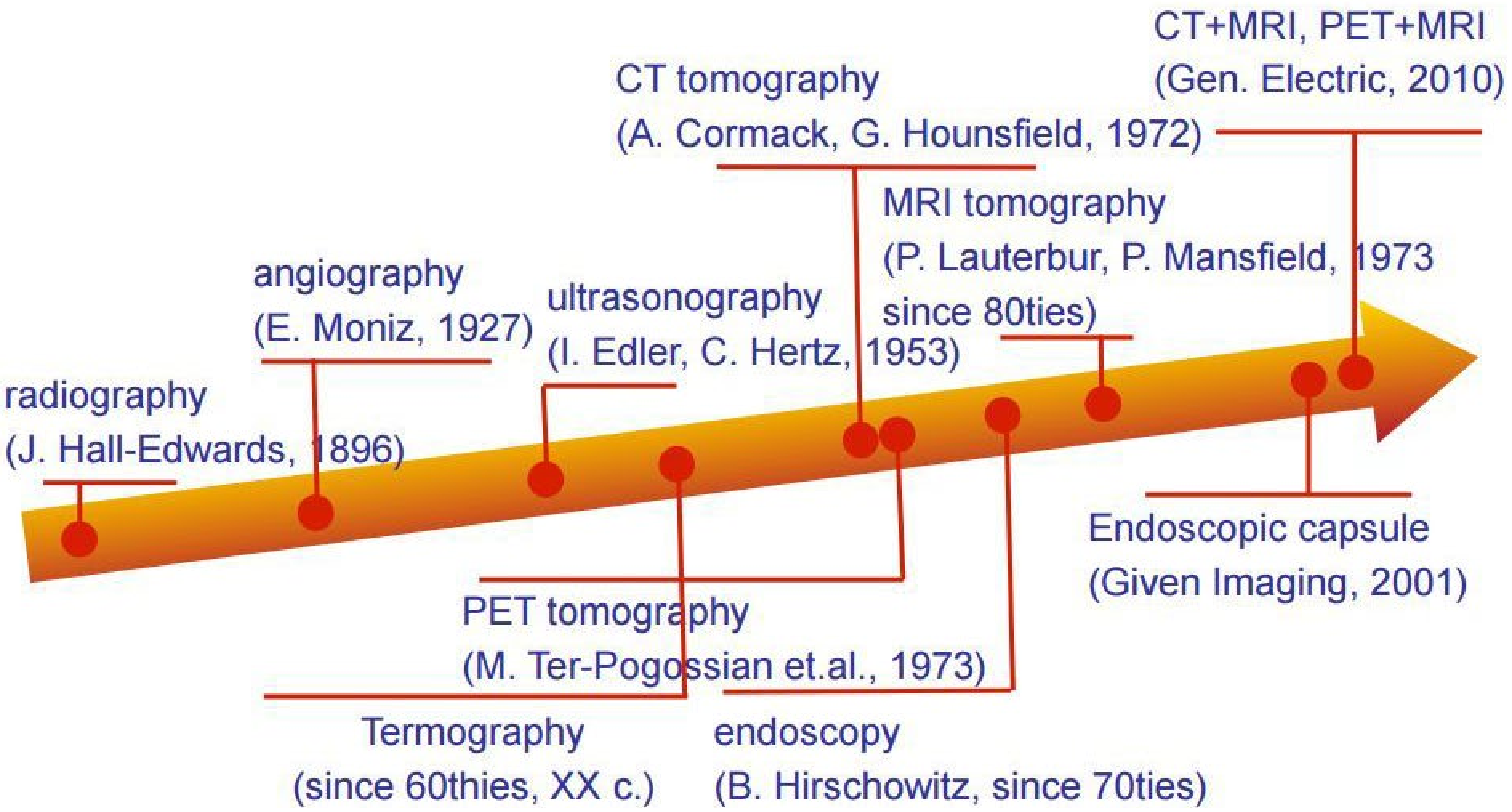
https://iceland-photo-tours.com/articles/landscape-and-nature-photography/a-brief-history-of-photography

https://www.sony.com/za/electronics/interchangeable-lens-cameras/ilce-7rm4a

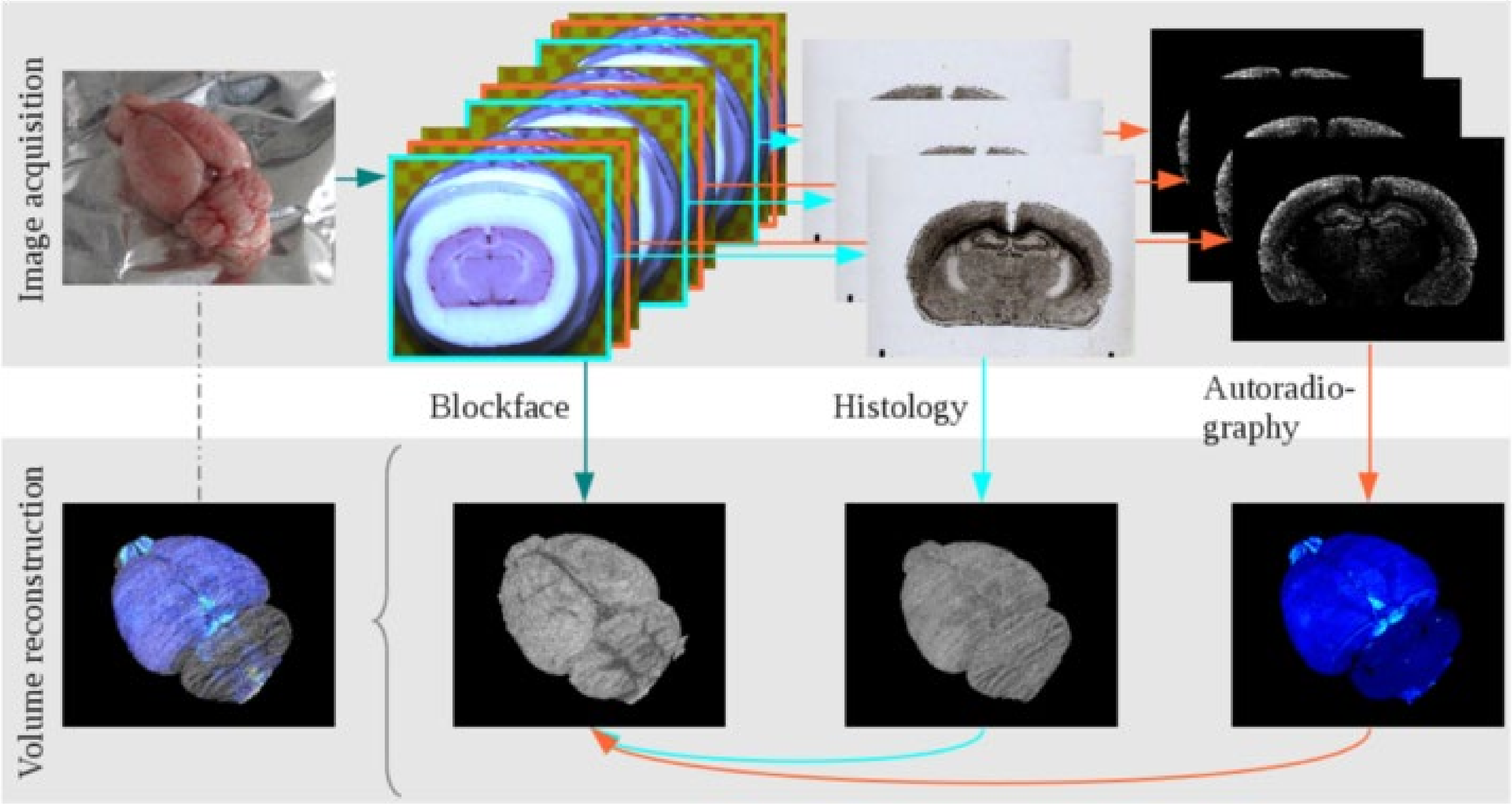


Mandal, Subhamoy. (2018). Visual Quality Enhancement in Optoacoustic Tomography: Methods in Multiscale Imaging and Image Processing.

History of Medical Imaging

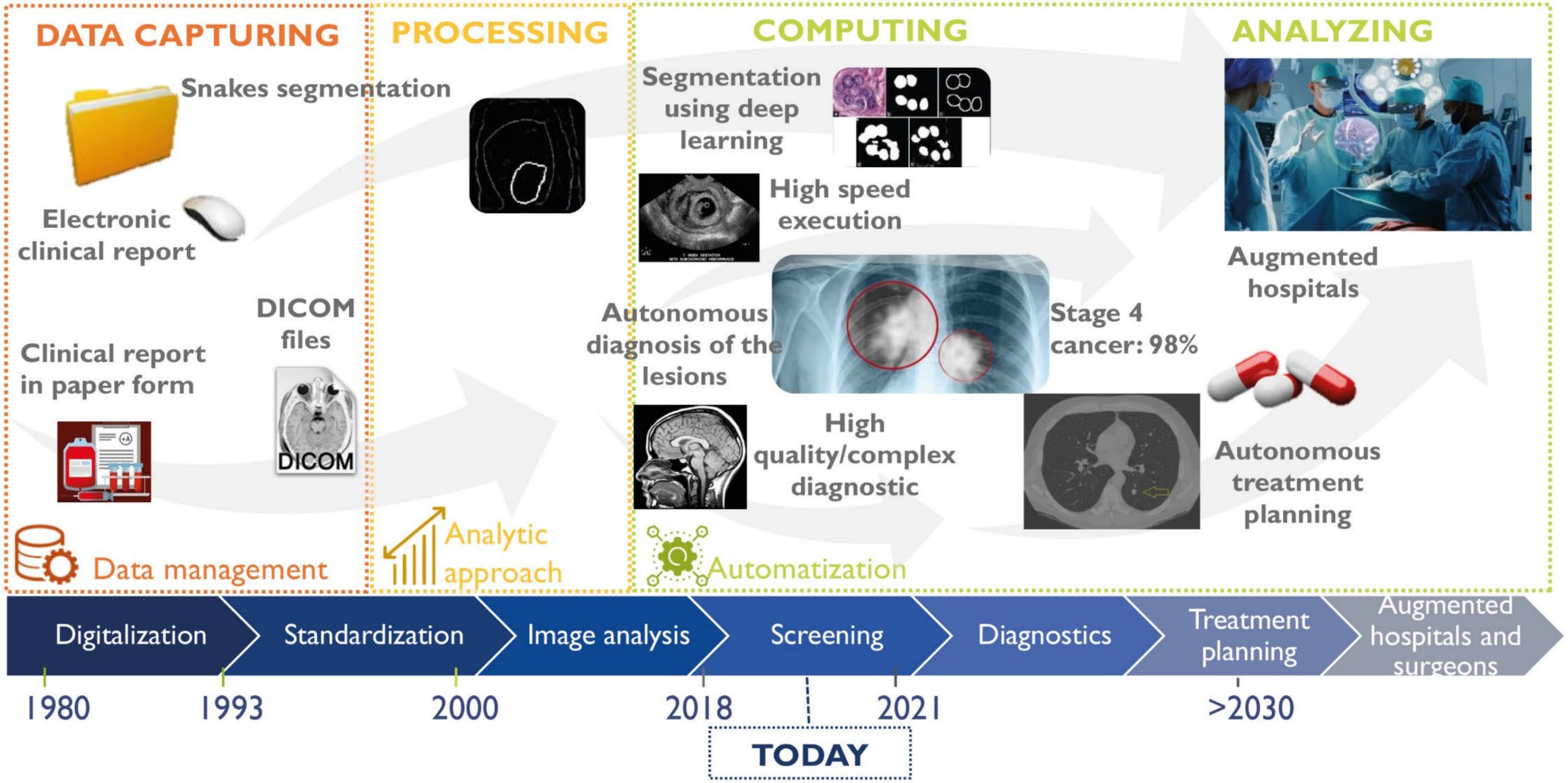


3D reconstruction



Schubert, Nicole & Axer, Markus & Schober, Martin & Huynh, Anh-Minh & Huysegoms, Marcel & Palomero-Gallagher, Nicola & Bjaalie, Jan & Leergaard, Trygve & Kirlangic, Mehmet & Amunts, Katrin & Zilles, Karl. (2016). 3D Reconstructed Cyto-, Muscarinic M2 Receptor, and Fiber Architecture of the Rat Brain Registered to the Waxholm Space Atlas. Frontiers in Neuroanatomy. 10. 10.3389/fnana.2016.00051.

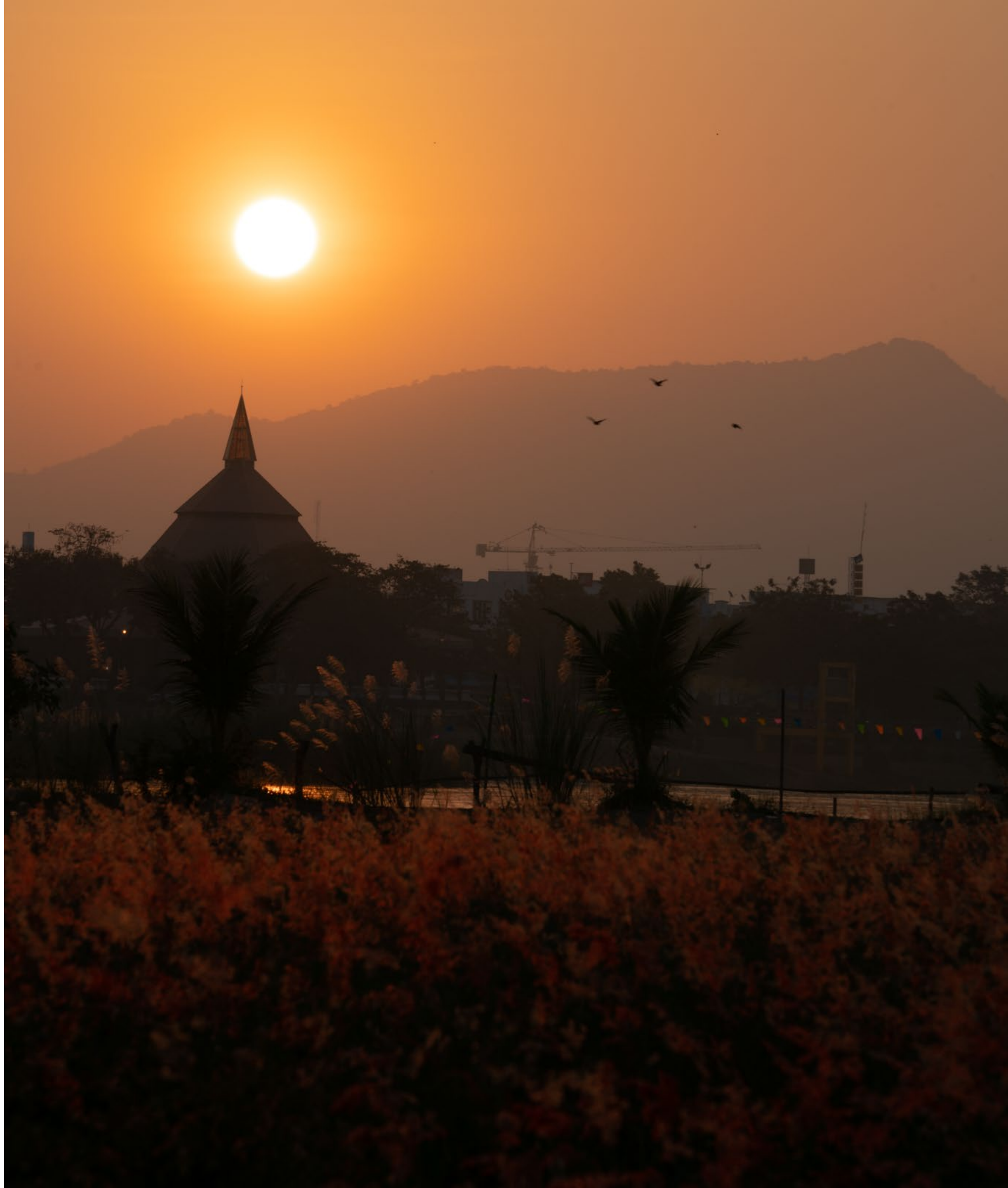
Automatic treatment planning



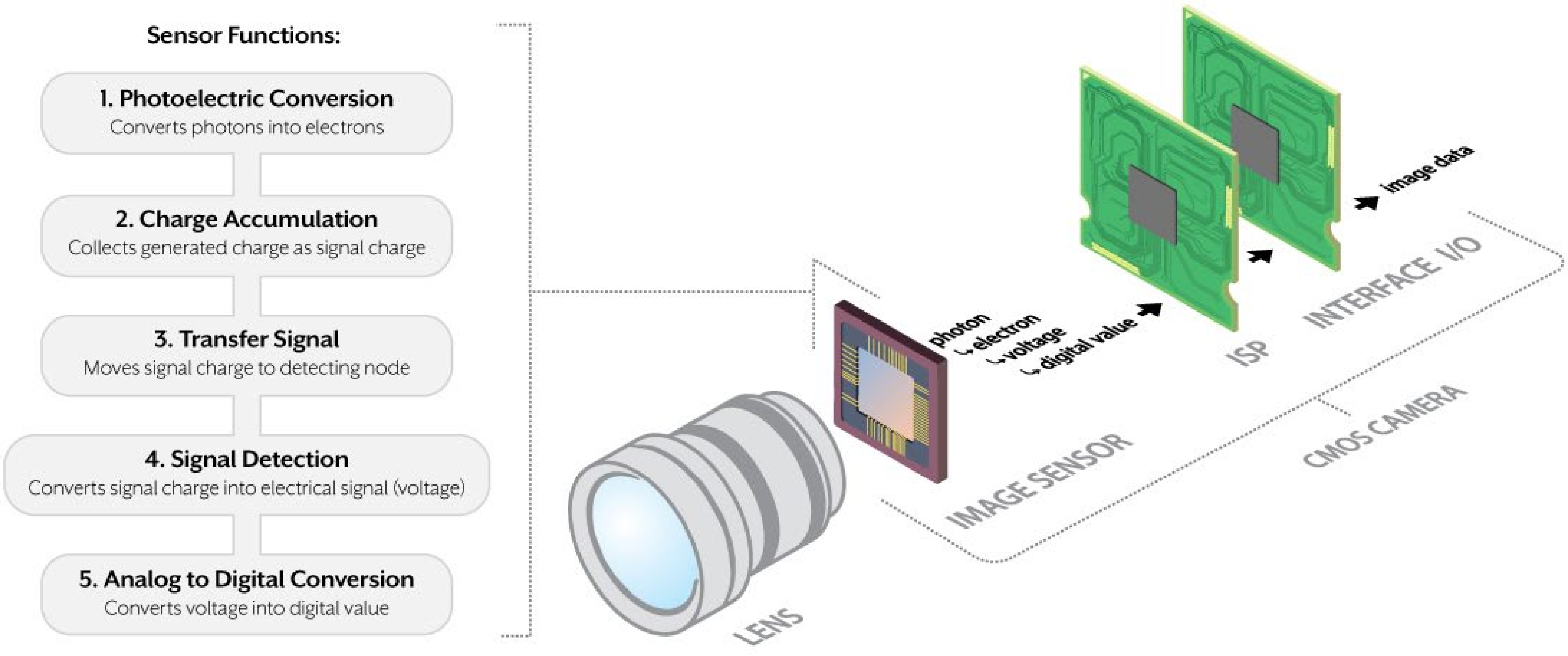
Src. Artificial Intelligence for Medical Imaging, 2020 report, Yole Development

Image

- **Image:** a visual representation in form of a function $f(x,y)$ where f is related to the brightness (or color) at point (x,y)
- Most images are defined over a rectangle
- Continuous in amplitude and space



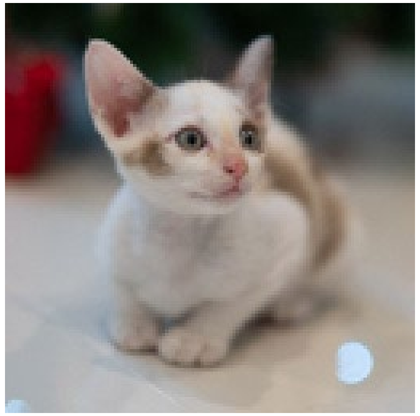
Imaging

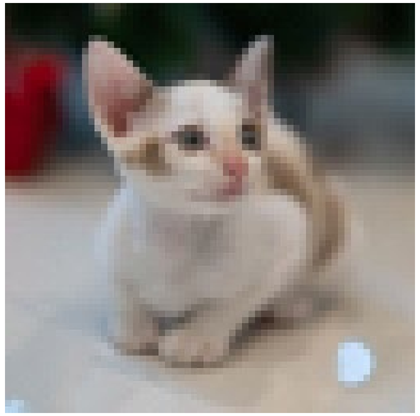

Sensor Functions:
1. Photoelectric Conversion
Converts photons into electrons
2. Charge Accumulation
Collects generated charge as signal charge
3. Transfer Signal
Moves signal charge to detecting node
4. Signal Detection
Converts signal charge into electrical signal (voltage)
5. Analog to Digital Conversion
Converts voltage into digital value
photon
electron
voltage
digital value
image data
LENS
IMAGE SENSOR
ISP
INTERFACE I/O
CMOS CAMERA

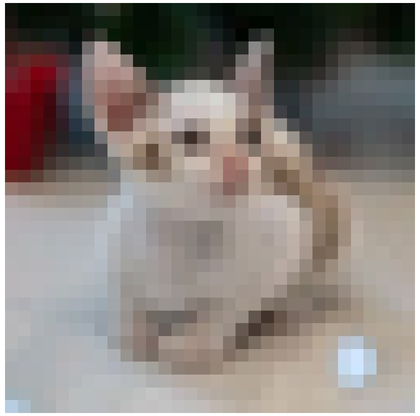
Digital Images and Pixels

- Digital image: discrete samples $f\,[x,y]$ representing continuous image $f\,(x,y)$
- Each element of the 2-d array $f\,[x,y]$ is called a pixel or pel (from “picture element“)

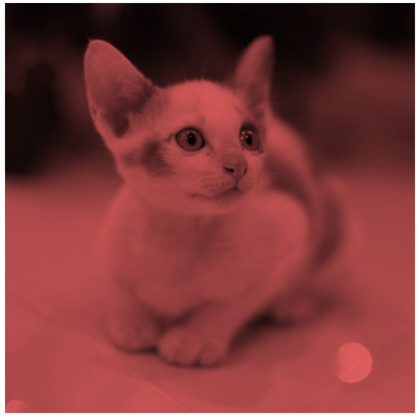

256 x 256


128 x 128

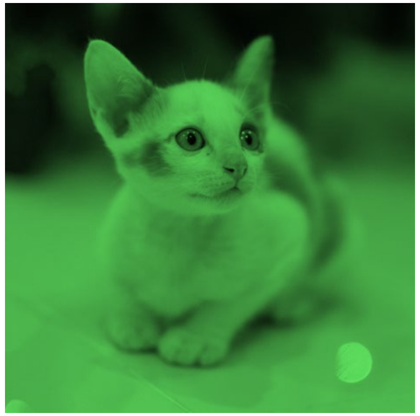

64 x 64


32 x 32

Color Components



Red $R[x,y]$



Green $G[x,y]$

Blue $B[x,y]$

Monochrome

$R[x,y] = G[x,y] = B[x,y]$

Why do we process images?

- Acquire an image
  - Correct aperture and color balance
  - Reconstruct image from projections
- Prepare for display or printing
  - Adjust image size
  - Color mapping
- Facilitate picture storage and transmission
  - Compression and transmission
- Enhance and restore images
  - Restore artifacts in images
  - Noise reduction
- Extract information from images
  - Character recognition
  - Face recognition
- Many other applications…





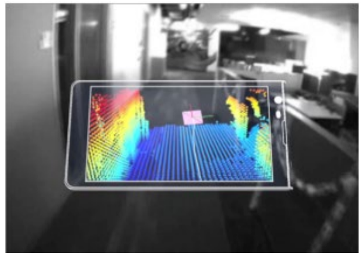
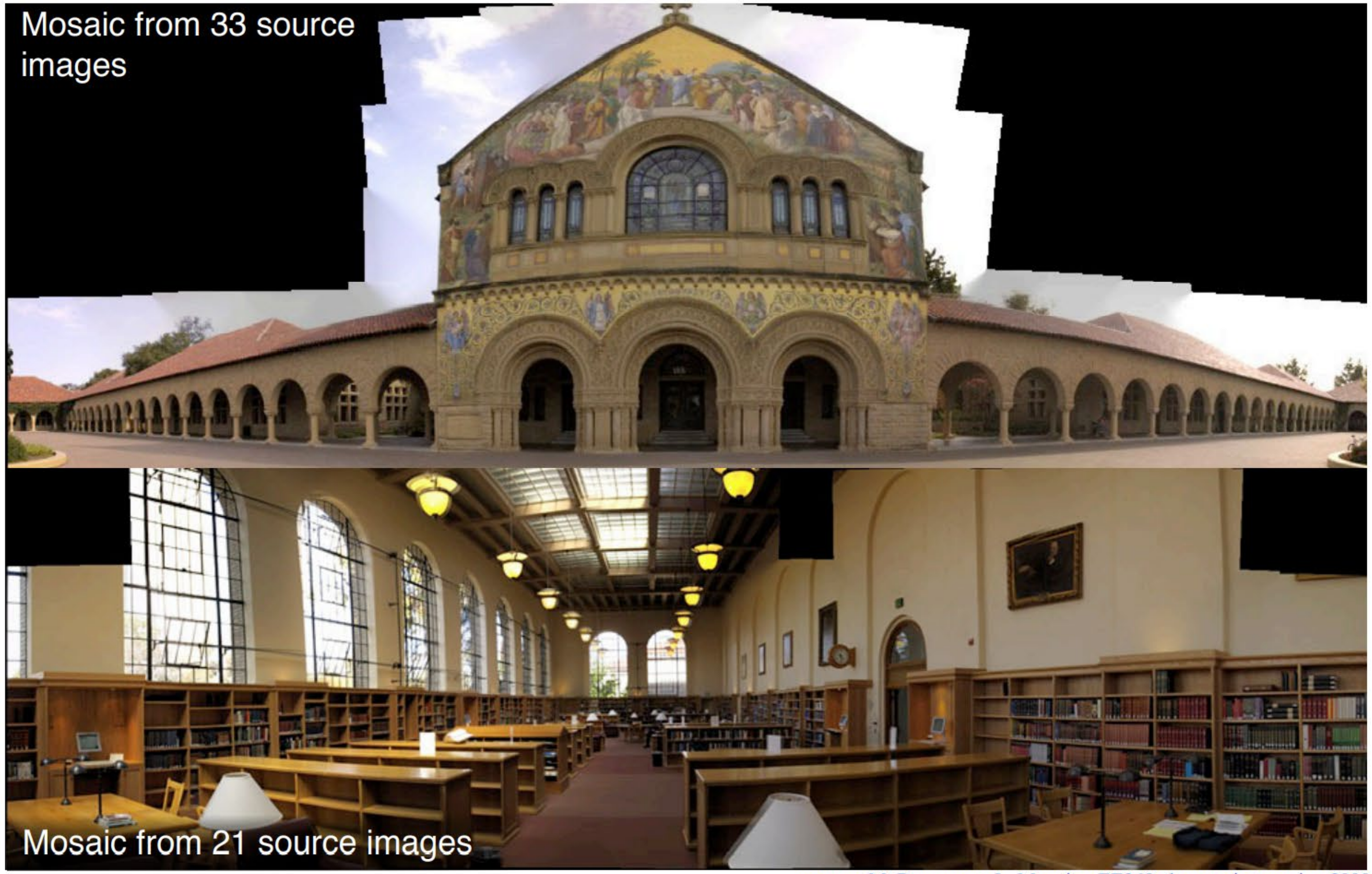



Image processing Examples



source: M. Borgmann, L. Meunier, EE368 class project, spring 2000.

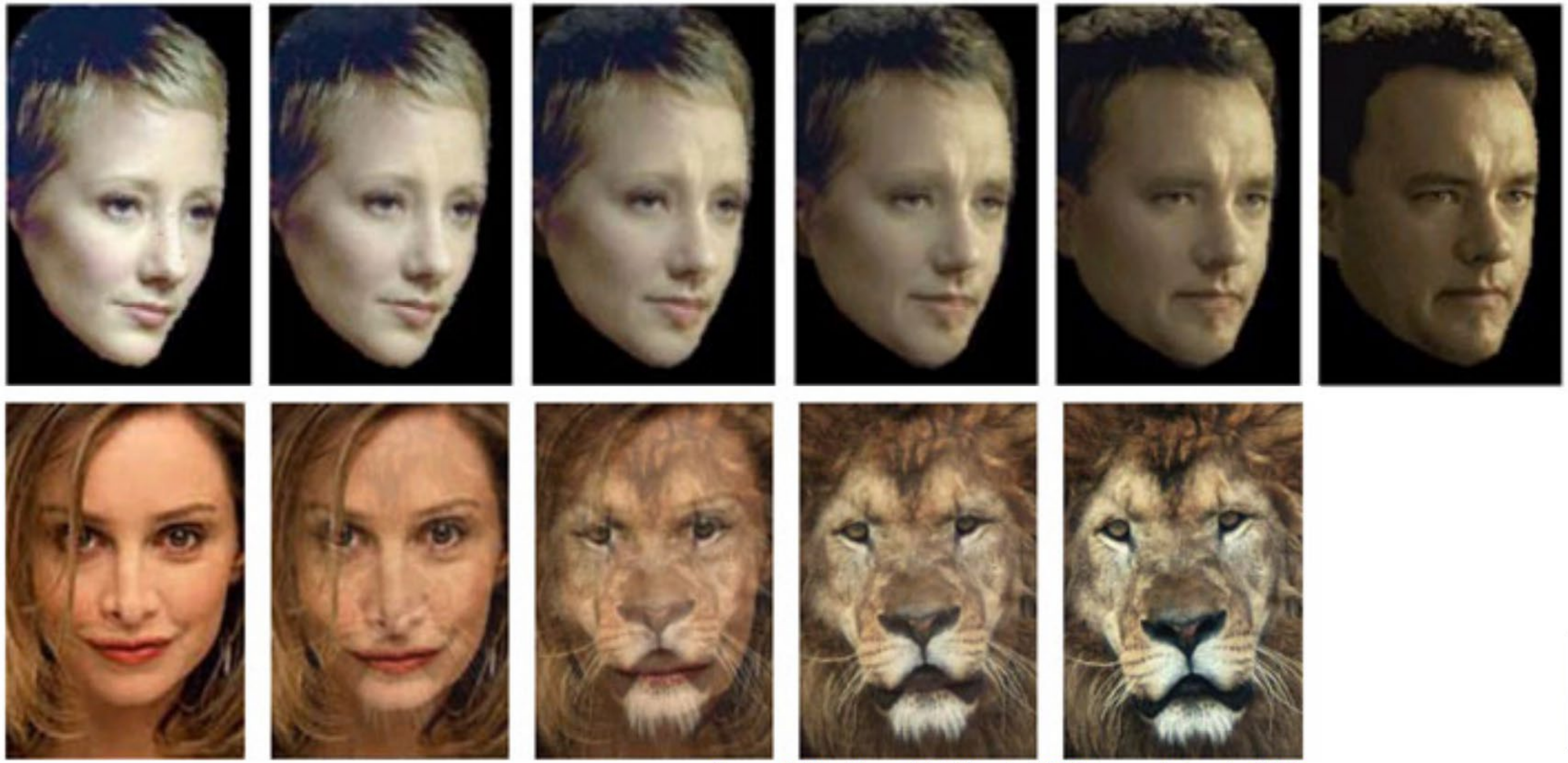
Google Jump

facebook 360

light.co

Image Processing Examples

Face morphing



Source: Yi-Wen Liu and Yu-Li Hsueh, EE368 class project, spring 2000.

Image Processing Examples

Face Detection

source: Henry Chang, Ulises Robles, EE368 class project, spring 2000.

Image Processing Examples

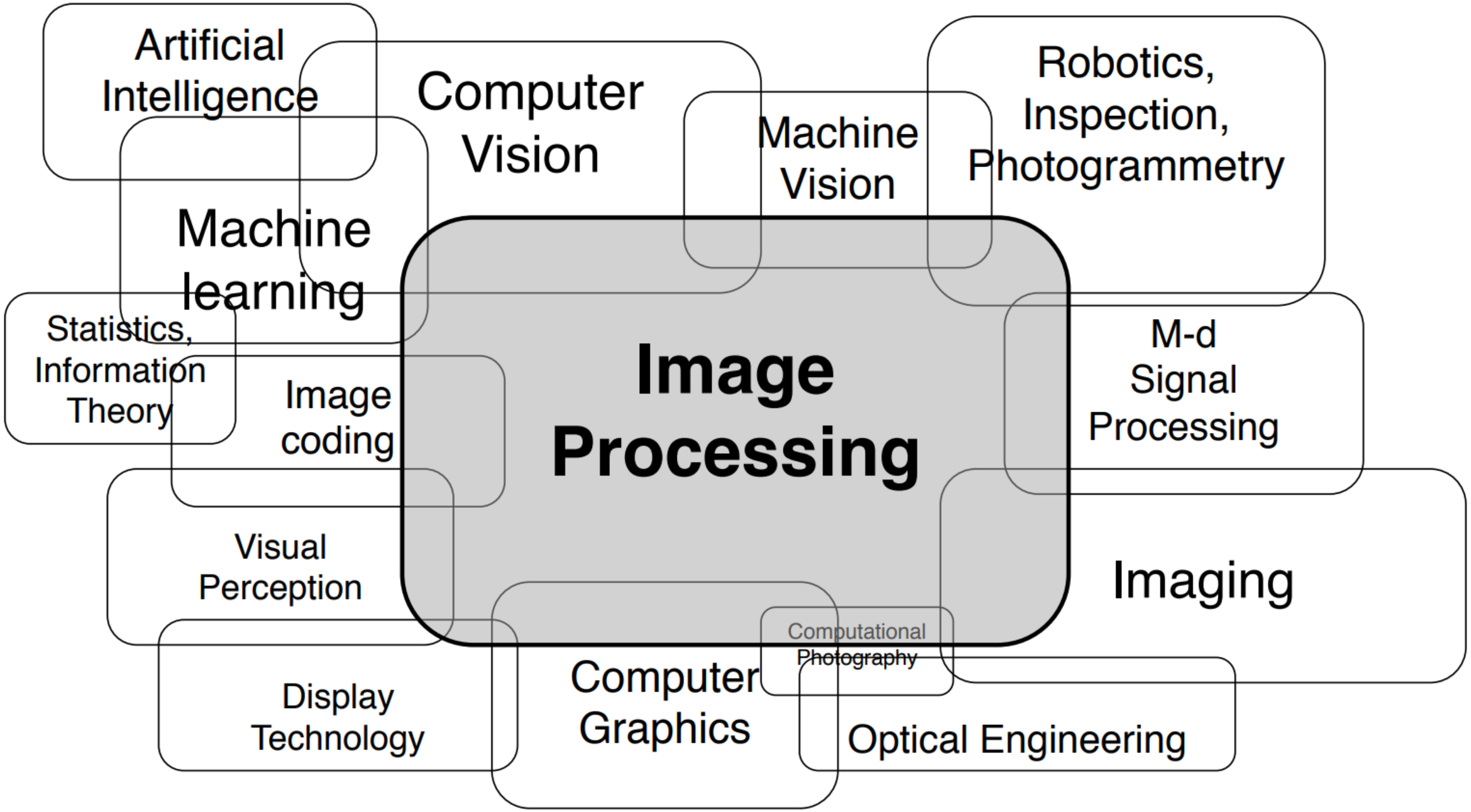
Style Transfer

Original photos

Style examples

Elias Wang, Nicholas Tan, EE368, 2016/17

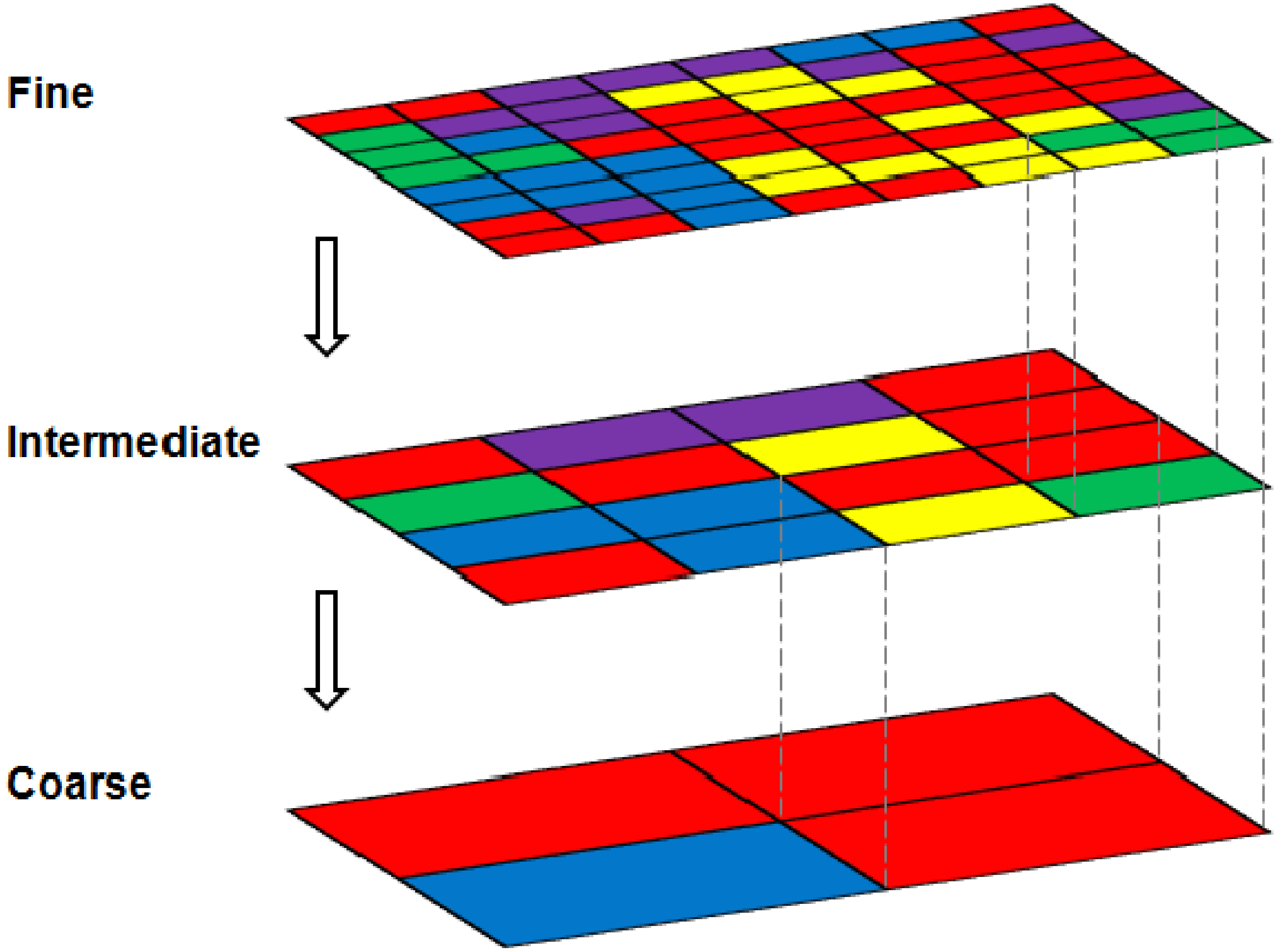
Image Processing and Related Fields



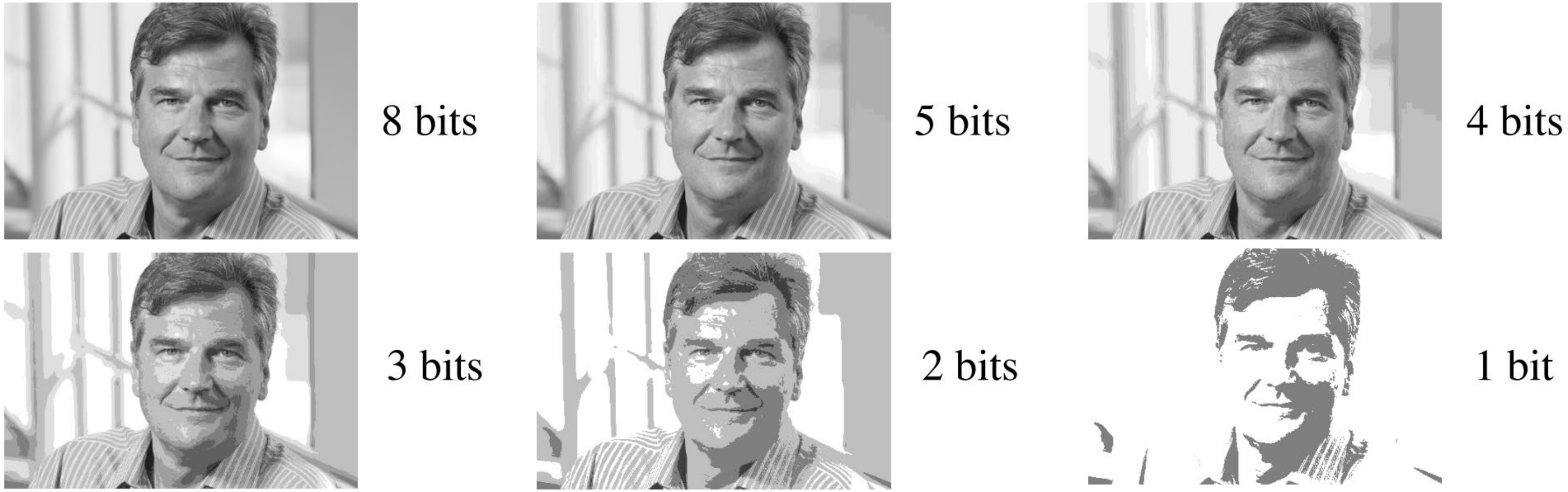
Point Operations

- Quantization
- Brightness
- Contrast

Image Resolution

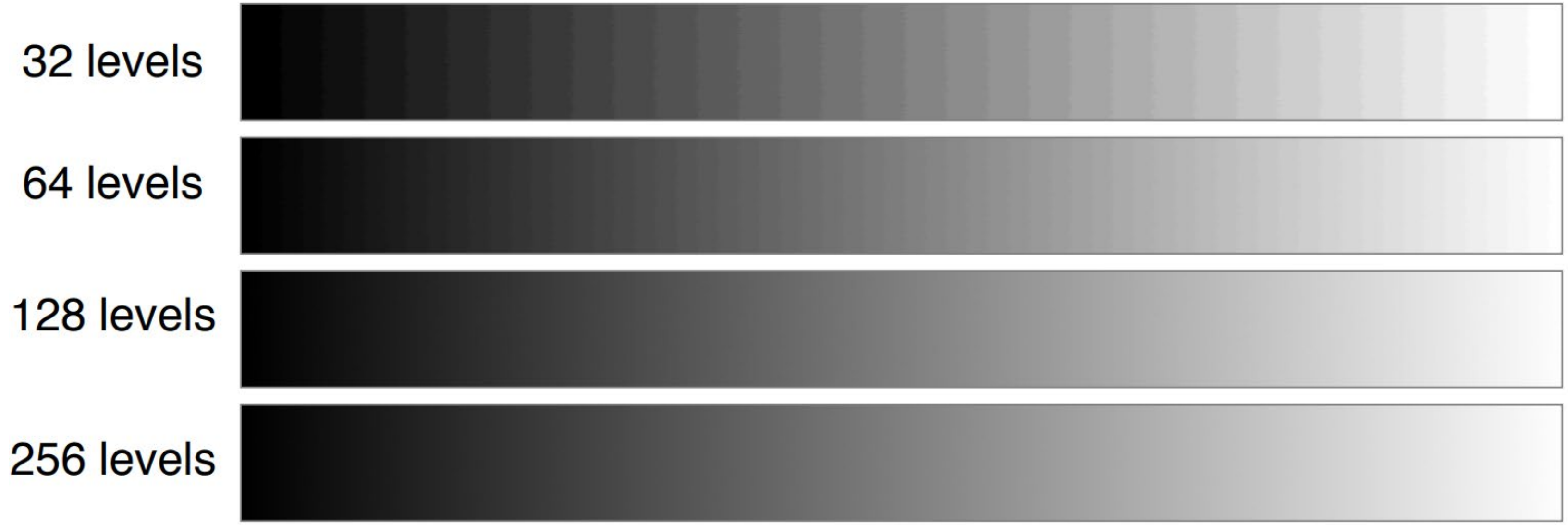


Quantization: how many bits per pixel?



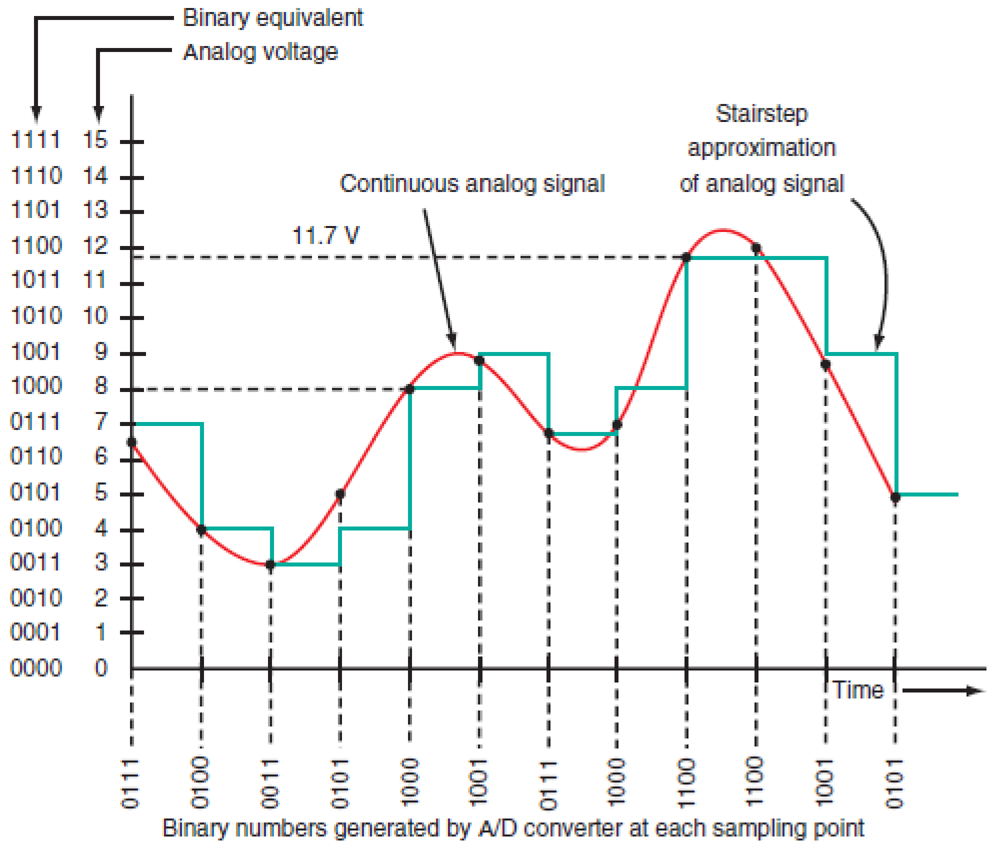
How many gray levels are required?

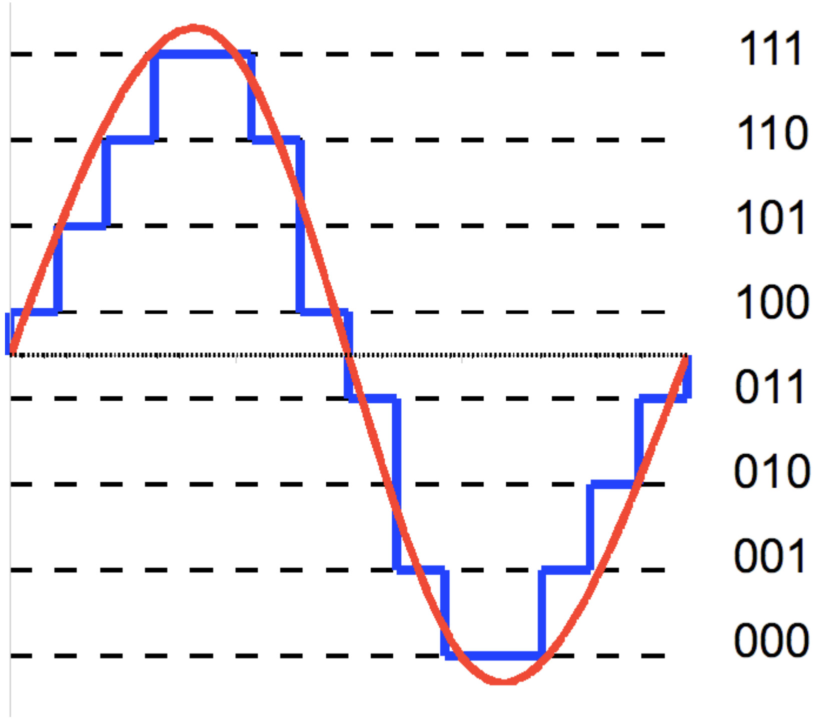
- Contouring is most visible for a ramp



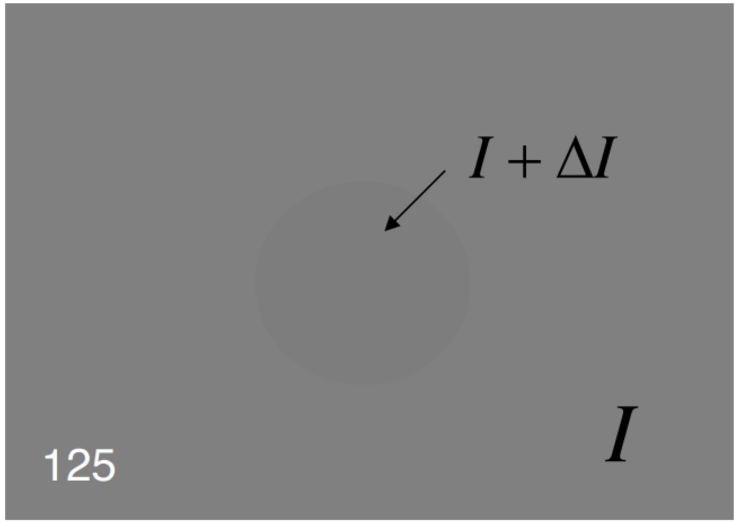
- Digital images typically are quantized to 256 gray levels.

Quantization





Brightness Discrimination



Visibility threshold

$$\boxed{\Delta I / I \approx 1 \ldots 2\%}$$

„Weber fraction“
„Weber‘s Law“

Note: I is luminance, measured in cd/m^2

Can you see the circle?

Human brightness perception is uniform in the $\log(I)$ domain („Fechner‘s Law“)

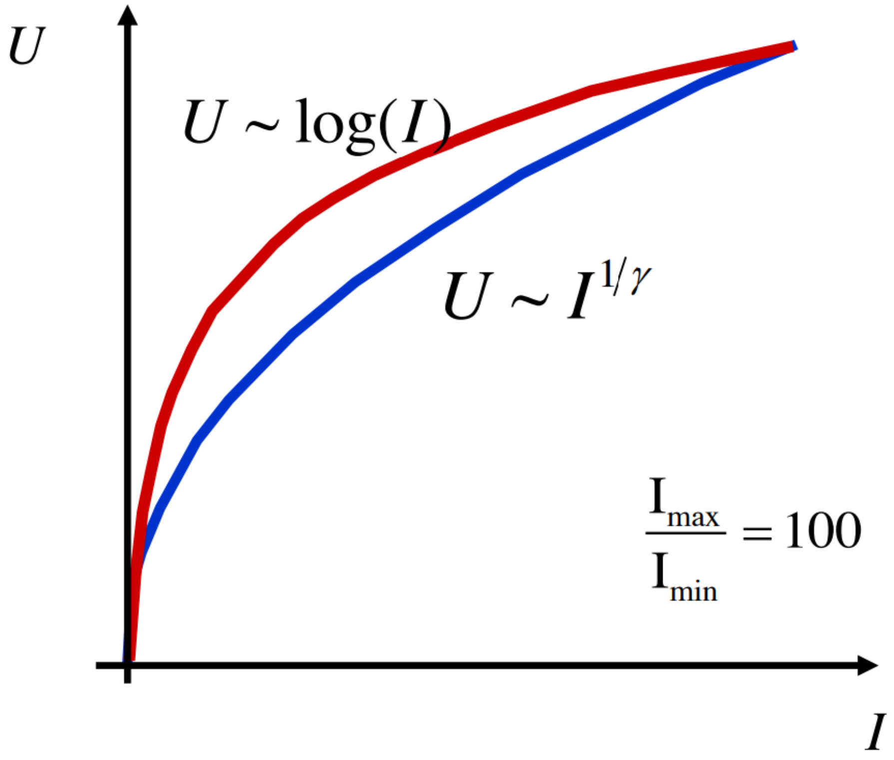
Contrast ratio

- Luminance ratio between two successive quantization levels at visibility threshold

$$\frac{I_{\max}}{I_{\min}} = \left(1 + K_{Weber}\right)^{N-1}$$

- For $K_{Weber} = 0.01 \ldots 0.02 \quad N = 256 \quad \mathrm{I}_{\max} / \mathrm{I}_{\min} = 13 \ldots 156$
- Typical display contrast ratio
  - Modern flat panel display in dark room 1000:1
  - Cathode ray tube 100:1
  - Print on paper 10:1

Log vs γ-predistortion



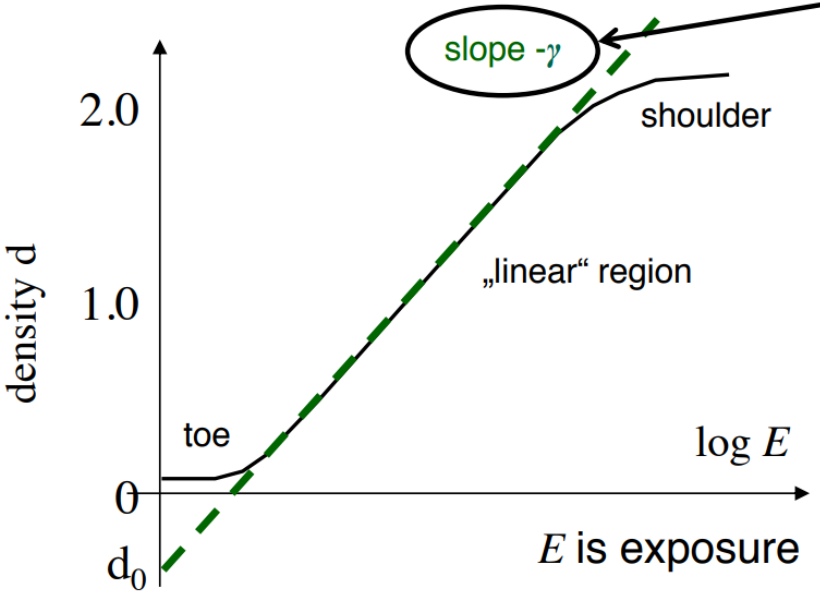
- Weber's Law suggests uniform perception in the $\log(I)$ domain
- Similar enough for most practical applications

Photographic film

<u>Luminance</u>

$$I = I_0 \cdot 10^{-d}$$
$$= I_0 \cdot 10^{-(-\gamma \log E + d_0)}$$
$$= I_0 \cdot 10^{-d_0} \cdot E^{\gamma}$$

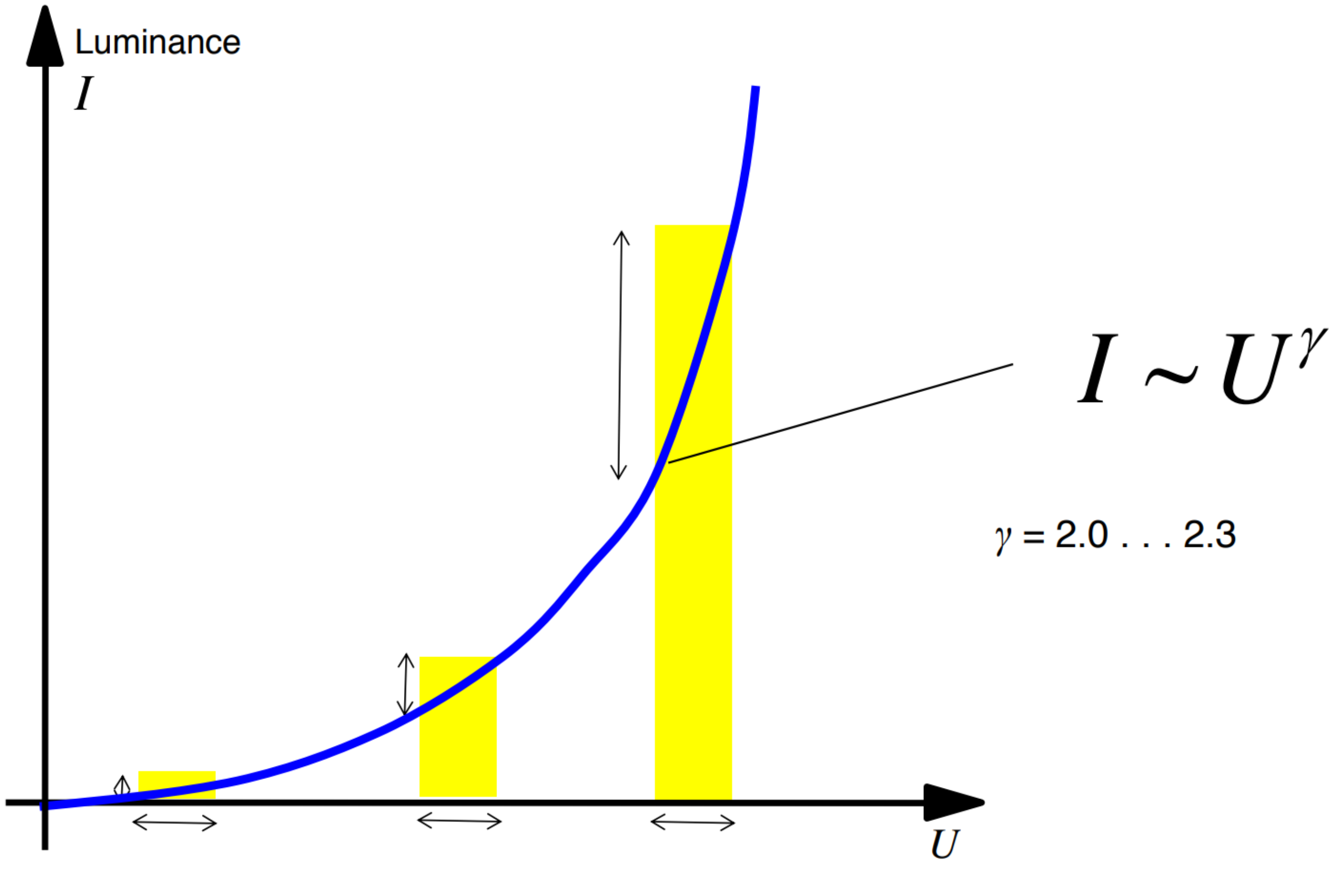
Hurter & Driffield curve (H&D curve)
for photographic negative



γ measures film contrast

- General purpose films
  γ = -0.7 . . . -1.0
- High-contrast films
  γ = -1.5 . . . -10
- Lower speed films tend to have higher absolute γ

Image Adjustment



Brightness adjustment by intensity scaling

Original image

$f[x,y]$

Scaled image

$a \cdot f[x,y]$

Scaling in the γ-domain is equivalent to scaling in the linear luminance domain

$$I \sim \left(a \cdot f[x,y]\right)^{\gamma} = a^{\gamma} \cdot \left(f[x,y]\right)^{\gamma}$$

. . . same effect as changing camera exposure time.

Contrast adjustment by changing γ

Original image

$f[x,y]$

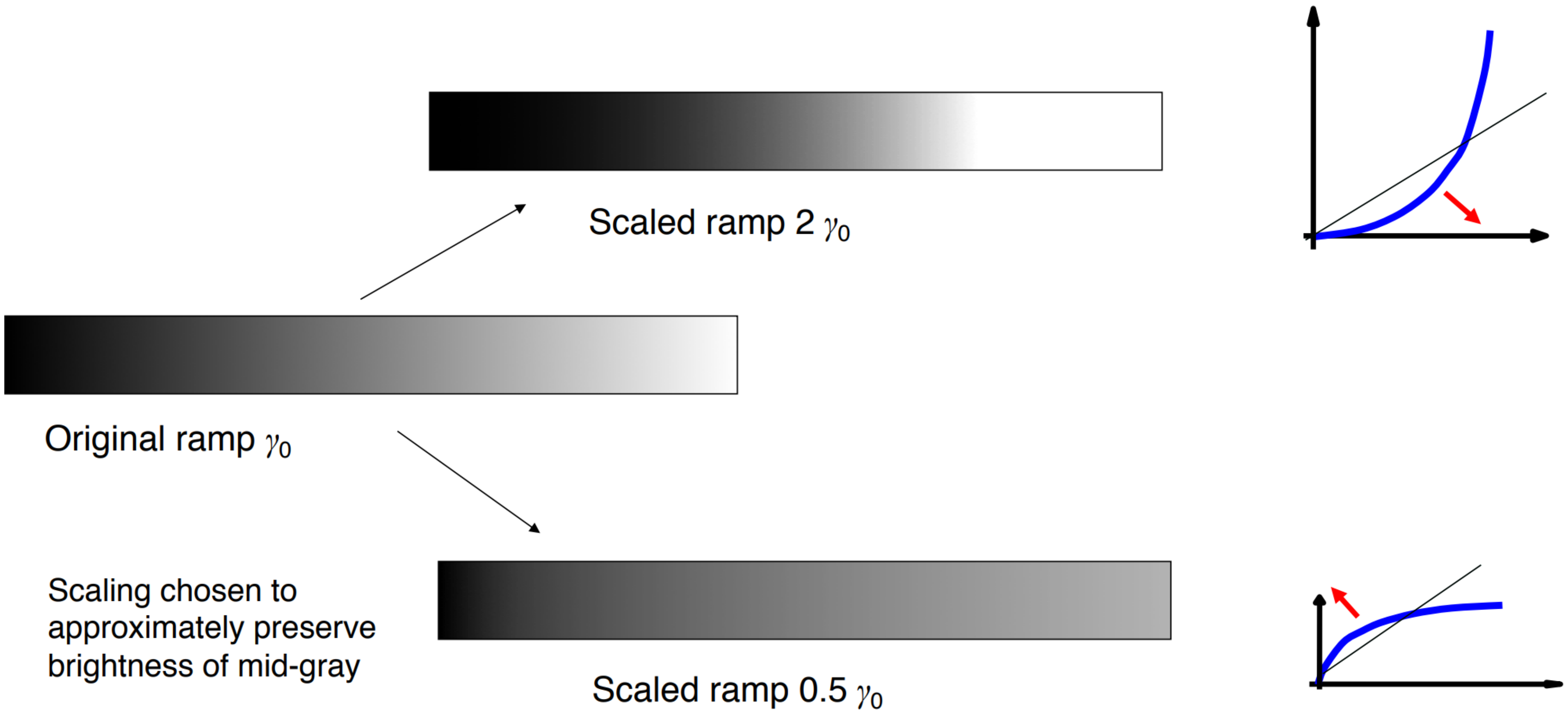
γ increased by 50%

$a \cdot (f[x,y])^{\gamma}$

with $\gamma = 1.5$

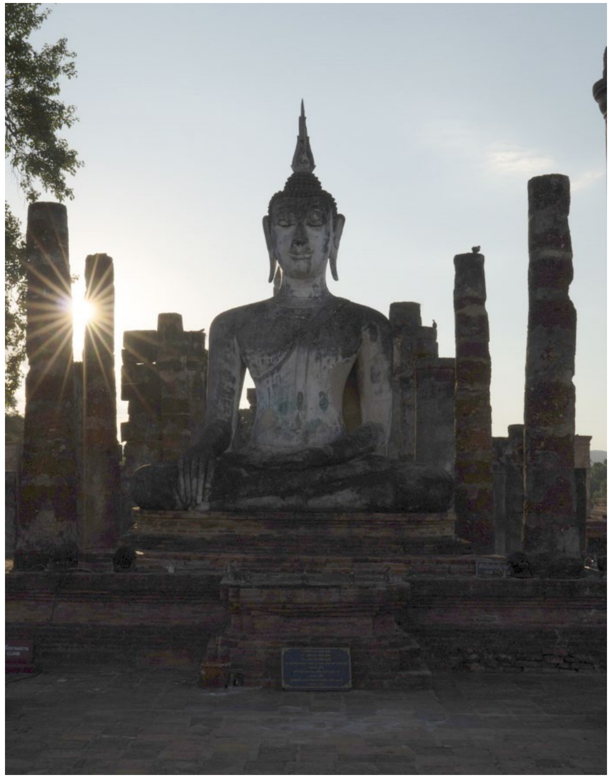
. . . same effect as using a different photographic film . . .

Contrast adjustment by changing γ



Gamma adjustment

$\gamma = 0.34$



$\gamma = 2.4$

Spatial Filtering

w(-1,-1)	w(-1,0)	w(-1,1)
w(0,-1)	w(0,0)	w(0,1)
w(1,-1)	w(1,0)	w(1,1)

Mask coefficients showing coordinate arrangement

Convolution

$$g(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} \omega(s,t) f(x-s, y-t)$$

$$g = \omega * f$$

Convolution

Convolution kernel, ω

1	-1	-1
1	2	-1
1	1	1

Rotate 180°

1	1	1
-1	2	1
-1	-1	1

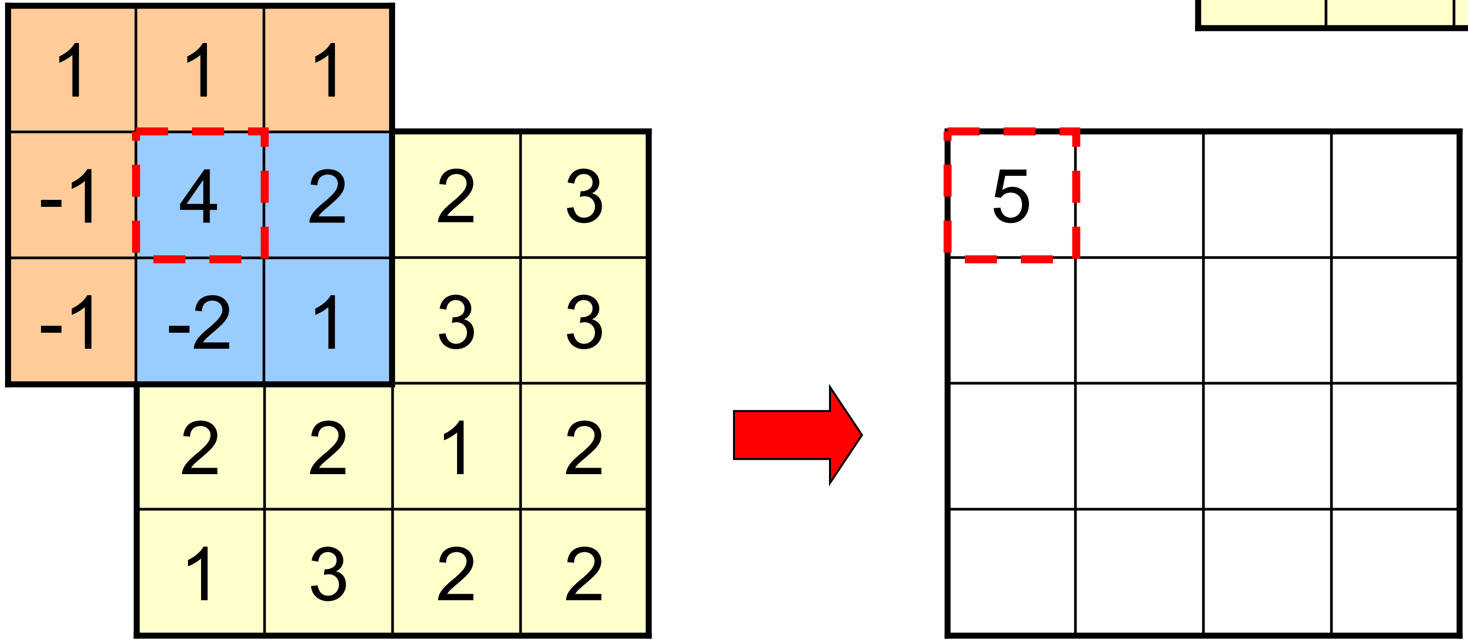
Input Image, f

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

Convolution

1	1	1
-1	2	1
-1	-1	1

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2



Input Image, *f*

Output Image, *g*

Convolution

1	1	1
-1	2	1
-1	-1	1

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

1	1	1	
-2	4	2	3
-2	-1	3	3
2	2	1	2
1	3	2	2

Input Image, *f*

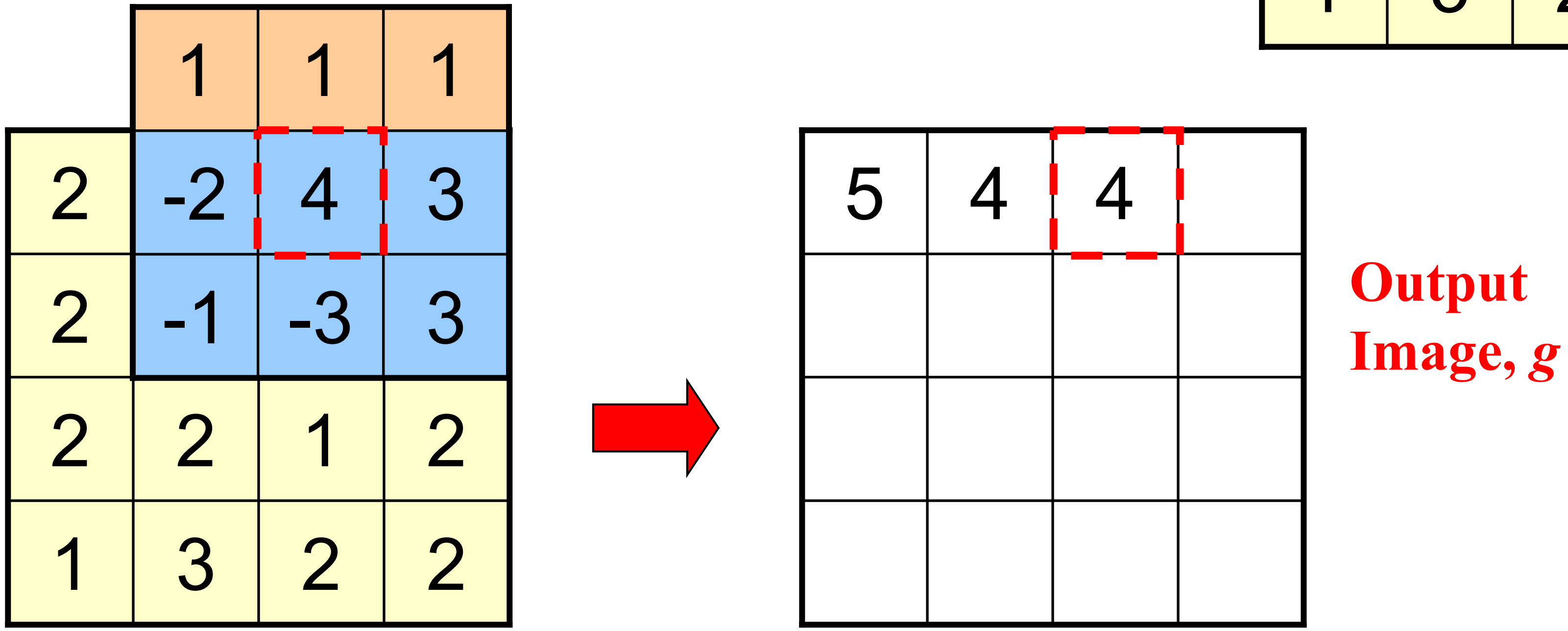
5	4		

Output Image, *g*

Convolution

1	1	1
-1	2	1
-1	-1	1

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

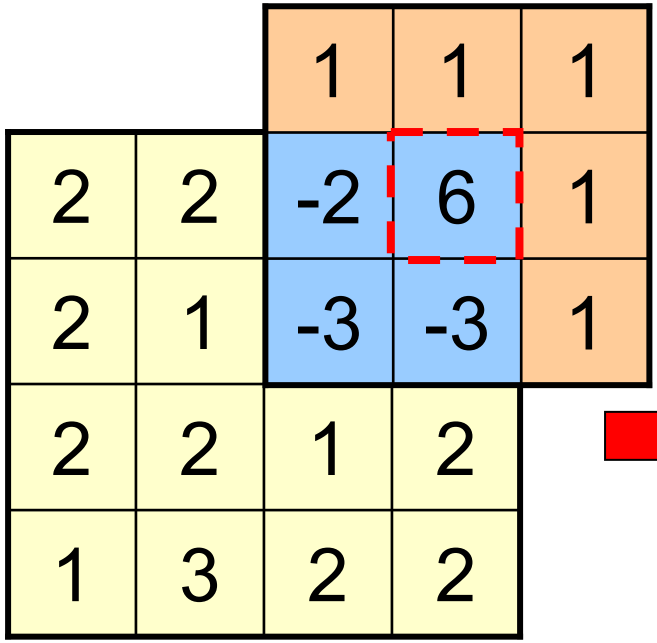


Input Image, *f*

Convolution

1	1	1
-1	2	1
-1	-1	1

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2



Input Image, *f*

5	4	4	-2

Output Image, *g*

Convolution

1	1	1
-1	2	1
-1	-1	1

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

1	2	2	2	3
-1	4	1	3	3
-1	-2	2	1	2
	1	3	2	2

Input Image, *f*

5	4	4	-2
9			

Output Image, *g*

Convolution

1	1	1
-1	2	1
-1	-1	1

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

2	2	2	3
-2	2	3	3
-2	-2	1	2
1	3	2	2

Input Image, *f*

5	4	4	-2
9	6		

Output Image, *g*

Convolution

5	4	4	-2
9	6	14	5
11	7	6	5
9	12	8	5

Final output Image, *g*

Linear Spatial Filtering

$$R = \omega(-1,-1) f(x-1, y-1) + \omega(-1,0) f(x-1, y) + \ldots$$
$$+ \omega(0,0) f(x, y) + \ldots + \omega(1,0) f(x+1, y) + \omega(1,1) f(x+1, y+1)$$

Smoothing Spatial Filters

Types of Smoothing Filters : linear and nonlinear

Smoothing Linear Filters : known as averaging filter or lowpass filters.

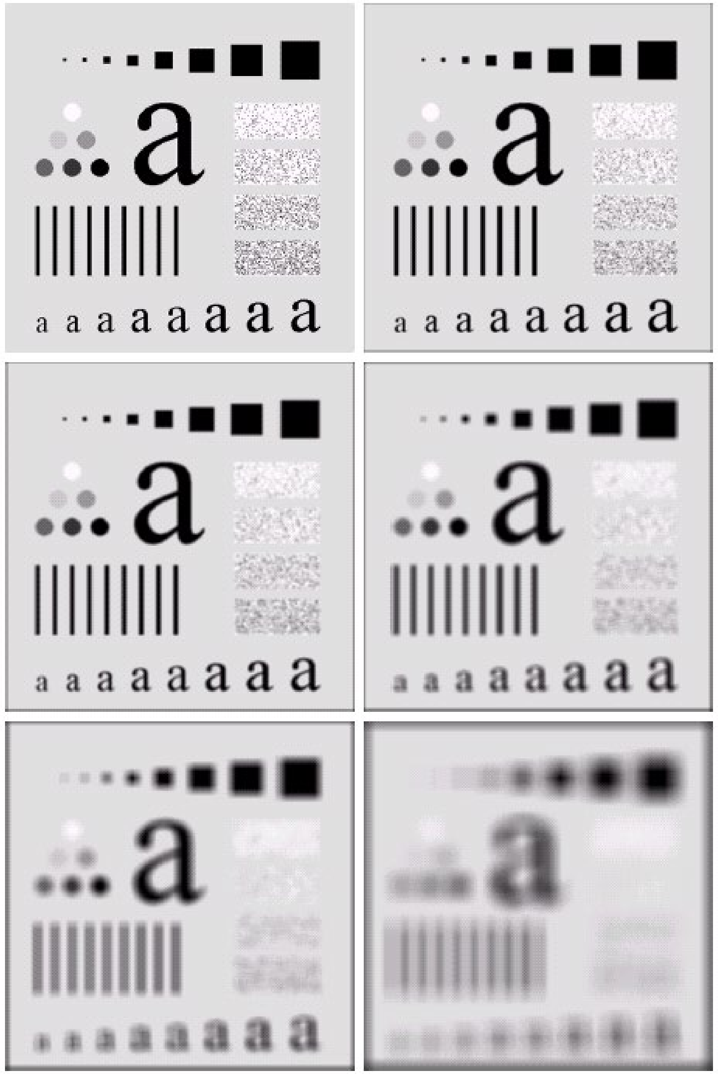
Smoothing Linear Filters

$$\frac{1}{9} \times \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array} \qquad \frac{1}{16} \times \begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline 2 & 4 & 2 \\ \hline 1 & 2 & 1 \\ \hline \end{array}$$

Box filter

Weighted average filter

Smoothing Linear Filters

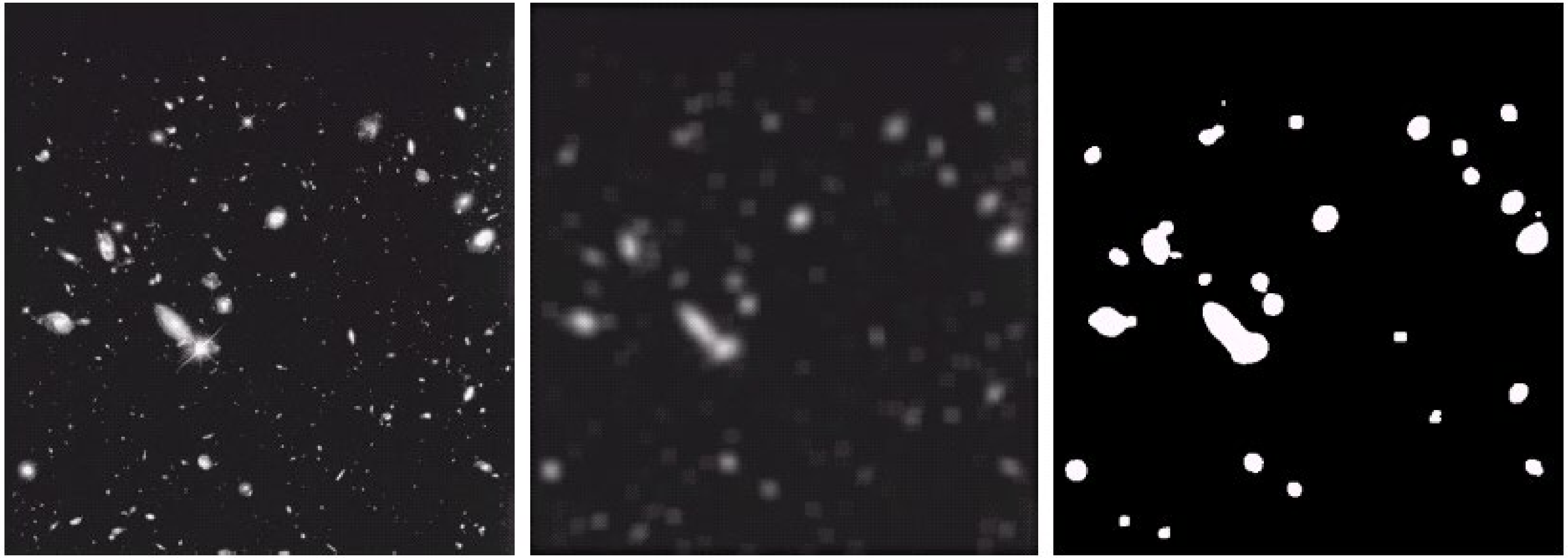


Original *3x3*

5x5 *9x9*

15x15 *35x35*

Smoothing Linear Filters



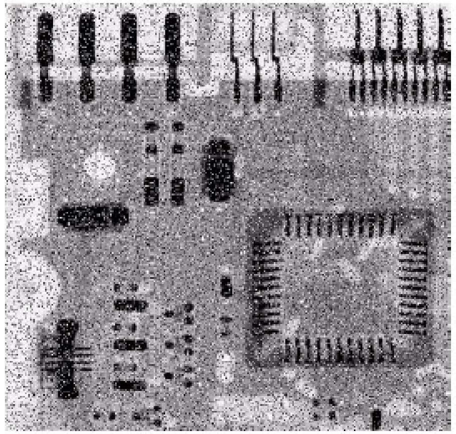
original *blurred* *thresholded*

Order-Statistics Filters

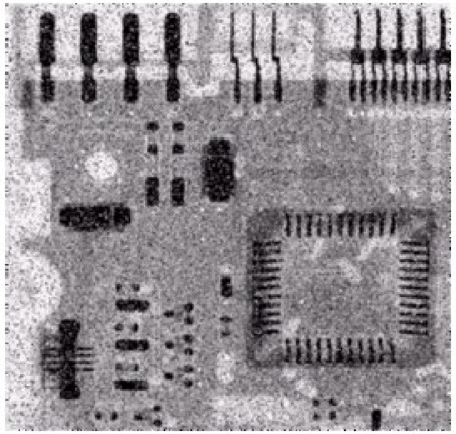
Median filter

$a_1 < a_2 < \ldots < a_n$ then median is $a_{(1+n)/2}$

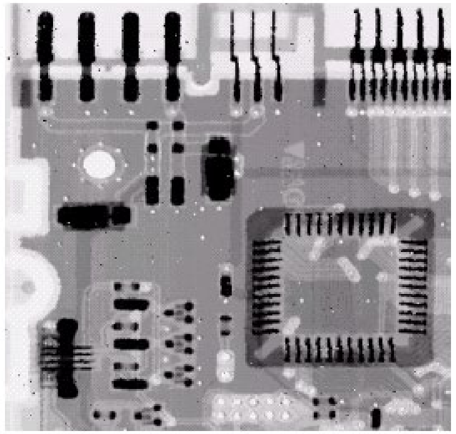
Median filters



Corrupted by salt and pepper noise



Averaging filter



Median filter

Sharpening Spatial Filters

$$\frac{\partial f}{\partial x} = f(x+1) - f(x)$$

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) - f(x) - (f(x) - f(x-1))$$

$$= f(x+1) + f(x-1) - 2f(x)$$

Sharpening Spatial Filters

The Laplacian

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

$$\frac{\partial^2 f}{\partial x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y)$$

$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y)$$

Sharpening Spatial Filters

The 2D Laplacian

$$\nabla^2 f = \left[f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) \right] - 4 f(x, y)$$

Sharpening Spatial Filters

The 2D Laplacian

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

0	−1	0
−1	4	−1
0	−1	0

−1	−1	−1
−1	8	−1
−1	−1	−1

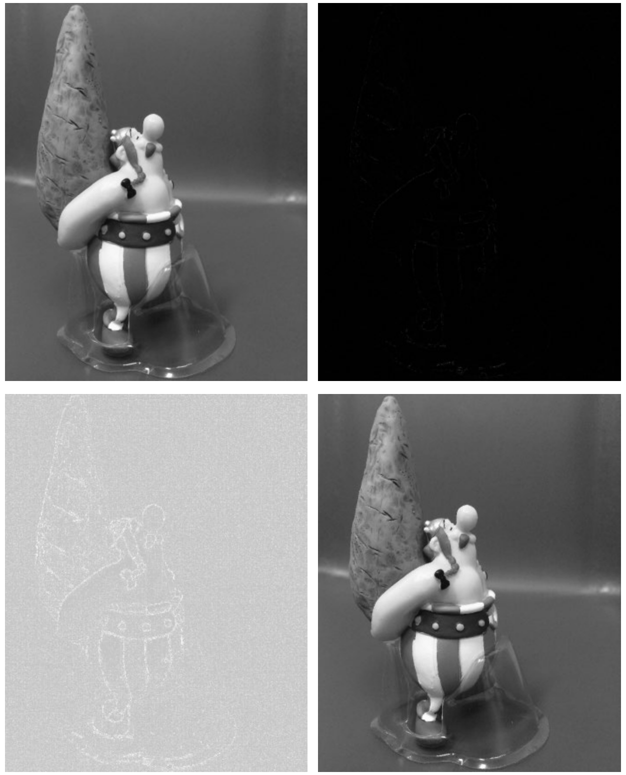
Sharpening Spatial Filters

The 2D Laplacian

$$g(x,y)=\begin{cases} f(x,y)-\nabla^2 f(x,y) & \text{If the center coefficient of the Laplacian mask is negative} \\ \\ f(x,y)+\nabla^2 f(x,y) & \text{If the center coefficient of the Laplacian mask is positive} \end{cases}$$

Sharpening Spatial Filters

The 2D Laplacian



The First Derivatives for Enhancement

The Gradient

$$\nabla \mathbf{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f}{\partial x} \\ \dfrac{\partial f}{\partial y} \end{bmatrix}$$

$$\nabla f = mag(\nabla \mathbf{f}) = \left[G_x^{\ 2} + G_y^{\ 2}\right]^{1/2} = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

The First Derivatives for Enhancement

The Gradient

$$\nabla f \approx |G_x| + |G_y|$$

$$\nabla f \approx |G_x| + |G_y| = |(z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)|$$
$$+ |(z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)|$$

The First Derivatives for Enhancement

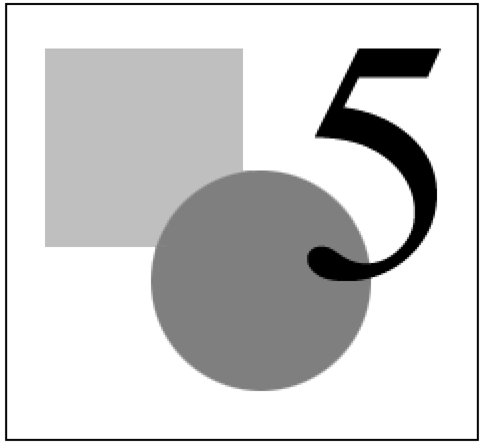
The Sobel Operator

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

The First Derivatives for Enhancement

The Sobel Operator



Horizontal Vertical

Summary

- 2D data plays important roles in today data representation
- Image analysis may be found in numerous applications to process 2D data
- Point processing and filter mask design allows us to transform image data and extract more information from the image

Lab

Signal

- Find your signal data
- Show the plot in time (or equivalent) domain
- Explain the content of the signal

Image

- Find your image data
- Show the image
- Perform filtering on the image and explain what you see

End of Lecture 6

Question?