

# CS4501: Introduction to Computer Vision

## Filtering, Frequency, and Edges



Various slides from previous courses by:

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# Last Class

- Image Processing: Brightness
- Image Filtering: Mean Filter
- Image Blurring
- Image Gradients: The Sobel Operator

# Today's Class

- Recap on Convolutional Operations
- Image Gradients: The Sobel Operator
- Frequency Domain
- Filtering in Frequency
- Google Colaboratory

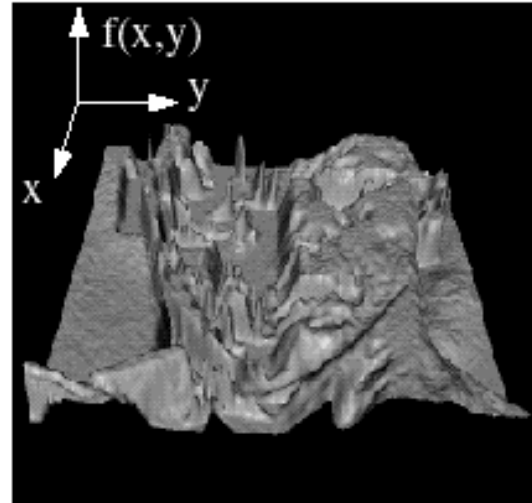
# Images as Matrices



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

# Images as Functions

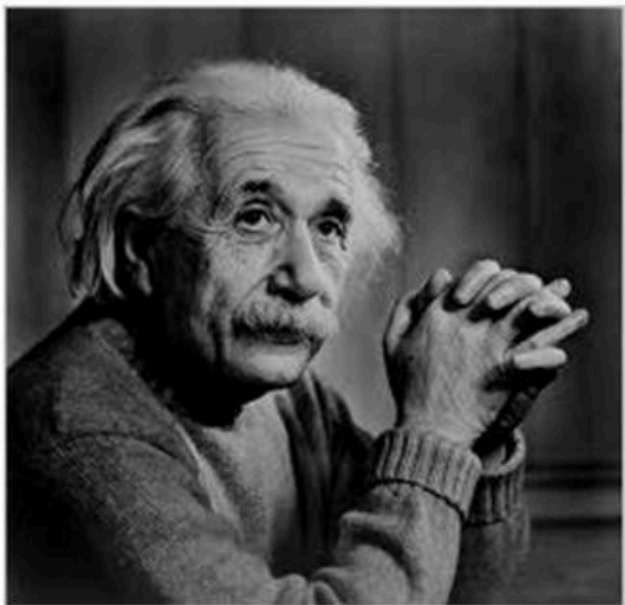
$$z = f(x, y)$$



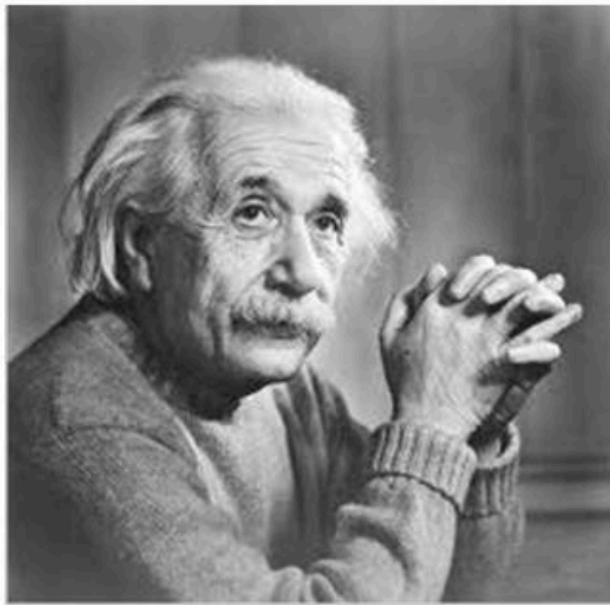
- The domain of  $x$  and  $y$  is  $[0, \text{img-width})$  and  $[0, \text{img-height})$
- $x$ , and  $y$  are discretized into integer values.

# Basic Image Processing

$I$



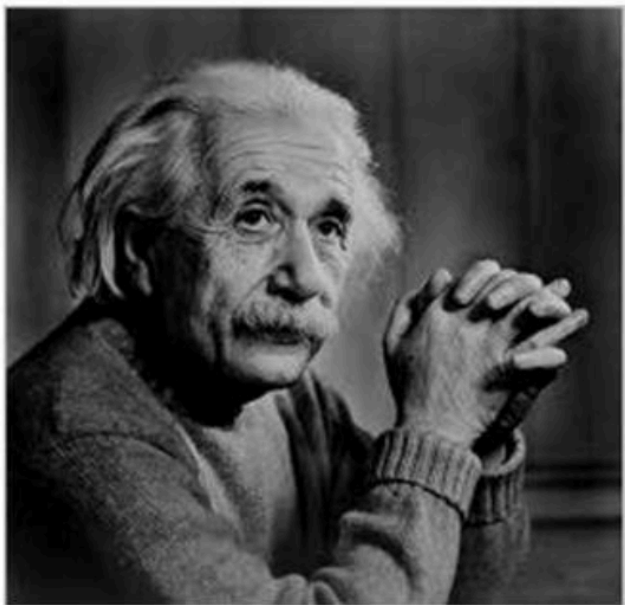
$\alpha I$



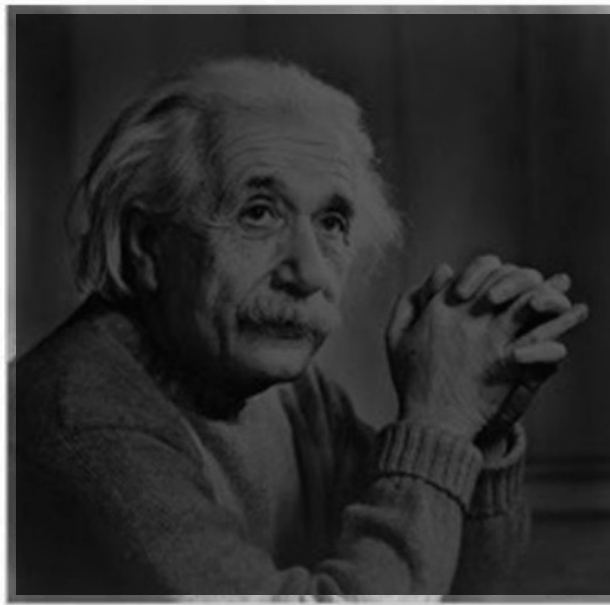
$\alpha > 1$

# Basic Image Processing

$I$

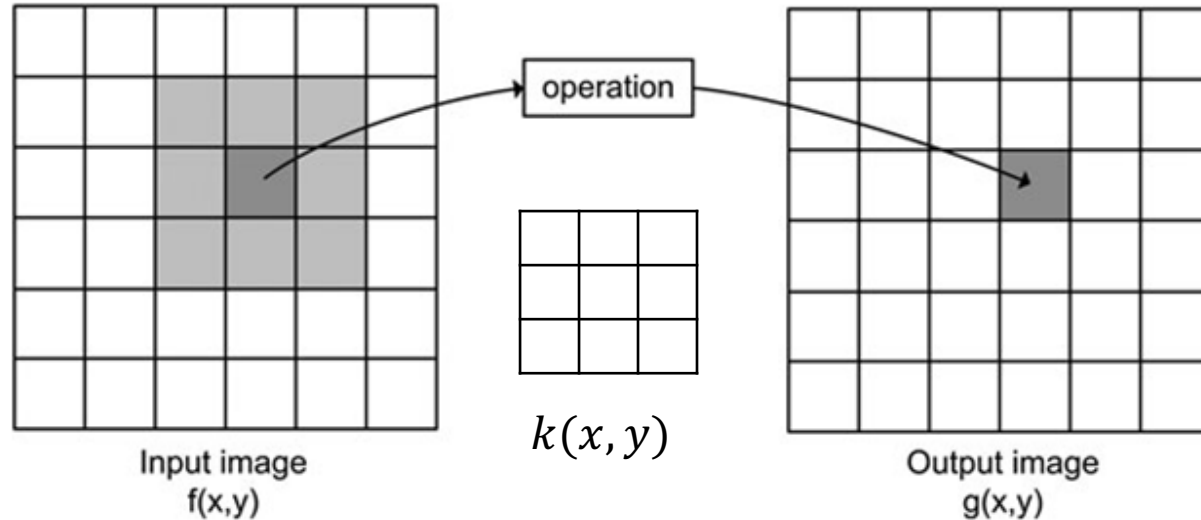


$\alpha I$



$$0 < \alpha < 1$$

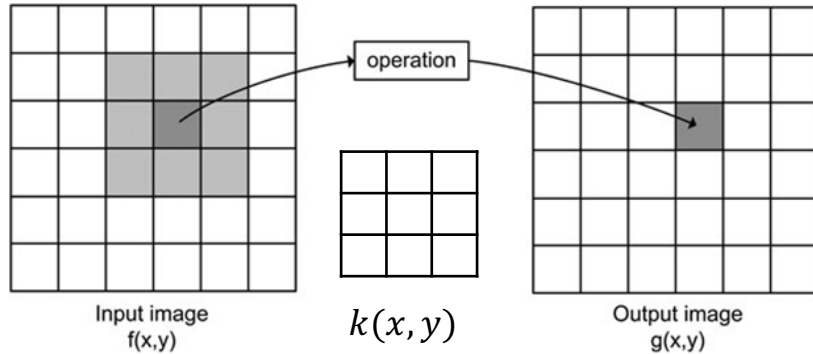
# Image filtering: Convolution operator



$$g(x,y) = \sum_v \sum_u k(u,v) f(x-u, y-v)$$

# Image filtering: Convolution operator

## e.g. mean filter



$$k(x, y) =$$

$1/9$	$1/9$	$1/9$
$1/9$	$1/9$	$1/9$
$1/9$	$1/9$	$1/9$

# Image filtering

$$g[\cdot, \cdot] = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$f[\cdot, \cdot]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

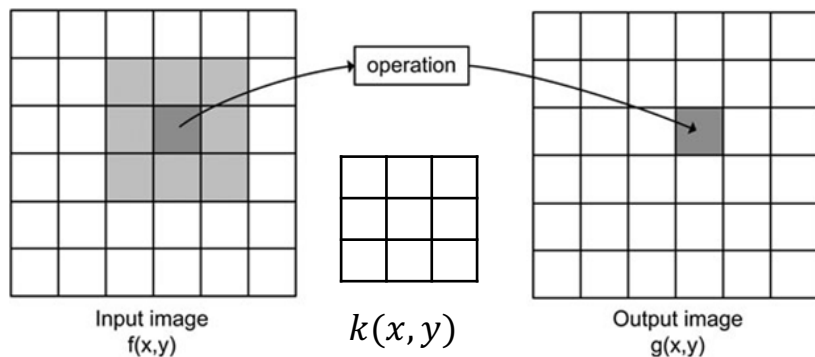
$$h[\cdot, \cdot]$$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

$$h[m, n] = \sum_{k, l} g[k, l] f[m + k, n + l]$$

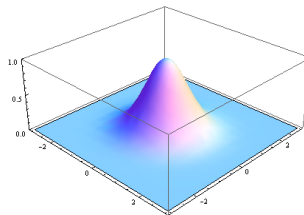
# Image filtering: Convolution operator

## Important filter: gaussian filter (gaussian blur)



$$k(x, y) =$$

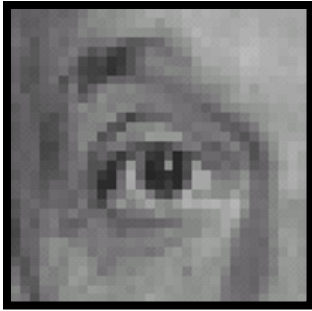
1/16	1/8	1/16
1/8	1/4	1/8
1/16	1/8	1/16



# Image filtering: Convolution operator e.g. gaussian filter (gaussian blur)



# Sharpening Filter



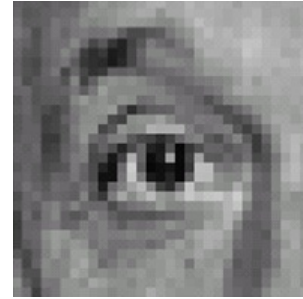
Original

0	0	0
0	2	0
0	0	0

-

$\frac{1}{9}$

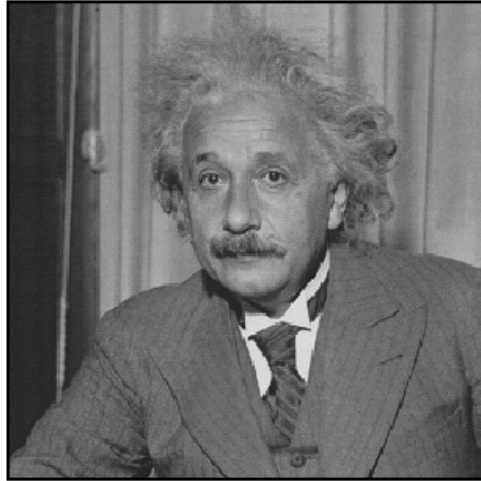
1	1	1
1	1	1
1	1	1



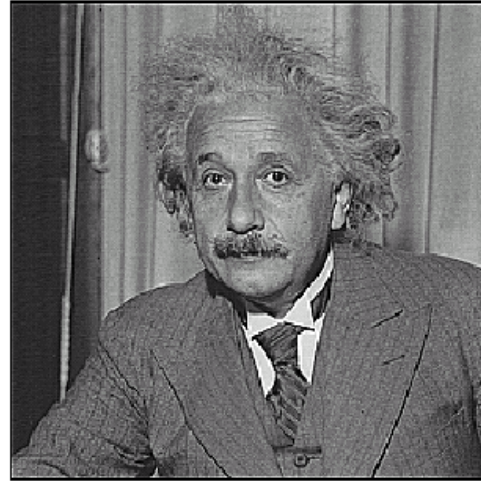
## Sharpening filter

- Accentuates differences with local average

# Sharpening Filter



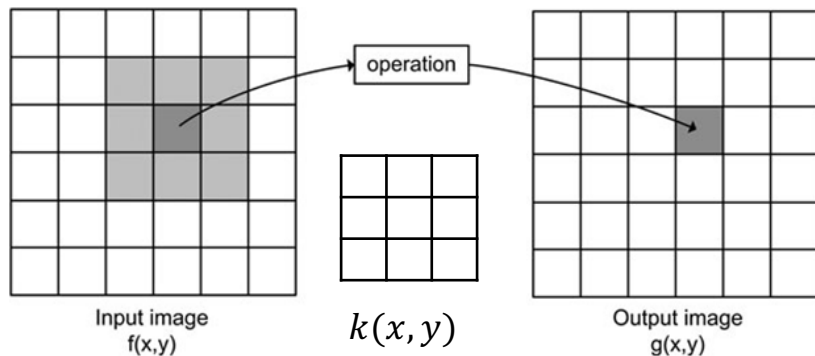
**before**



**after**

# Image filtering: Convolution operator

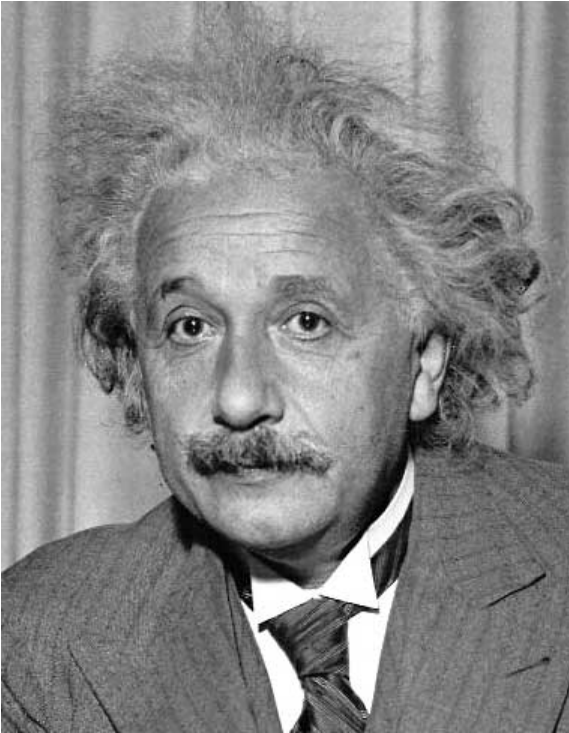
## Important Filter: Sobel operator



$$k(x, y) =$$

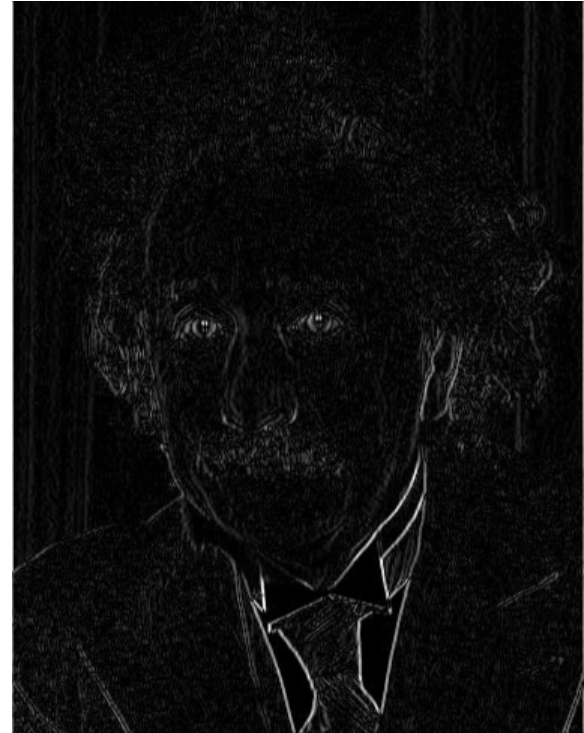
1	0	-1
2	0	-2
1	0	-1

# Sobel in X



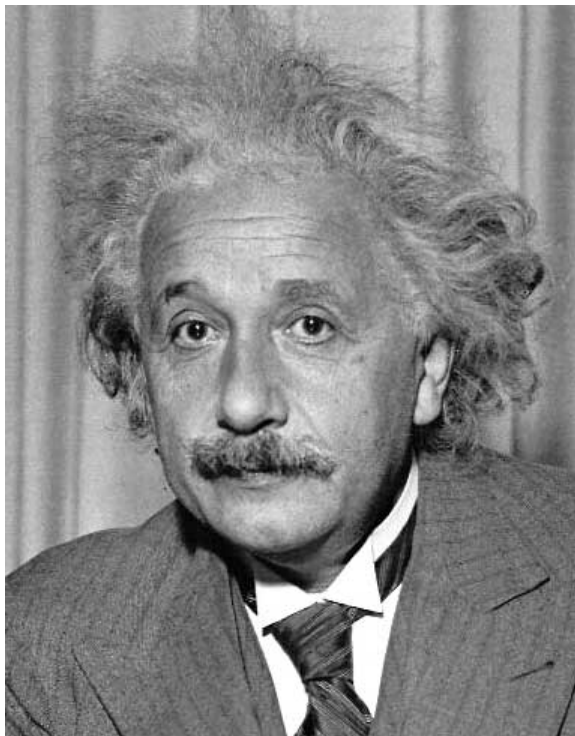
1	0	-1
2	0	-2
1	0	-1

Sobel



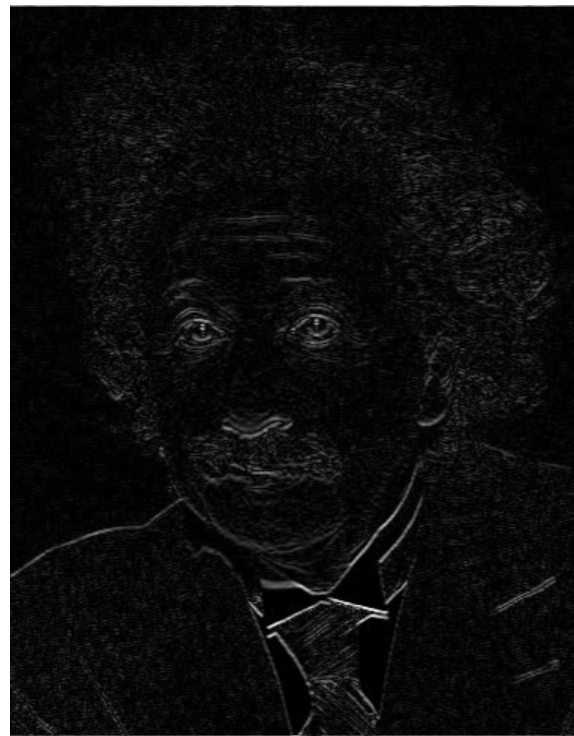
Vertical Edge  
(absolute value)

# Sobel in Y



1	2	1
0	0	0
-1	-2	-1

Sobel

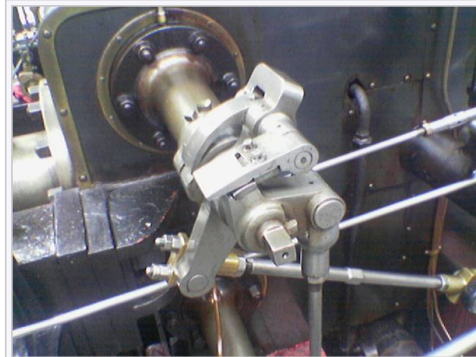


Horizontal Edge  
(absolute value)

# Sobel operators are equivalent to 2D partial derivatives of the image

- Vertical sobel operator – Partial derivative in X (width)
- Horizontal sobel operator – Partial derivative in Y (height)
- Can compute magnitude and phase at each location.
- Useful for detecting edges

[https://en.wikipedia.org/wiki/Sobel\\_operator](https://en.wikipedia.org/wiki/Sobel_operator)



A color picture of a steam engine



The Sobel operator applied to that image



# Sobel filters are (approximate) partial derivatives of the image

Let  $f(x, y)$  be your input image, then the partial derivative is:

$$\frac{\partial f(x, y)}{\partial x} = \lim_{h \rightarrow 0} \frac{f(x + h, y) - f(x, y)}{h}$$

Also:

$$\frac{\partial f(x, y)}{\partial x} = \lim_{h \rightarrow 0} \frac{f(x + h, y) - f(x - h, y)}{2h}$$

But digital images are not continuous, they are discrete

Let  $f[x, y]$  be your input image, then the partial derivative is:

$$\Delta_x f[x, y] = f[x + 1, y] - f[x, y]$$

Also: 
$$\Delta_x f[x, y] = f[x + 1, y] - f[x - 1, y]$$

But digital images are not continuous, they are discrete

Let  $f[x, y]$  be your input image, then the partial derivative is:

$$\Delta_x f[x, y] = f[x + 1, y] - f[x, y]$$

$$k(x, y) =$$

-1	1
----	---

Also:

$$\Delta_x f[x, y] = f[x + 1, y] - f[x - 1, y]$$

$$k(x, y) =$$

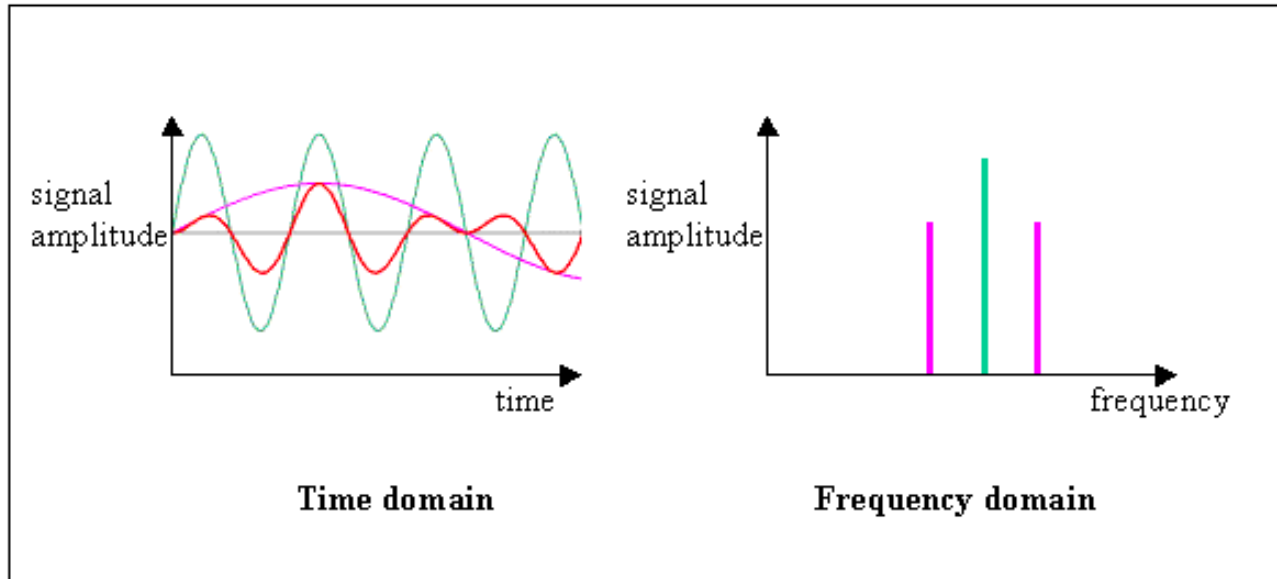
-1	0	1
----	---	---

# Sobel Operators Smooth in Y and then Differentiate in X

$$k(x, y) = \begin{array}{|c|} \hline 1 \\ \hline 2 \\ \hline 1 \\ \hline \end{array} * \begin{array}{|c|c|c|} \hline 1 & 0 & -1 \\ \hline \end{array} = \begin{array}{|c|c|c|} \hline 1 & 0 & -1 \\ \hline 2 & 0 & -2 \\ \hline 1 & 0 & -1 \\ \hline \end{array}$$

Similarly to differentiate in Y

# Frequency



# Any function can be approximated by a polynomial function

Taylor Series expansion

$$f(x) = f(a) + \frac{f'(a)}{1!} (x - a) + \frac{f''(a)}{2!} (x - a)^2 + \frac{f^{(3)}(a)}{3!} (x - a)^3 + \dots$$

...if you let your polynomial have a high degree

...AND you can compute the derivatives of the original function easily.

$$e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \frac{x^4}{4!} + \dots$$

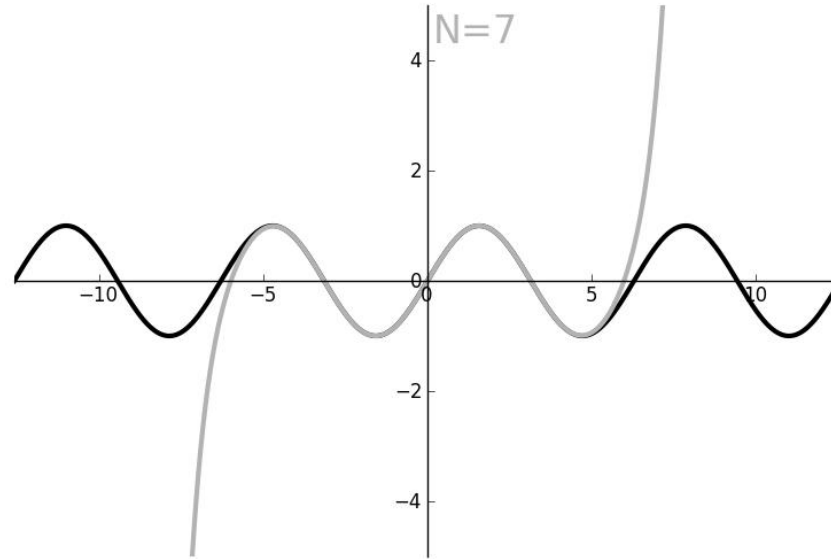
$$\sin x = x - \frac{x^3}{3!} + \frac{x^5}{5!} - \frac{x^7}{7!} + \dots$$

$$\cos x = 1 - \frac{x^2}{2!} + \frac{x^4}{4!} - \frac{x^6}{6!} + \dots$$

$$\ln(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \frac{x^4}{4} + \dots \quad \text{for } |x| < 1$$

$$\tan^{-1}(x) = x - \frac{x^3}{3} + \frac{x^5}{5} - \frac{x^7}{7} + \dots \quad \text{for } |x| < 1$$

# Difficult in practice



<https://brilliant.org/wiki/taylor-series-approximation/>

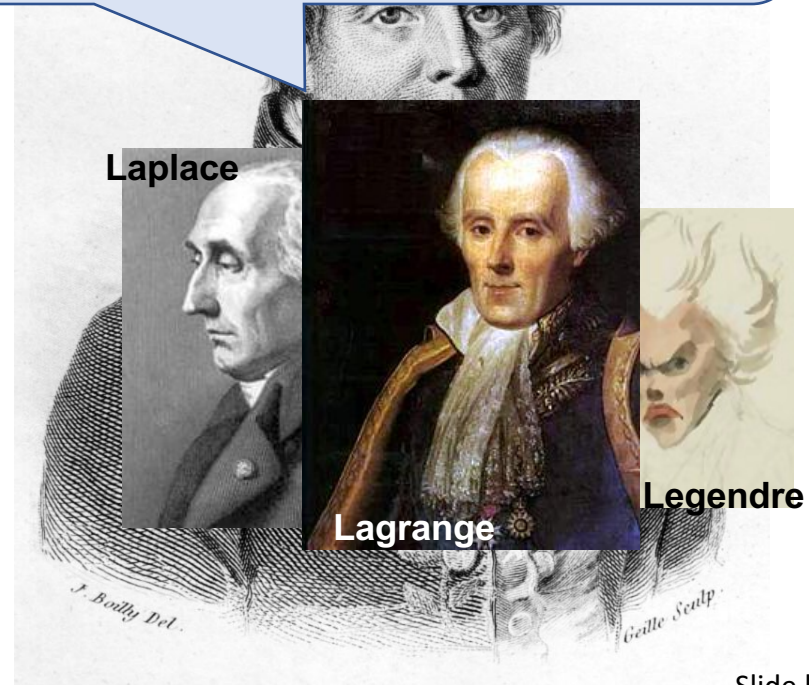
# Jean Baptiste Joseph Fourier (1768-1830)

had crazy idea (1807):

**Any** univariate function can be rewritten as a weighted sum of sines and cosines of different frequencies.

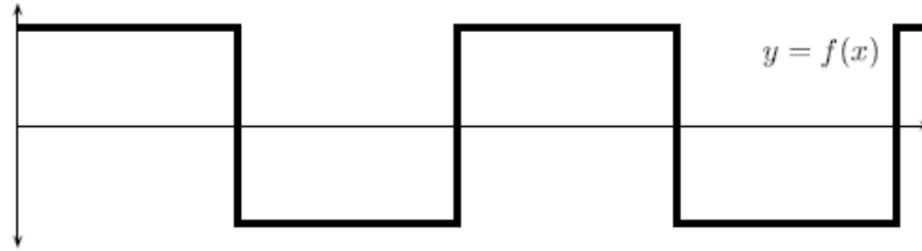
*...the manner in which the author arrives at these equations is not exempt of difficulties and...his analysis to integrate them still leaves something to be desired on the score of generality and even rigour.*

- Don't believe it?
  - Neither did Lagrange, Laplace, Poisson and other big wigs
  - Not translated into English until 1878!
- But it's (mostly) true!
  - called Fourier Series
  - there are some subtle restrictions

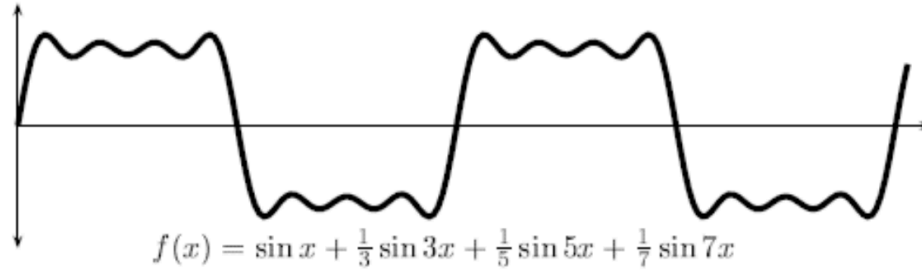


# Example

**Square wave**



**Approximation  
Using sines**



# Discrete Fourier Transform

$$F(u) = \sum_{x=0}^{N-1} f(x) \left[ \cos \left[ -2\pi \left( \frac{xu}{N} \right) \right] + i \sin \left[ -2\pi \left( \frac{xu}{N} \right) \right] \right]$$

$$F(u) = \sum_{x=0}^{N-1} f(x) \exp \left[ -2\pi i \left( \frac{xu}{N} \right) \right]$$

## Discrete Fourier Transform

$$F(u) = \sum_{x=0}^{N-1} f(x) \exp \left[ -2\pi i \left( \frac{xu}{N} \right) \right]$$

## Inverse Discrete Fourier Transform

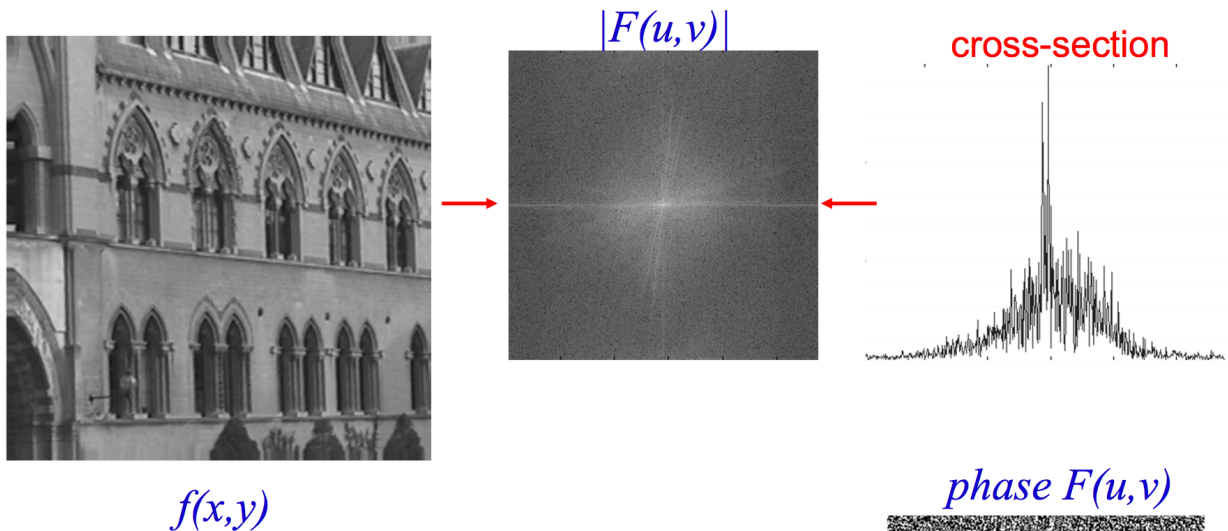
$$f(x) = \frac{1}{N} \sum_{u=0}^{N-1} F(u) \exp \left[ 2\pi i \left( \frac{xu}{N} \right) \right]$$

## More generally for images (2D DFT and iDFT)

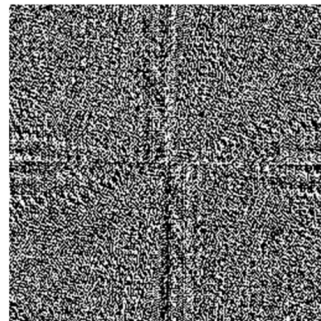
$$F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \exp \left[ -2\pi i \left( \frac{xu}{M} + \frac{yv}{N} \right) \right]$$

$$f(x, y) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) \exp \left[ 2\pi i \left( \frac{xu}{M} + \frac{yv}{N} \right) \right]$$

# Discrete Fourier Transform - Visualization



- $|f(u,v)|$  generally decreases with higher spatial frequencies
- phase appears less informative



# Fourier Transform

- Fourier transform stores the magnitude and phase at each frequency
  - Magnitude encodes how much signal there is at a particular frequency
  - Phase encodes spatial information (indirectly)
  - For mathematical convenience, this is often notated in terms of real and complex numbers

Amplitude:  $A = \pm \sqrt{R(\omega)^2 + I(\omega)^2}$

Phase:  $\phi = \tan^{-1} \frac{I(\omega)}{R(\omega)}$

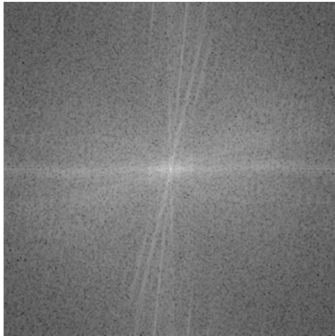
# Image Filtering in the Frequency Domain

original

$f(x,y)$



$|F(u,v)|$



# Image Filtering in the Frequency Domain

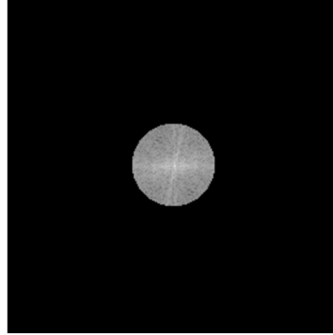
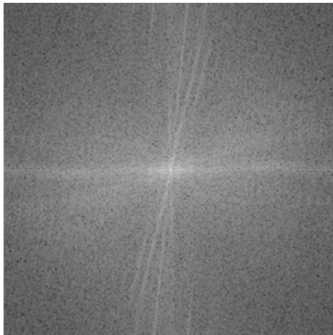
original

low pass

$f(x,y)$



$|F(u,v)|$



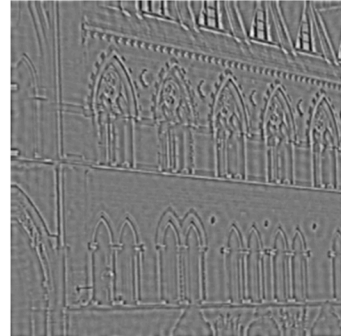
# Image Filtering in the Frequency Domain

original

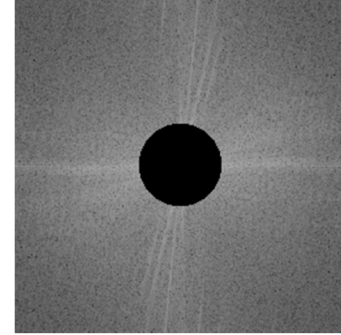
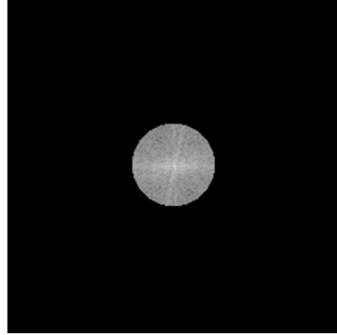
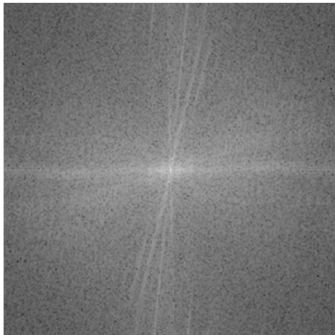
low pass

high pass

$f(x,y)$



$|F(u,v)|$



# The Convolution Theorem

- The Fourier transform of the convolution of two functions is the product of their Fourier transforms

$$F[g * h] = F[g]F[h]$$

- **Convolution** in spatial domain is equivalent to **multiplication** in frequency domain!

$$g * h = F^{-1}[F[g]F[h]]$$

How can this be useful?

# Questions?