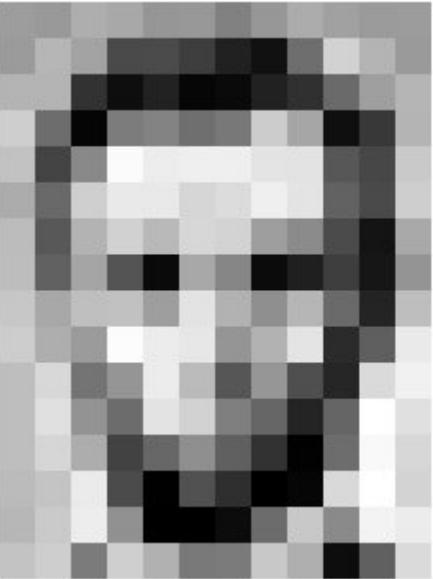


Linear Image filtering



157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	105	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	85	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	95	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	209	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	105	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	85	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	95	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	209	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Overview of today's lecture

- What is an image?
- Types of image transformations.
- Point image processing.
- Linear shift-invariant systems.
- Convolution.
- Linear image filters

What is an image?

What is an image?



What is an image?



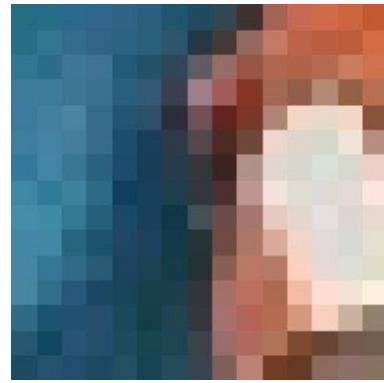
A (color) image
is a 3D tensor
of numbers.

Image as a Function



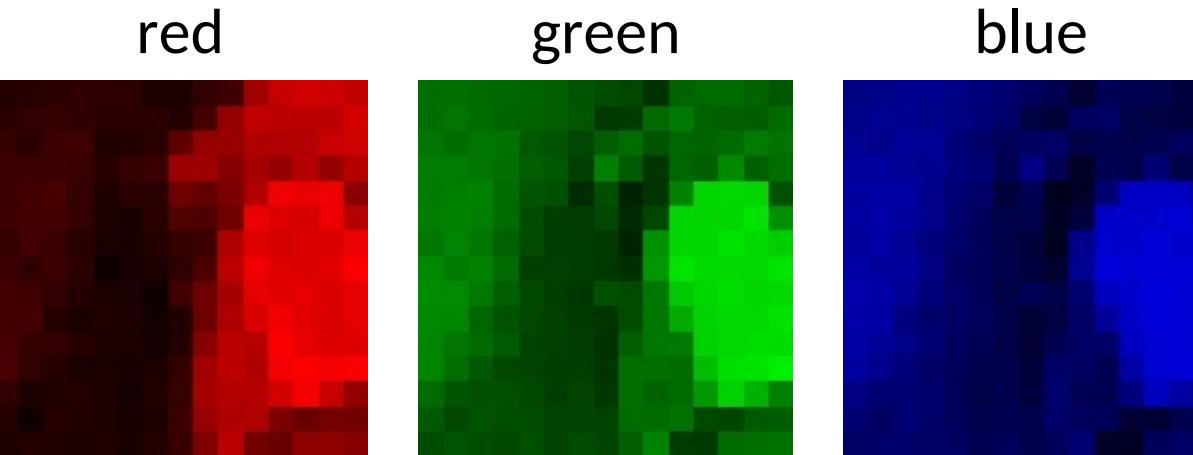
$f(x,y)$ is the image intensity at the spatial coordinates (or position) (x, y)

A color image



color image patch

How many bits are
the intensity values?



actual intensity values per channel

Each channel
is a 2D array of
numbers.

Types of image transformations

what types of image transformations can we do?



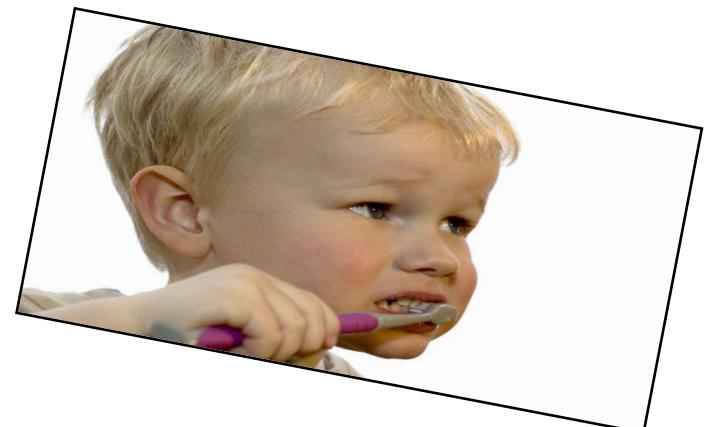
Filtering



changes pixel values



Warping



changes pixel locations

what types of image transformations can we do?

F

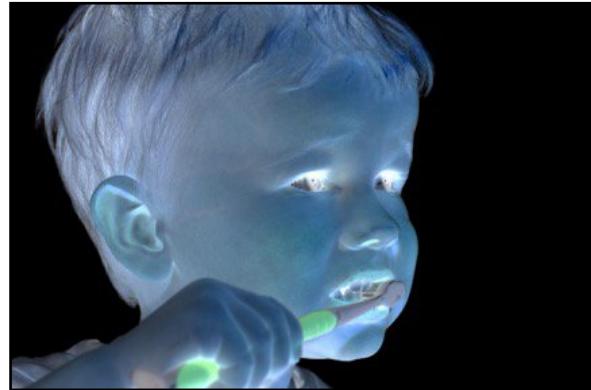


Filtering



$$G(\mathbf{x}) = h\{F(\mathbf{x})\}$$

G



changes range of image function

F

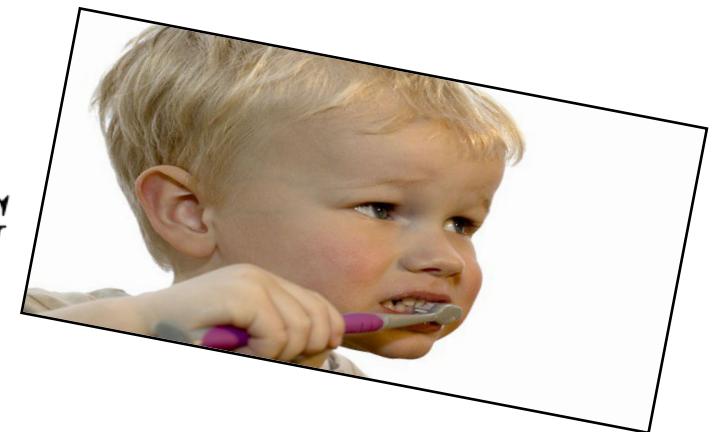


Warping



$$G(\mathbf{x}) = F(h\{\mathbf{x}\})$$

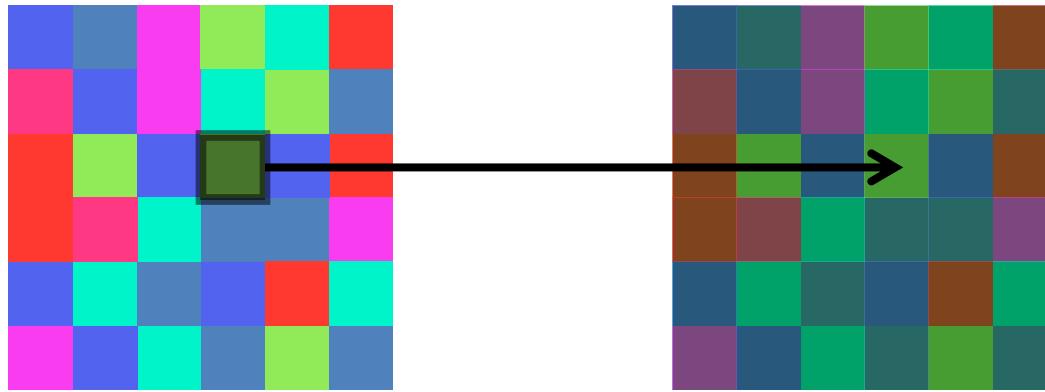
G



changes domain of image function

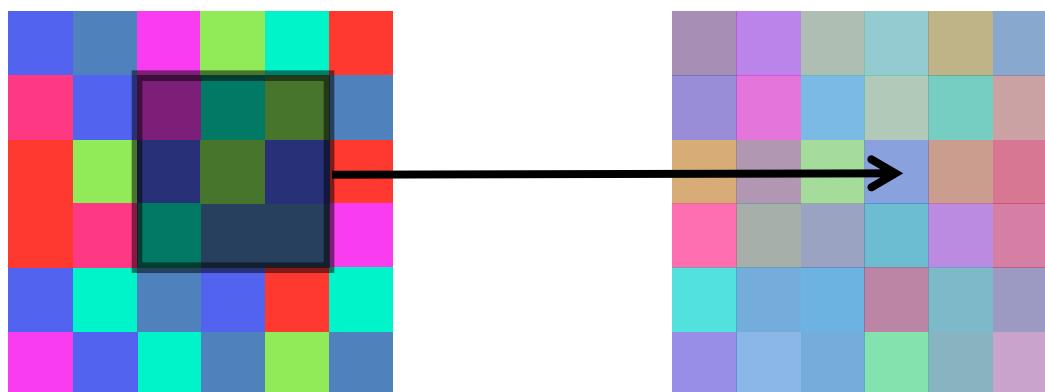
What types of image filtering can we do?

Point Operation



point processing

Neighborhood Operation



“filtering”

Point processing

Pixel (Point) Processing

Transformation T of intensity f at each pixel to intensity g :

$$g(x,y) = T(f(x,y))$$

How would you implement
these transformations?

Examples of point processing

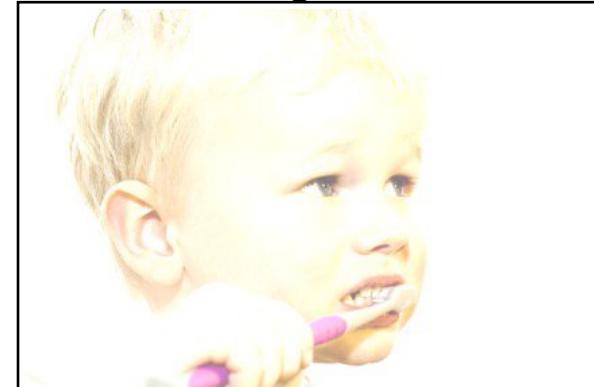
original



darker



lighten



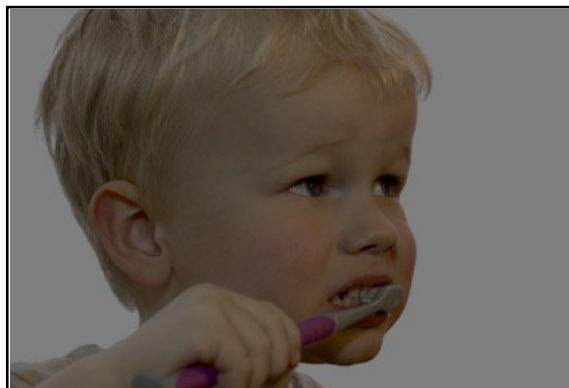
f

invert



...

lower contrast



...

raise contrast



...

...

...

How would you implement
these transformations?

Examples of point processing

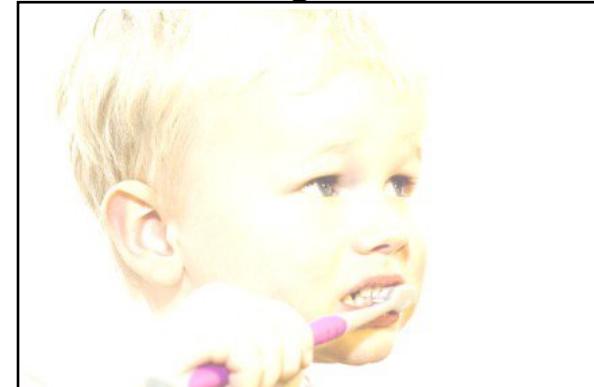
original



darker



lighten



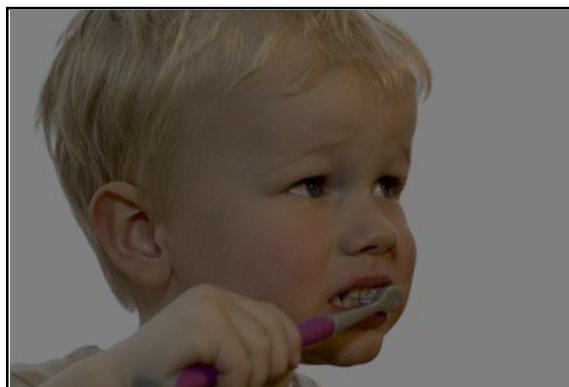
f

invert



$f - 128$

lower contrast



...

raise contrast



...

...

...

How would you implement
these transformations?

Examples of point processing

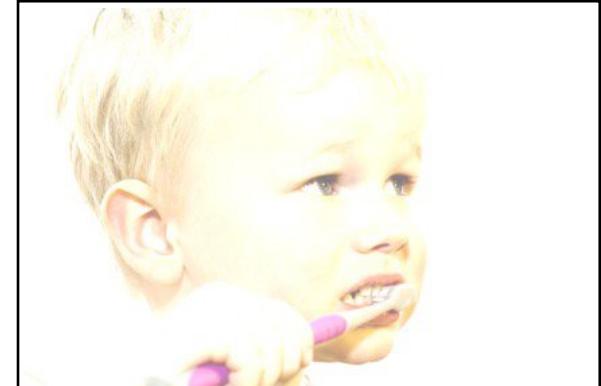
original



darker



lighten



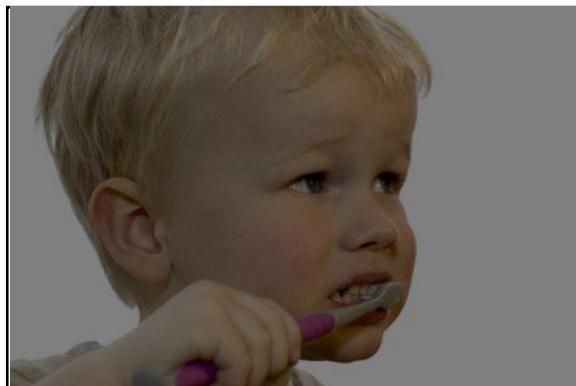
f

invert



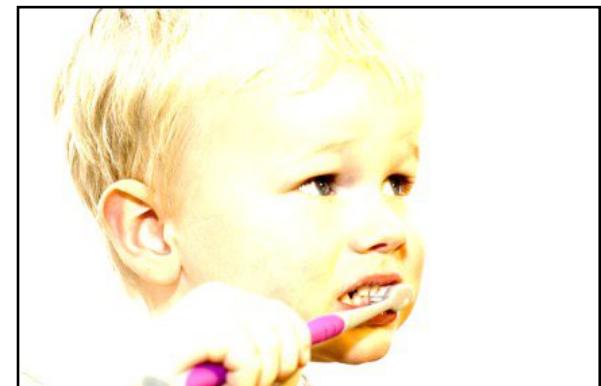
$f - 128$

lower contrast



$f + 128$

raise contrast



...

...

...

How would you implement
these transformations?

Examples of point processing

original



darker



lighten



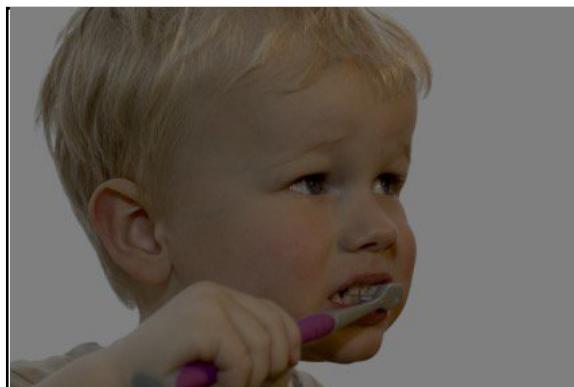
f

invert



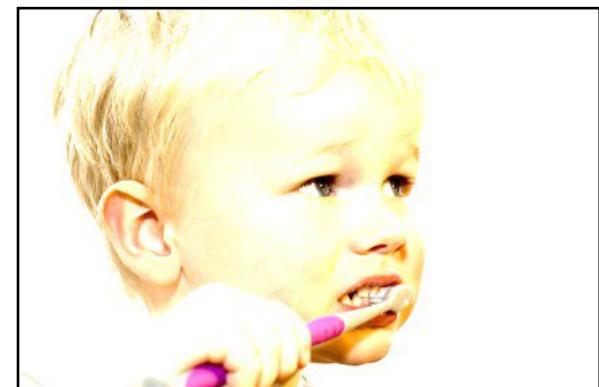
$f - 128$

lower contrast



$f + 128$

raise contrast



$255 - f$

...

...

How would you implement
these transformations?

Examples of point processing

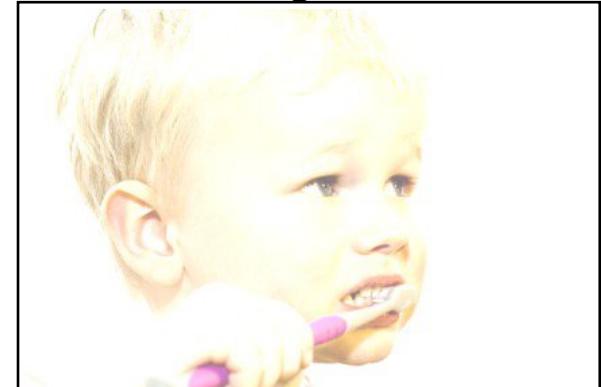
original



darker



lighten



f

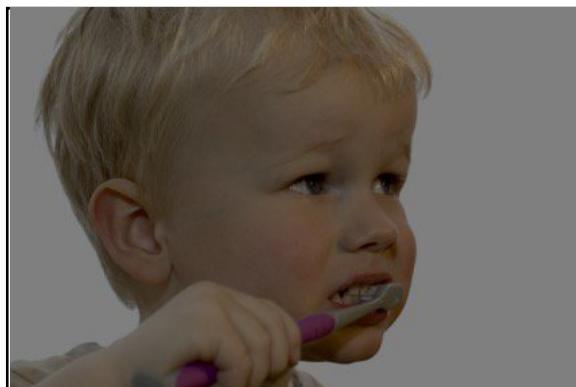
$f - 128$

$f + 128$

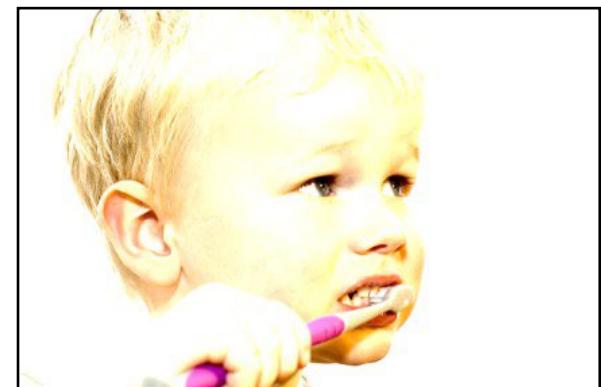
invert



lower contrast



raise contrast



$255 - f$

$f/2$

...

How would you implement
these transformations?

Examples of point processing

original

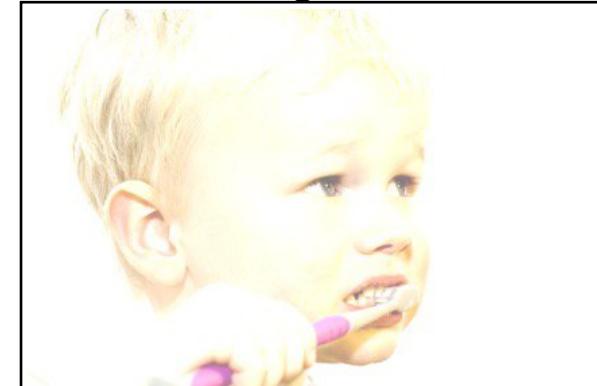


$$f$$

darker



lighten



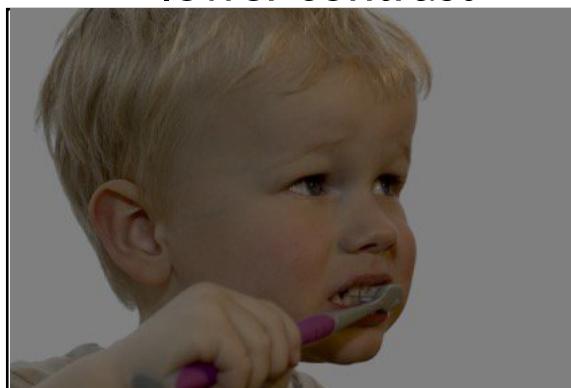
invert



$$255 - f$$

$$f - 128$$

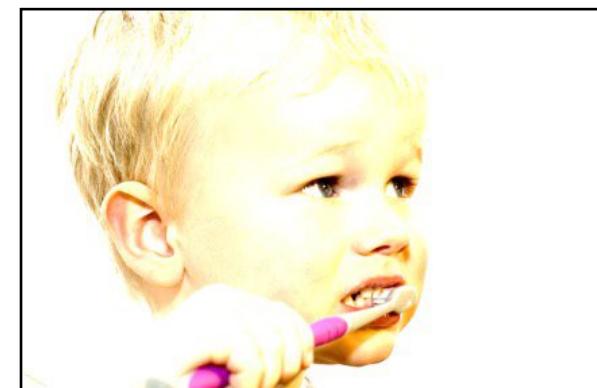
lower contrast



$$f/2$$

$$f + 128$$

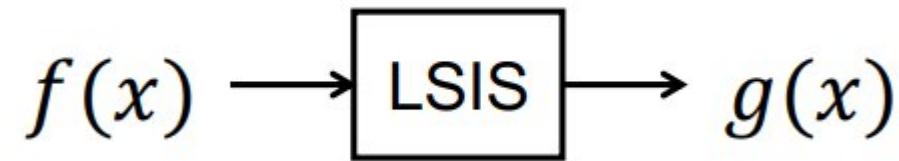
raise contrast



$$f \times 2$$

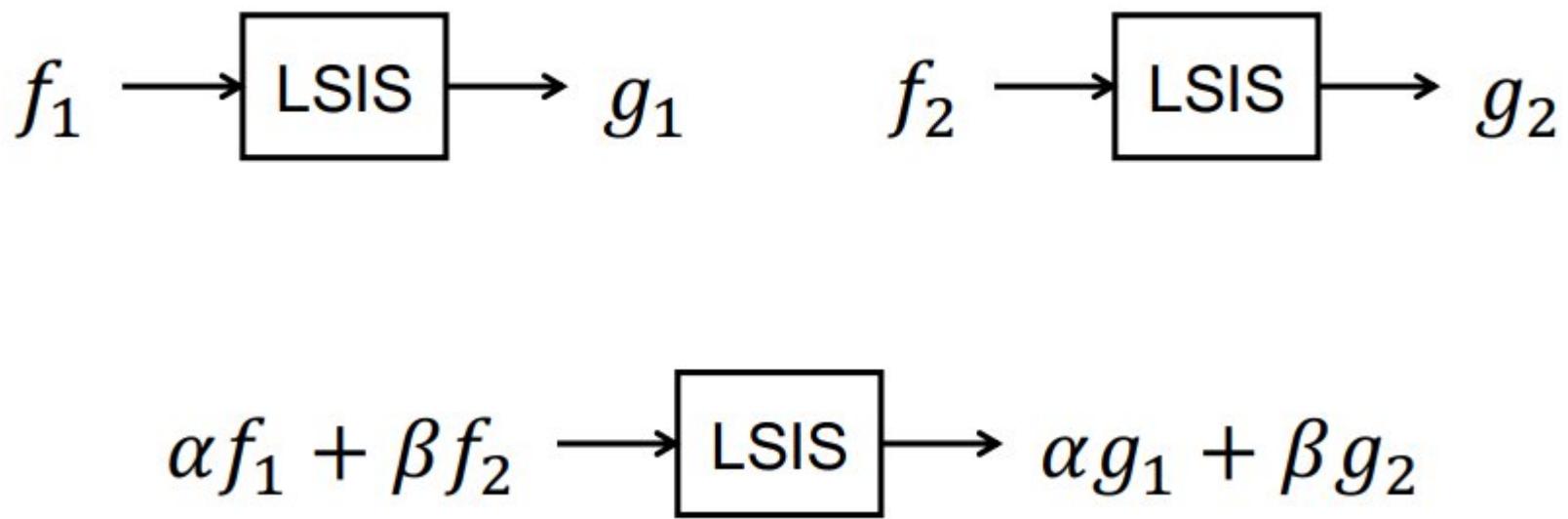
Linear shift-invariant systems

Linear shift-invariant system (LSIS)

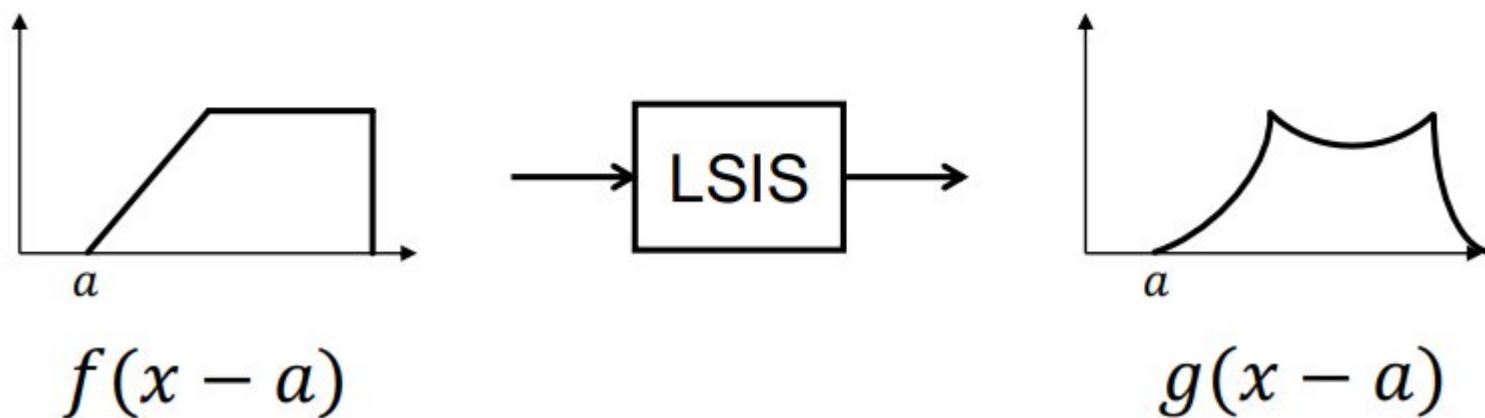
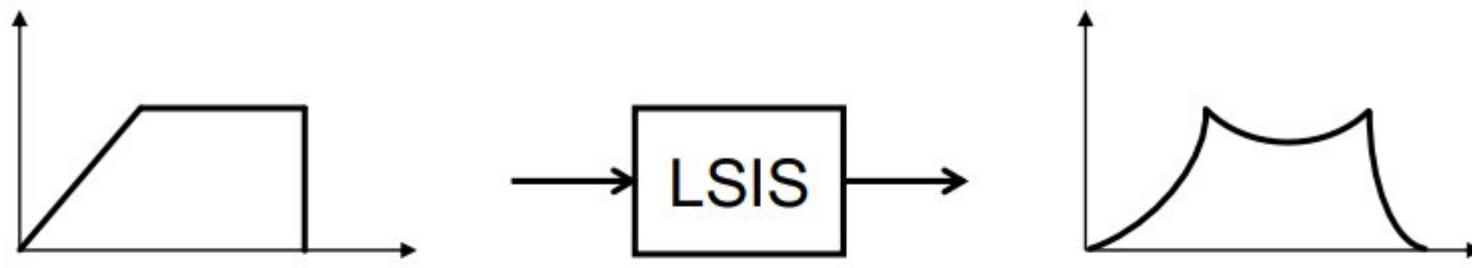


Study of Linear Shift Invariant Systems (LSIS) leads to useful image processing algorithms.

LSIS : Linearity



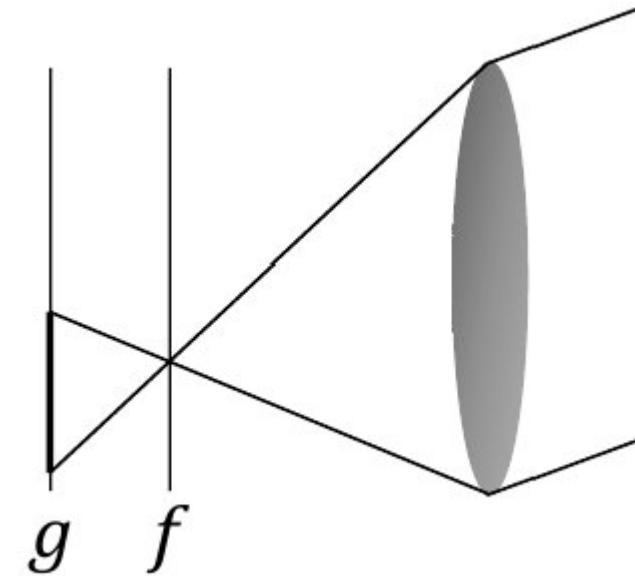
LSIS: Shift Invariance



Ideal Lens is an LSIS

Defocused Image (g) : Processed version of Focused Image (f)

- Linearity: Brightness variation
- Shift invariance: Scene movement



Why This Matters

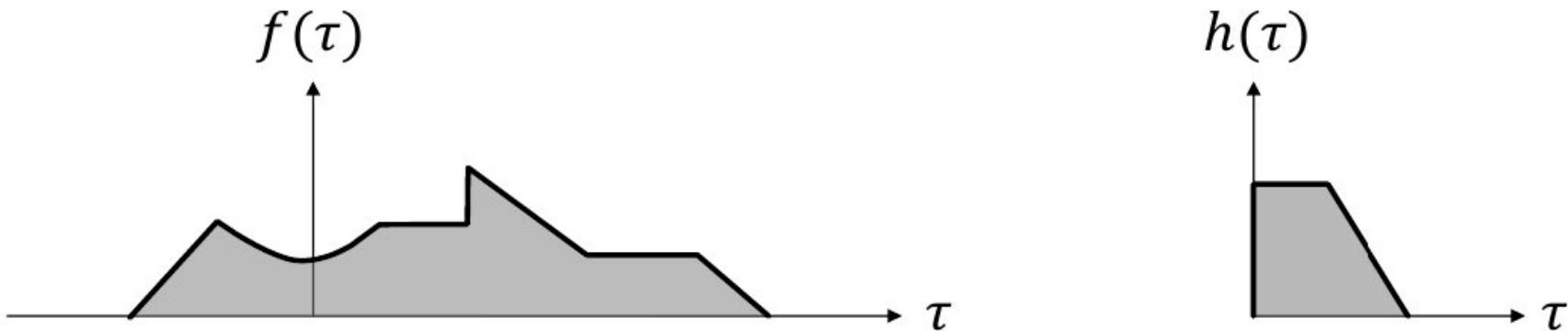
Any system that is both Linear and Shift Invariant can be represented as a **convolution** with some kernel!

Convolution

Convolution

The convolution of two functions $f(x)$ and $h(x)$ is:

$$g(x) = f(x) * h(x) = \int_{-\infty}^{\infty} f(\tau)h(x - \tau) d\tau$$

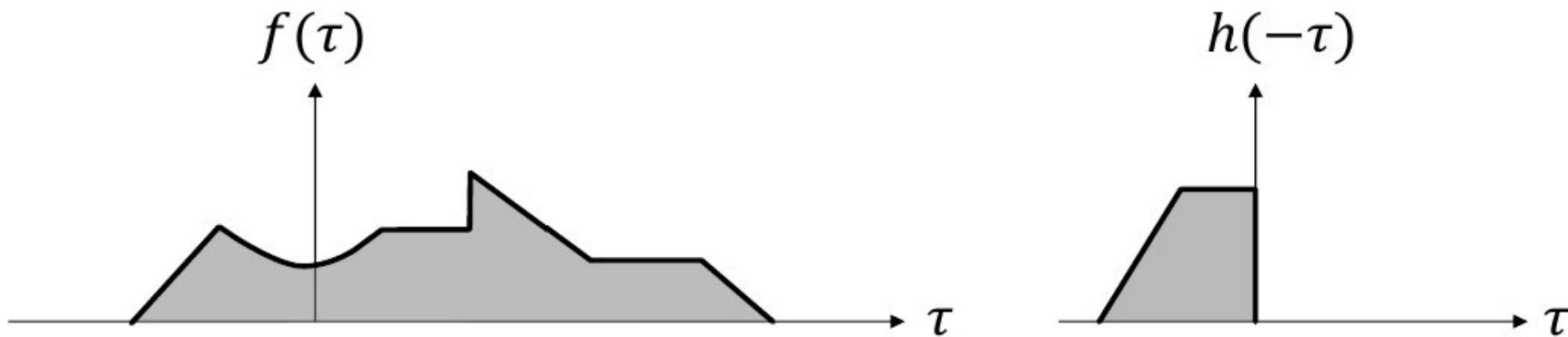


Convolution

The convolution of two functions $f(x)$ and $h(x)$ is:

$$g(x) = f(x) * h(x) = \int_{-\infty}^{\infty} f(\tau)h(x - \tau) d\tau$$

Step 1: we take $h(\tau)$ and flip it about the vertical axis to get $h(-\tau)$

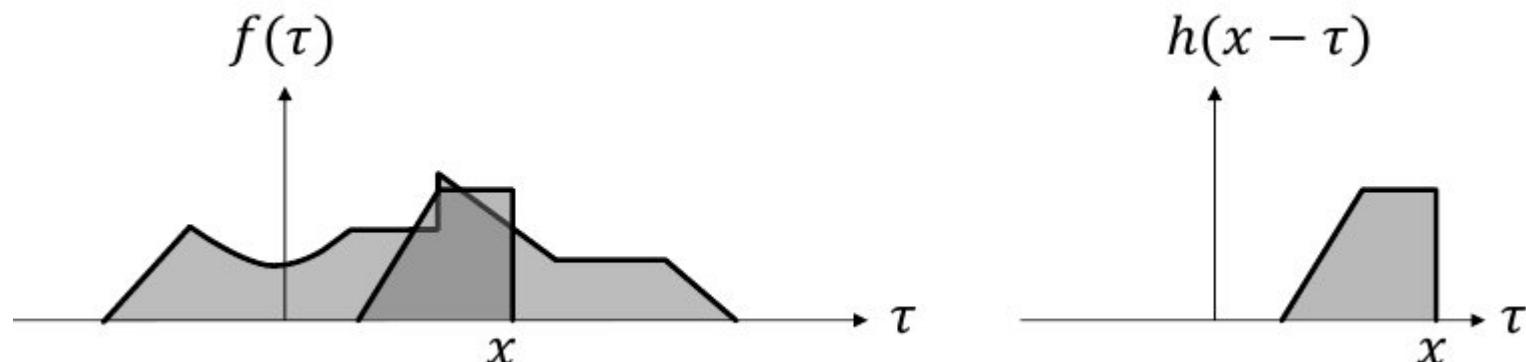


Convolution

The convolution of two functions $f(x)$ and $h(x)$ is:

$$g(x) = f(x) * h(x) = \int_{-\infty}^{\infty} f(\tau)h(x - \tau) d\tau$$

Step 2: we shift $h(-\tau)$ by x to get $h(x - \tau)$, which is then overlaid on $f(\tau)$

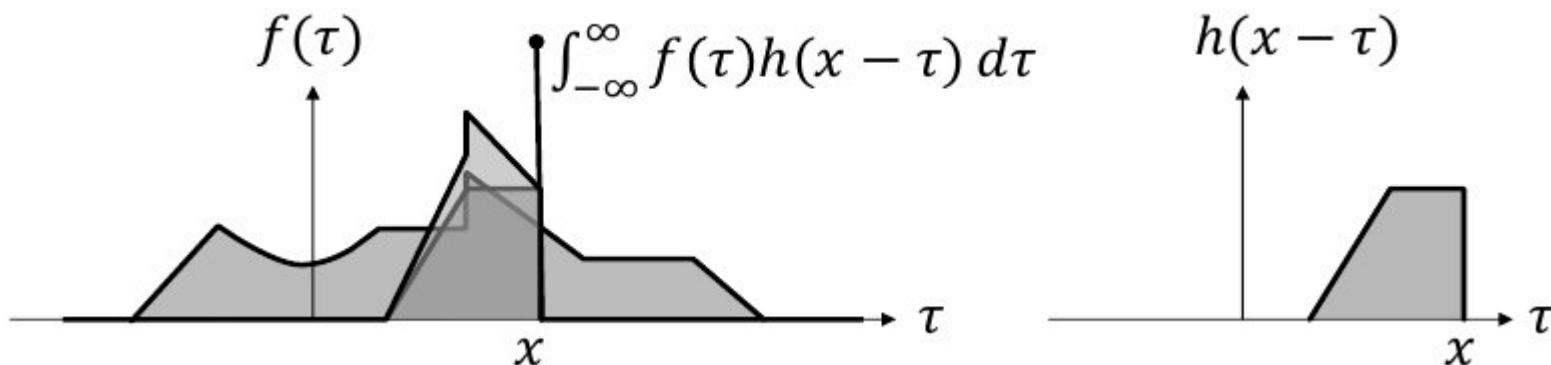


Convolution

The convolution of two functions $f(x)$ and $h(x)$ is:

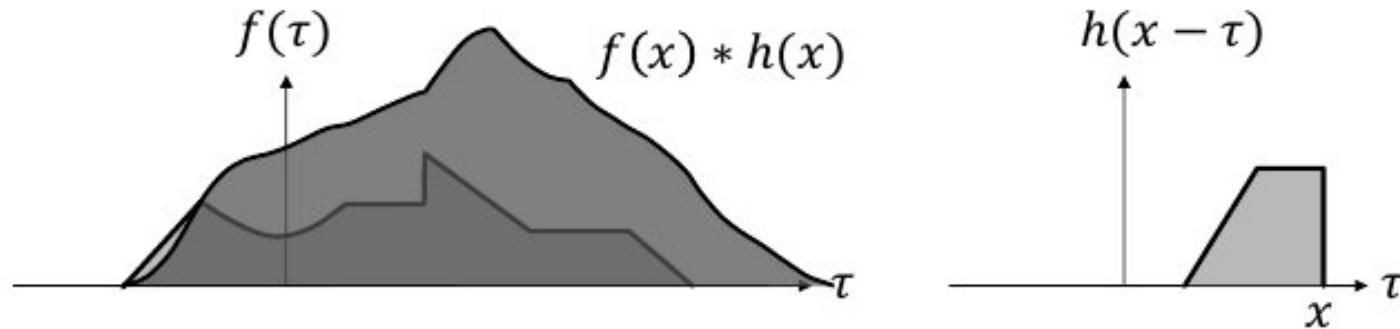
$$g(x) = f(x) * h(x) = \int_{-\infty}^{\infty} f(\tau)h(x - \tau) d\tau$$

Step 3: we take the product $f(\tau)h(x - \tau)$, and integrate it from -infinity to infinity



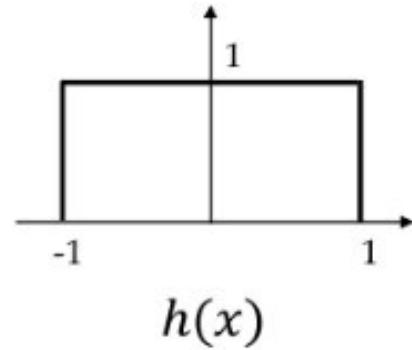
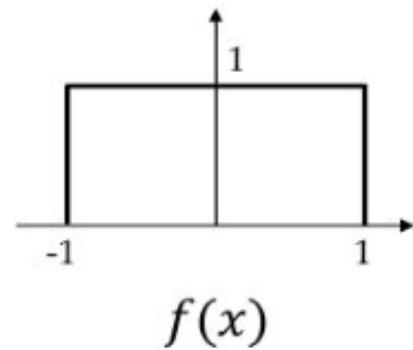
Convolution

Step 4: We then vary the shift from minus infinity to plus infinity by sliding the function $h(-\tau)$ over $f(\tau)$ from left to right.

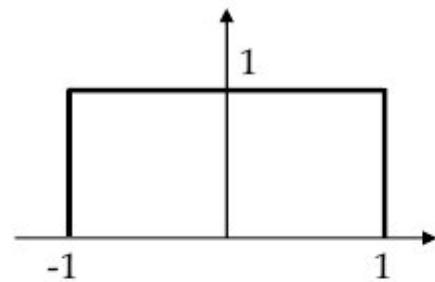


LSIS implies Convolution and Convolution implies LSIS

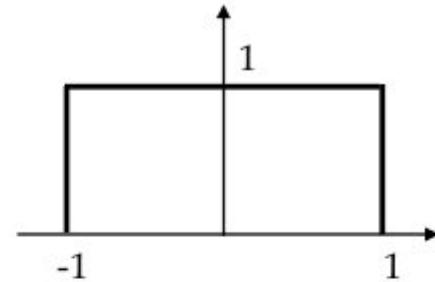
Convolution: Example



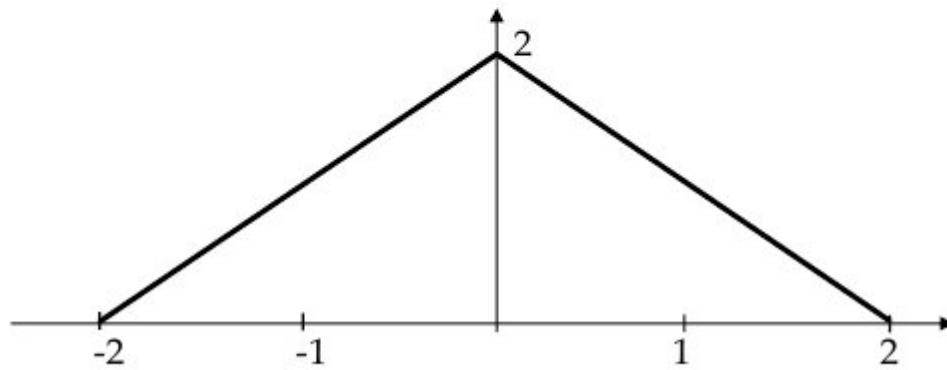
Convolution: Example



$$f(x)$$

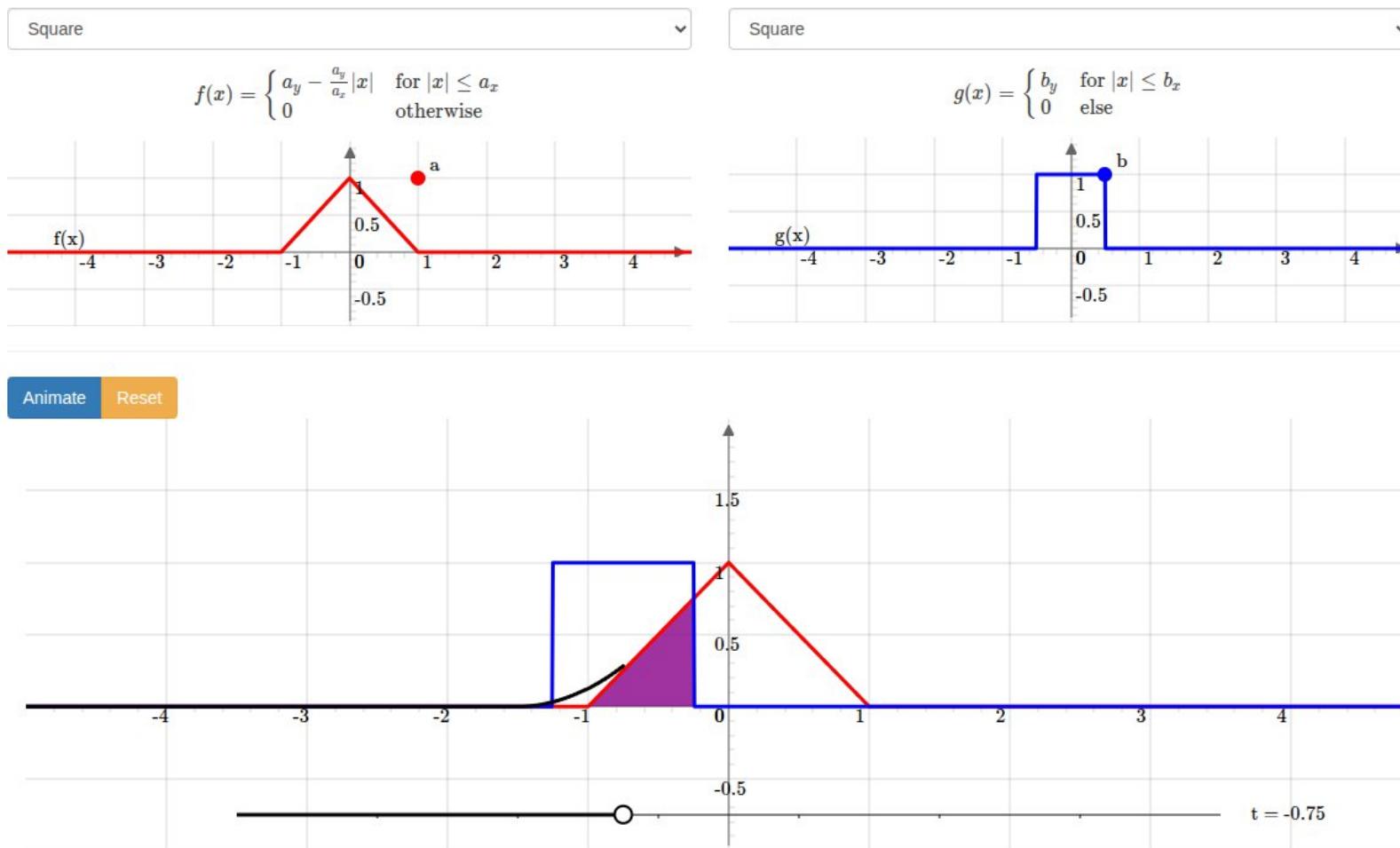


$$h(x)$$



$$f(x) * h(x)$$

Convolution: Online Demo



Convolution is LSIS

Linearity:

Let: $g_1(x) = \int_{-\infty}^{\infty} f_1(\tau)h(x - \tau) d\tau$ and $g_2(x) = \int_{-\infty}^{\infty} f_2(\tau)h(x - \tau) d\tau$

Then:

$$\int_{-\infty}^{\infty} (\alpha f_1(\tau) + \beta f_2(\tau))h(x - \tau) d\tau$$

$$= \alpha \int_{-\infty}^{\infty} f_1(\tau)h(x - \tau) d\tau + \beta \int_{-\infty}^{\infty} f_2(\tau)h(x - \tau) d\tau$$

$$= \alpha g_1(x) + \beta g_2(x)$$

Convolution is LSIS

Shift Invariance:

Let:
$$g(x) = \int_{-\infty}^{\infty} f(\tau)h(x - \tau) d\tau$$

Then:

$$\begin{aligned} & \int_{-\infty}^{\infty} f(\tau - a)h(x - \tau) d\tau \\ &= \int_{-\infty}^{\infty} f(\mu)h(x - a - \mu) d\mu \quad \boxed{1} \quad (\text{Substituting } \mu = \tau - a) \\ &= g(x - a) \end{aligned}$$

Can we find h ?

$$f \rightarrow \boxed{h} \rightarrow g \quad g(x) = \int_{-\infty}^{\infty} f(\tau)h(x - \tau) d\tau$$

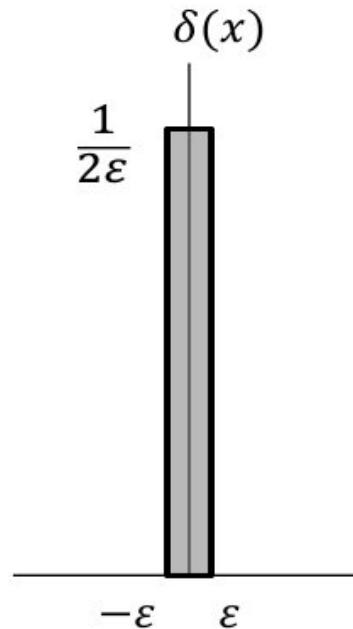
What input f will produce output $g = h$?

$$h(x) = \int_{-\infty}^{\infty} ?(\tau)h(x - \tau) d\tau$$

Unit Impulse Function

$$\delta(x) = \begin{cases} 1/2\varepsilon, & |x| \leq \varepsilon \\ 0, & |x| > \varepsilon \end{cases} \quad \varepsilon \rightarrow 0$$

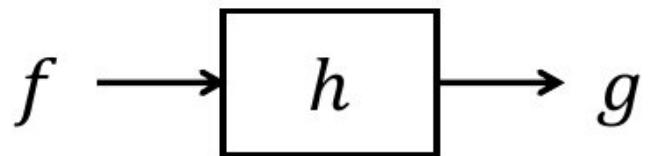
$$\int_{-\infty}^{\infty} \delta(\tau) d\tau = \frac{1}{2\varepsilon} \cdot 2\varepsilon = 1$$



$$\int_{-\infty}^{\infty} \delta(\tau) b(x - \tau) d\tau = b(x)$$

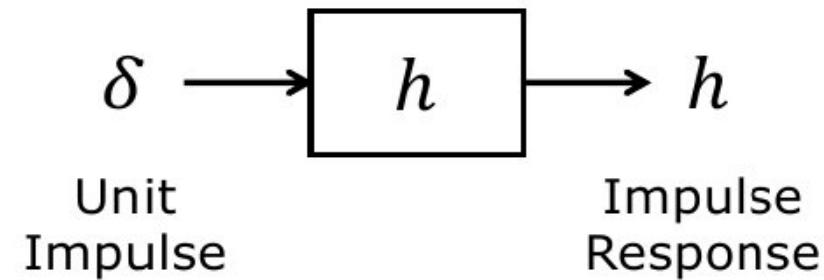
Sifting Property

Impulse Response



$$g(x) = f(x) * h(x)$$

$$g(x) = \int_{-\infty}^{\infty} f(\tau)h(x - \tau) d\tau$$



$$h(x) = \delta(x) * h(x)$$

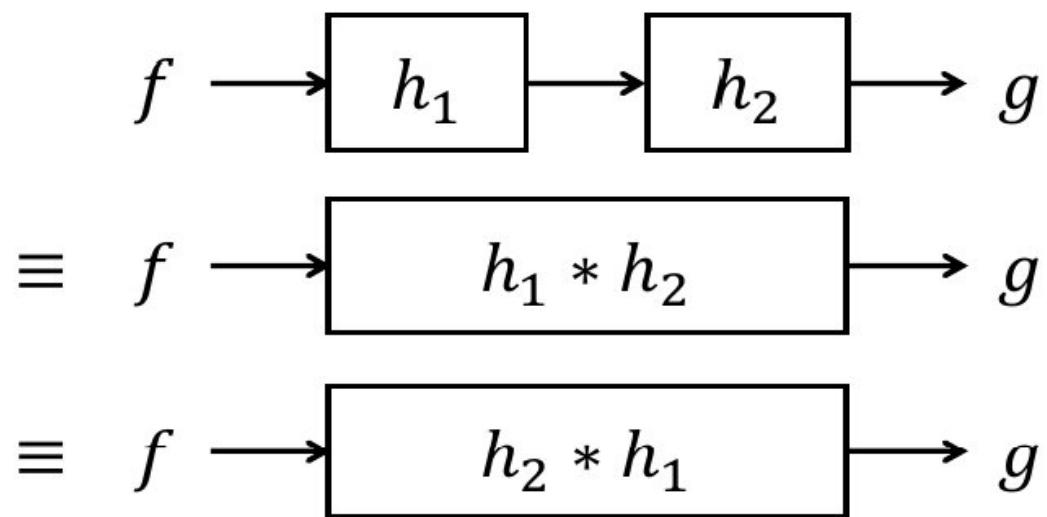
$$h(x) = \int_{-\infty}^{\infty} \delta(\tau)h(x - \tau) d\tau$$

Properties of Convolution

Commutative $a * b = b * a$

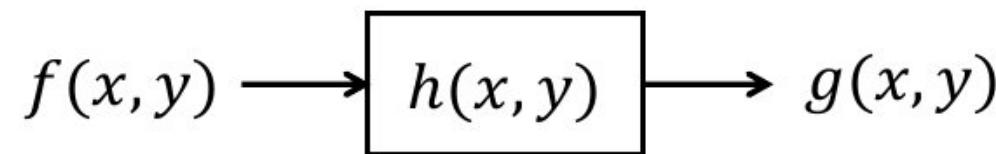
Associative $(a * b) * c = a * (b * c)$

Cascaded System



2D Convolution

LSIS:



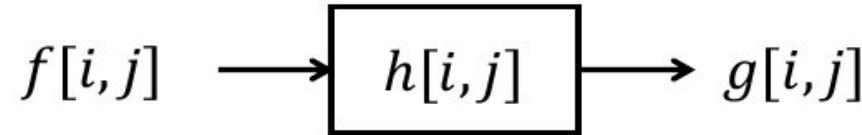
Convolution:

$$g(x, y) = \iint_{-\infty}^{\infty} f(\tau, \mu) h(x - \tau, y - \mu) d\tau d\mu$$

1

Linear shift-invariant image filtering

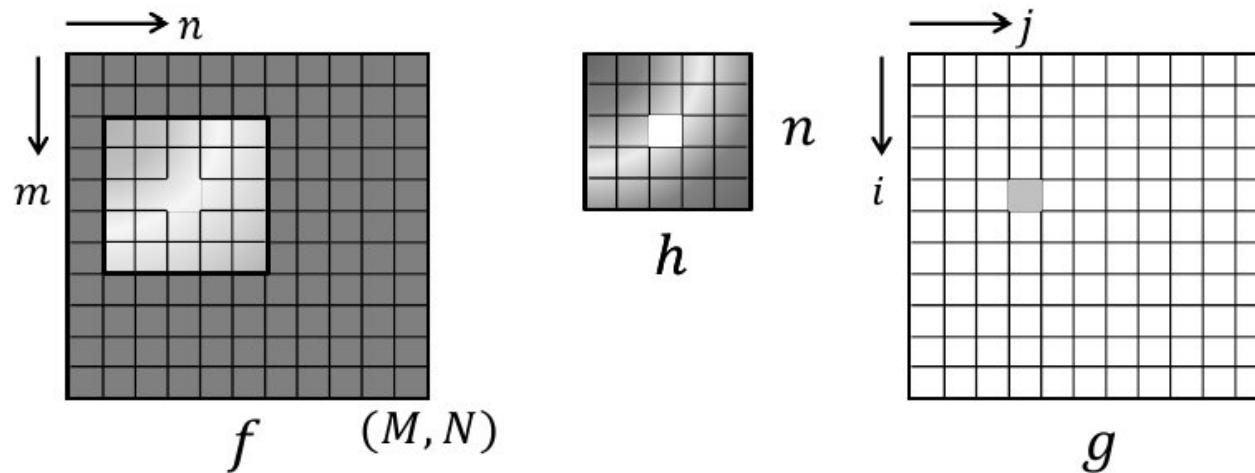
Convolution with Discrete Images



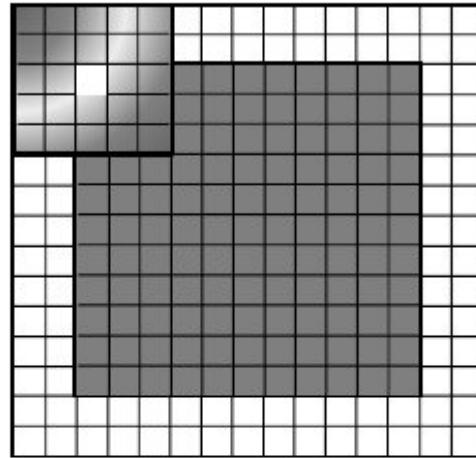
$$g[i, j] = \sum_{m=1}^M \sum_{n=1}^N f[m, n] h[i - m, j - n]$$

"Mask," "Kernel," "Filter"

1



Border Problem



Solution:

- Ignore border
- Pad with constant value
- Pad with reflection

Linear shift-invariant image filtering

- Replace each pixel by a linear combination of its neighbors (and possibly itself).
- The combination is determined by the filter's kernel.
- The same kernel is shifted to all pixel locations so that all pixels use the same linear combination of their neighbors.

Example: the box filter

Download more graphics at www.psdgraphics.com

- also known as the 2D rect (not rekt) filter
- also known as the square mean filter

$$\text{kernel } h(i,j) = \frac{1}{9} \begin{array}{|c|c|c|}\hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

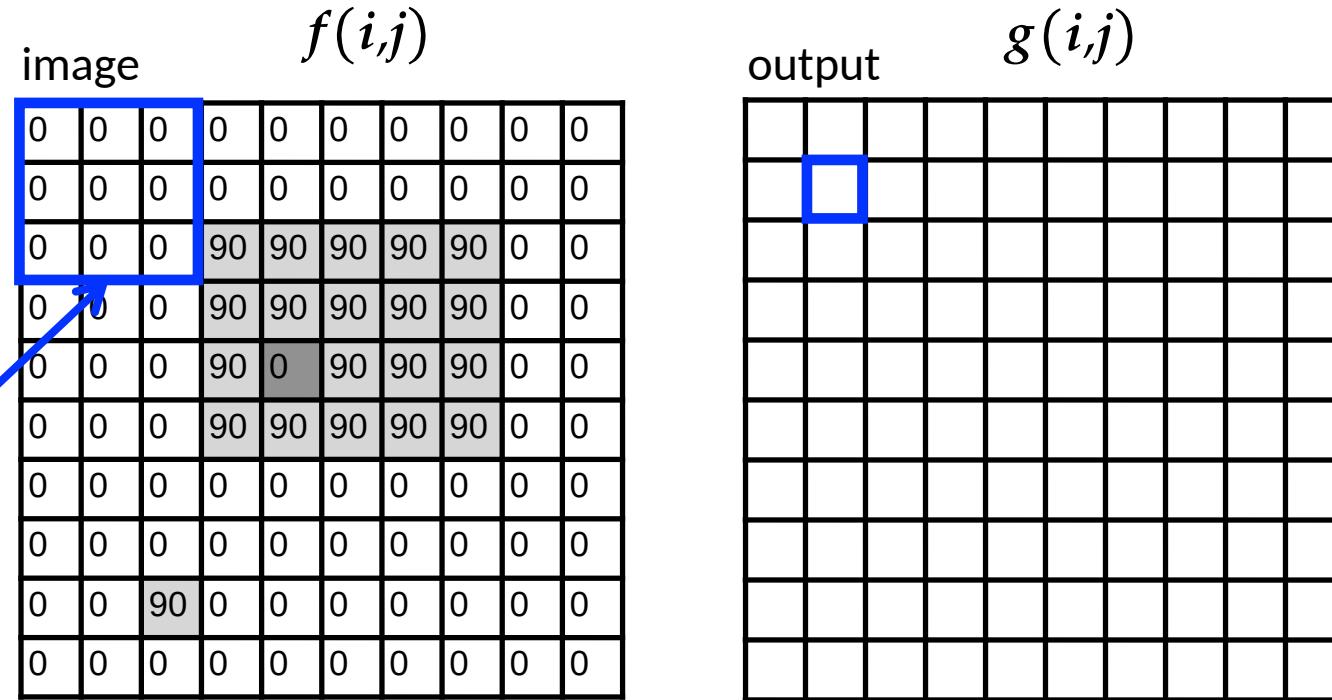
- replaces pixel with local average
- has smoothing (blurring) effect



Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

1	1	1
1	1	1
1	1	1



note that we assume that
the kernel coordinates
are centered

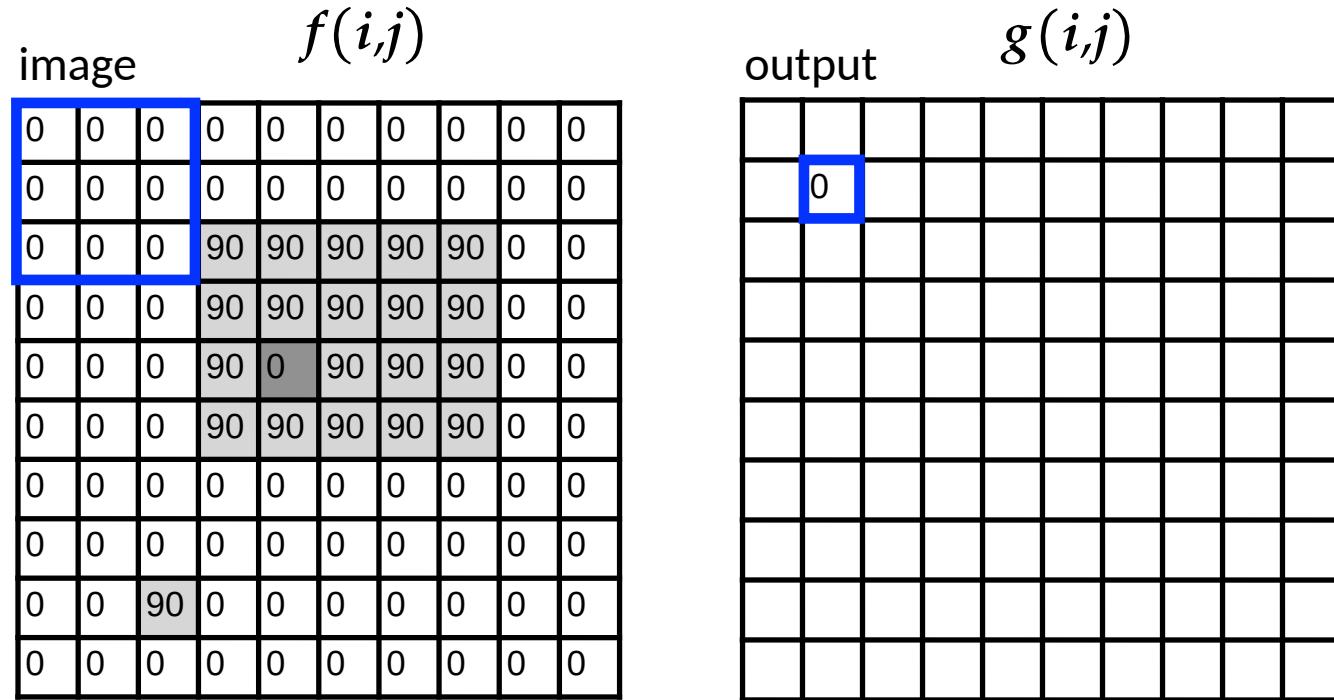
$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] \underbrace{h[i-m, j-n]}_{\text{"Mask," "Kernel," "Filter"}}$$

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

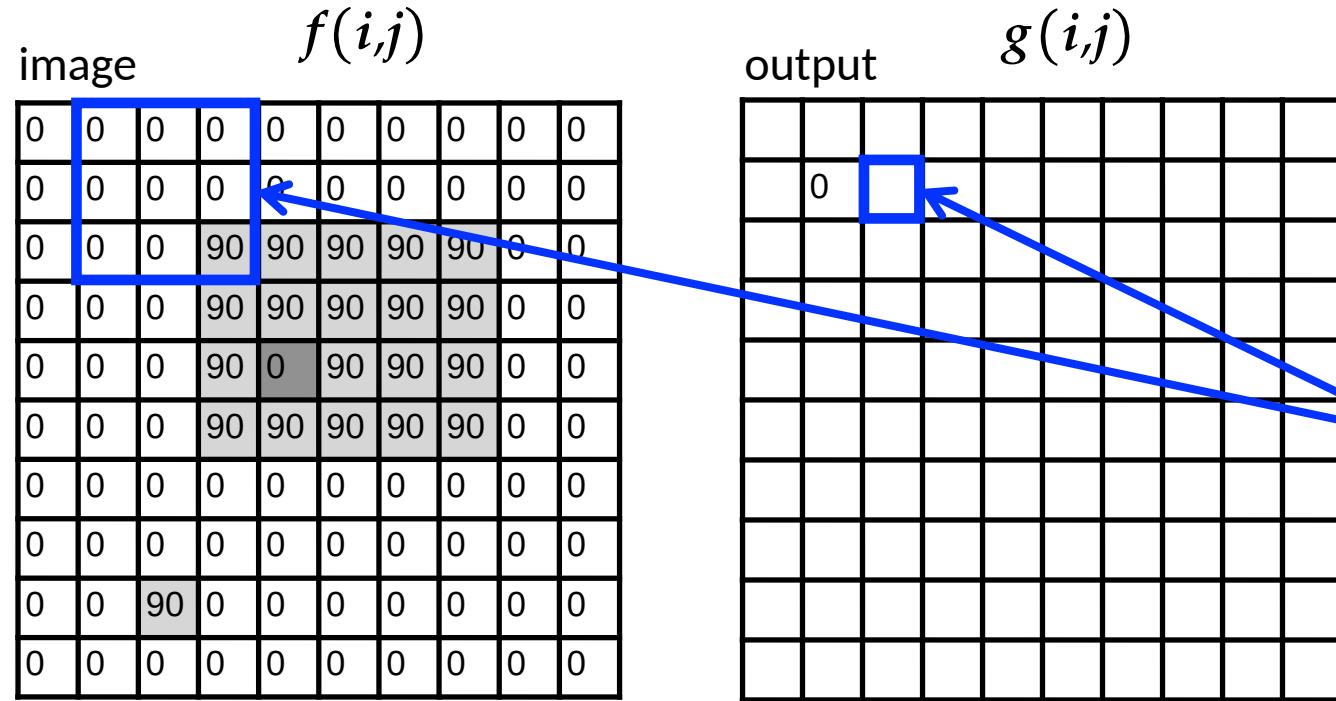
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



shift-invariant:
as the pixel
shifts, so does
the kernel

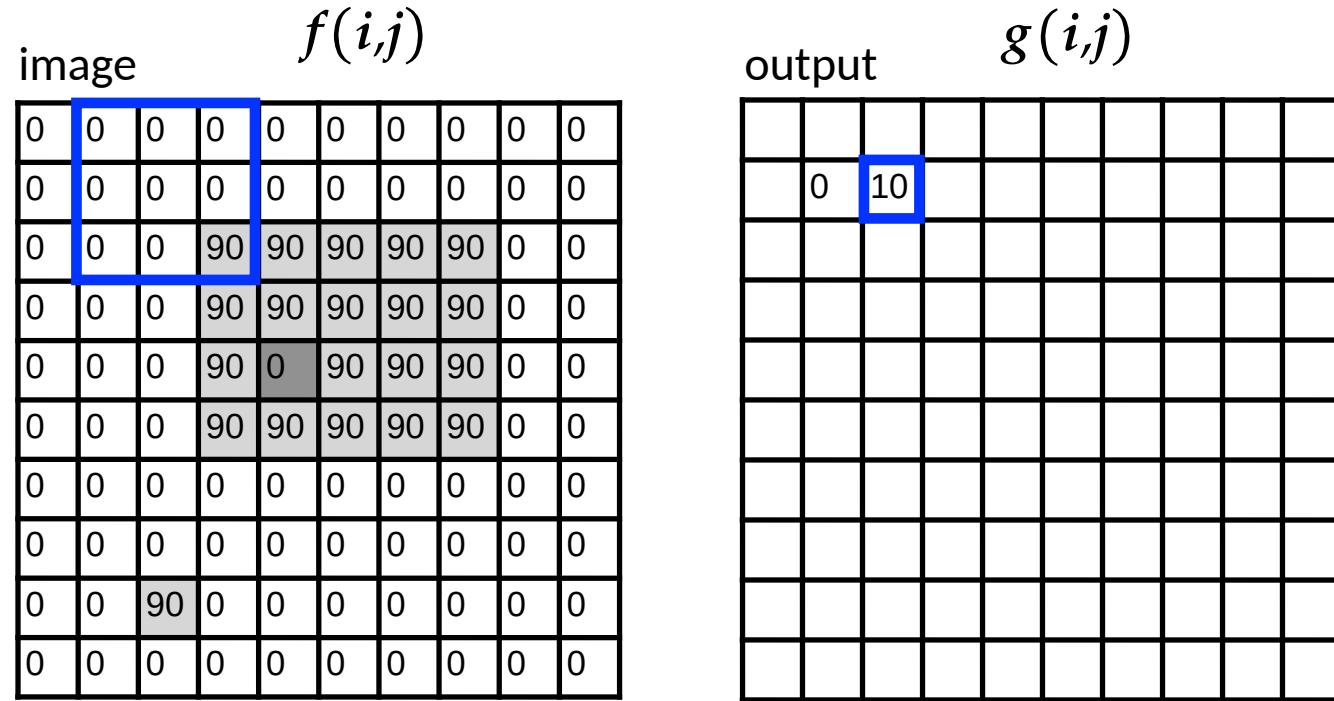
$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] \underbrace{h[i-m, j-n]}_{\text{"Mask," "Kernel," "Filter"}}$$

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

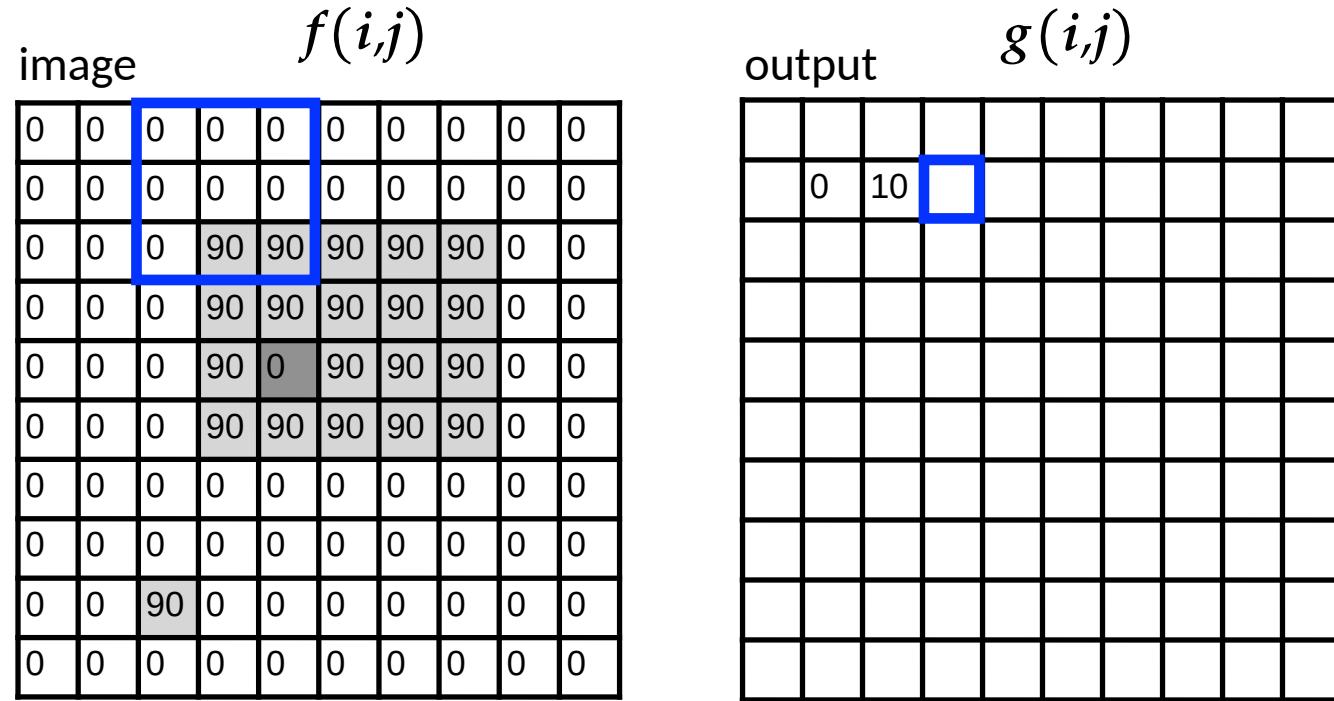
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

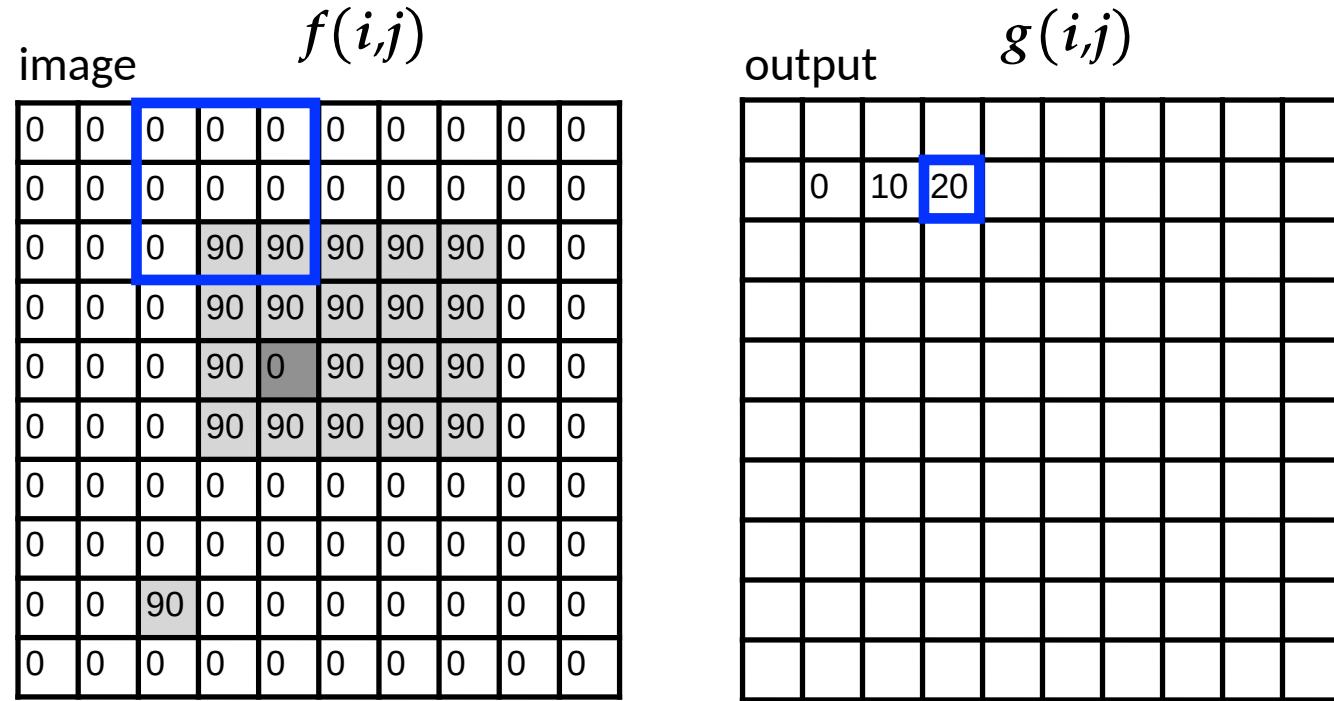
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

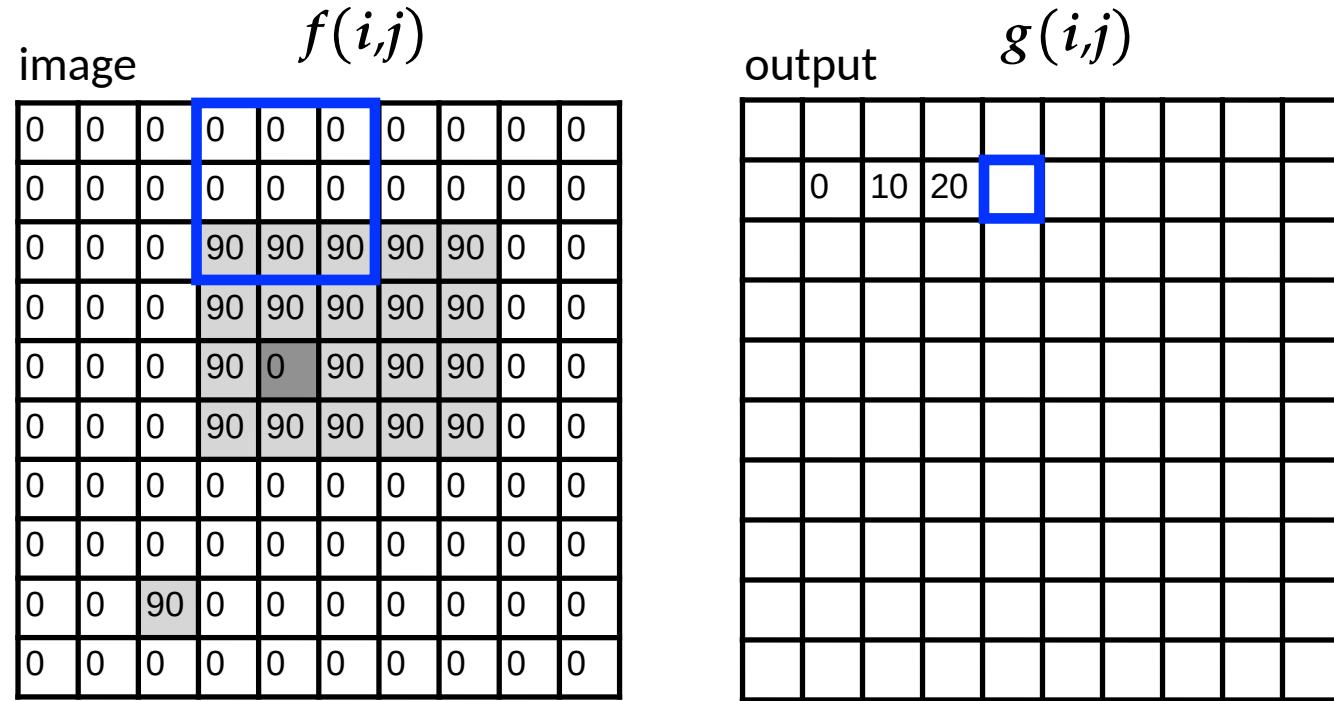
"Mask," "Kernel," "Filter"

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kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

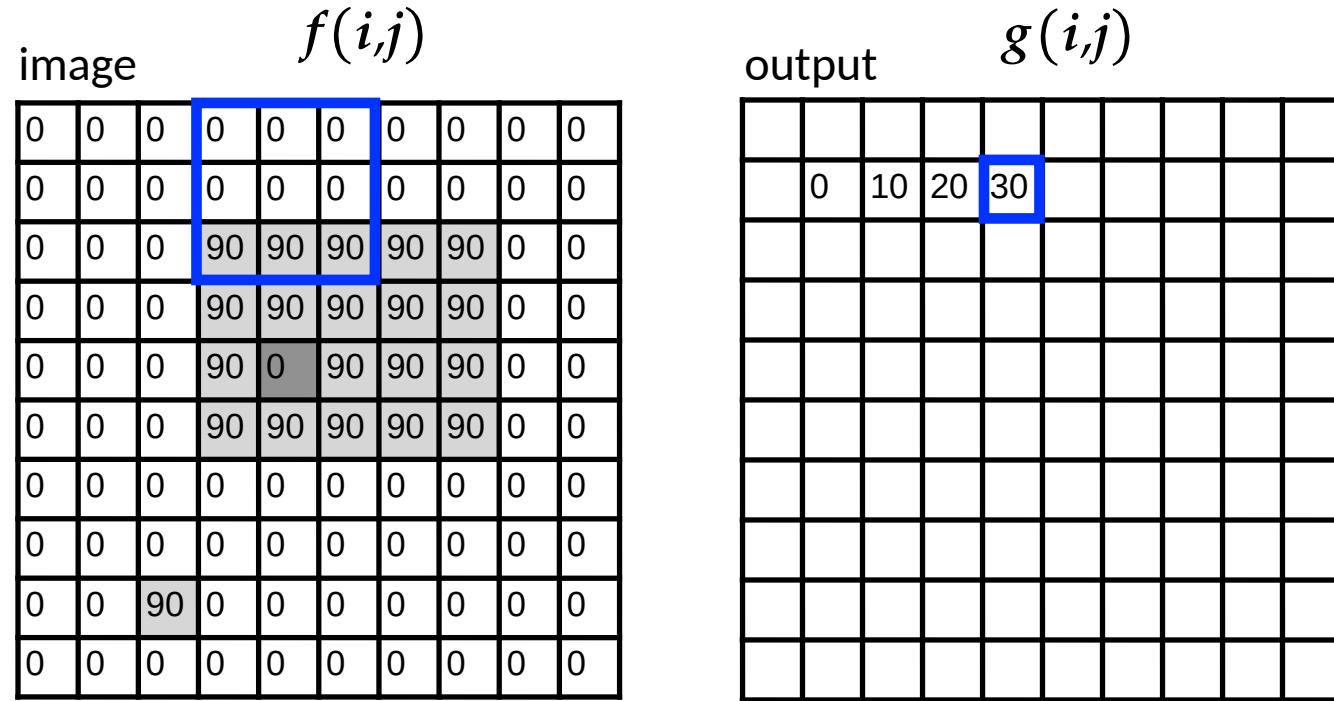
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9} \begin{array}{|c|c|c|} \hline & \text{kernel} & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

$$g[i, j] = \sum_{m=1}^M \sum_{n=1}^N f[m, n] h[i - m, j - n]$$

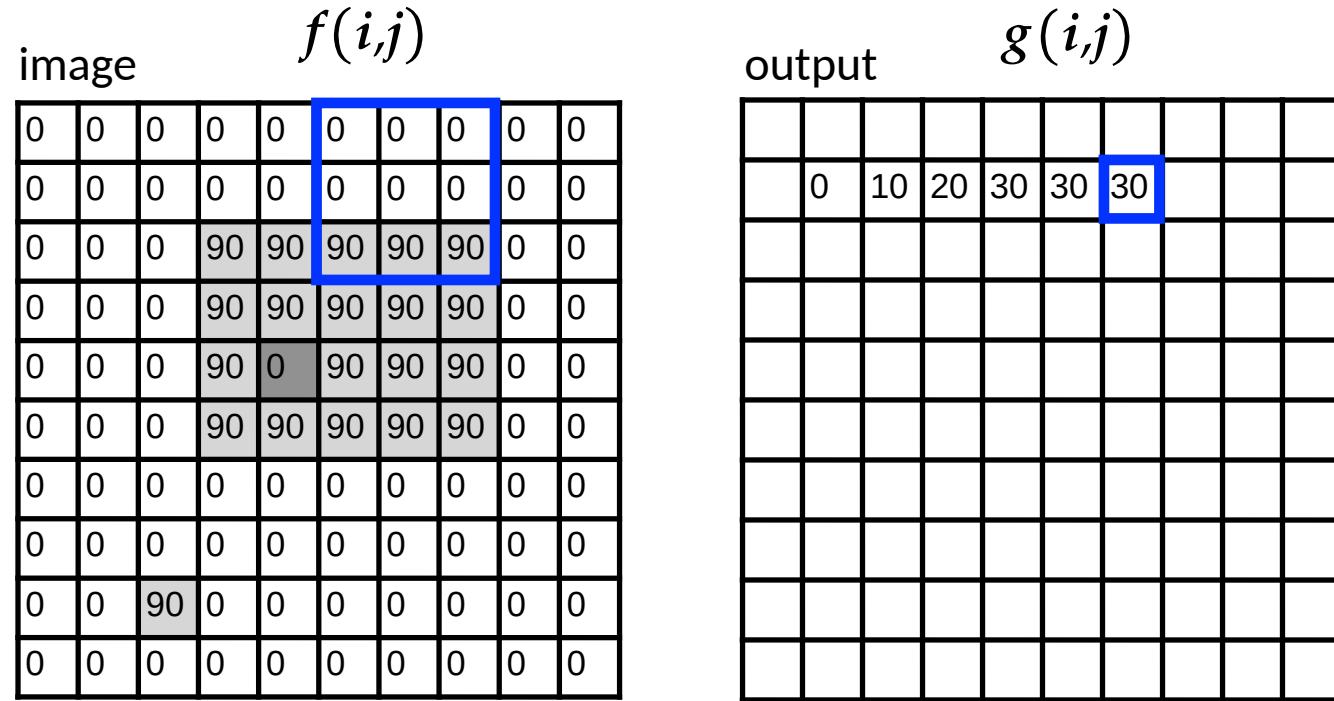
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] \underbrace{h[i-m, j-n]}_{\text{"Mask," "Kernel," "Filter"}}$$

Let's run the box filter

$$h(i,j) = \frac{1}{9} \begin{array}{|c|c|c|} \hline & \text{kernel} & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

$$g[i, j] = \sum_{m=1}^M \sum_{n=1}^N f[m, n] h[i - m, j - n]$$

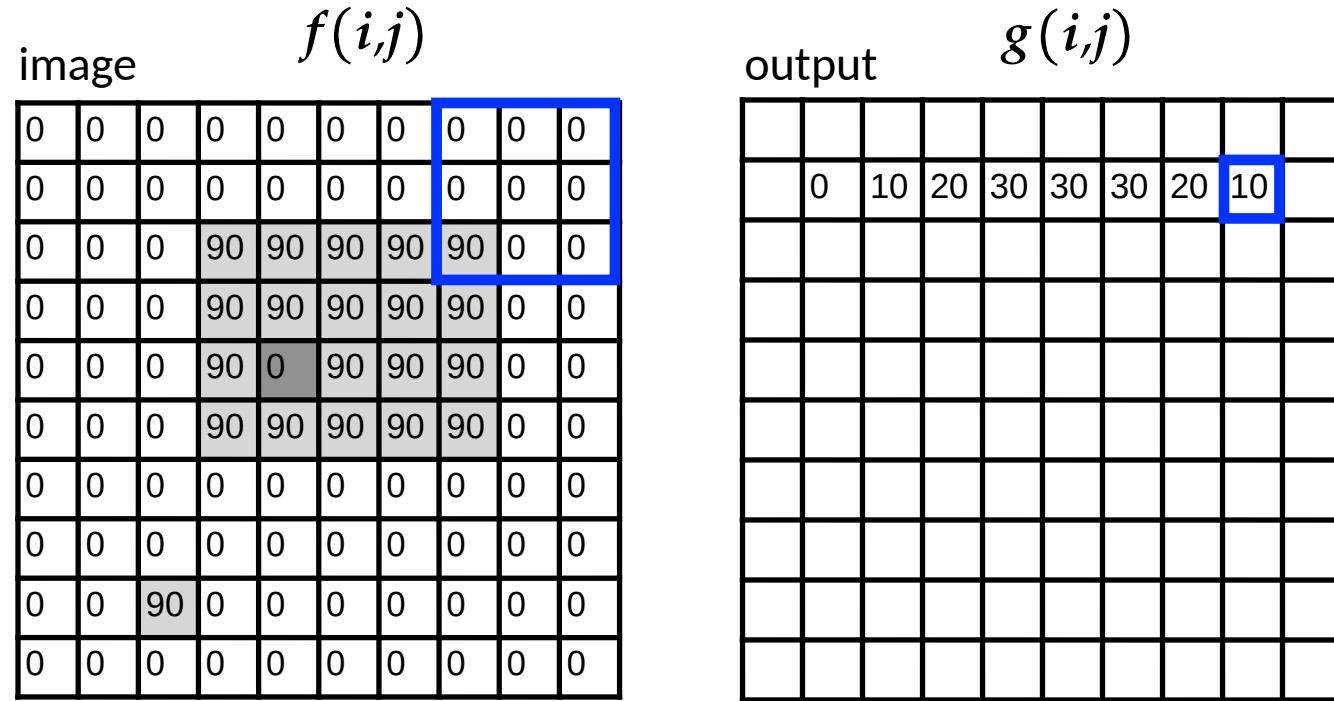
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

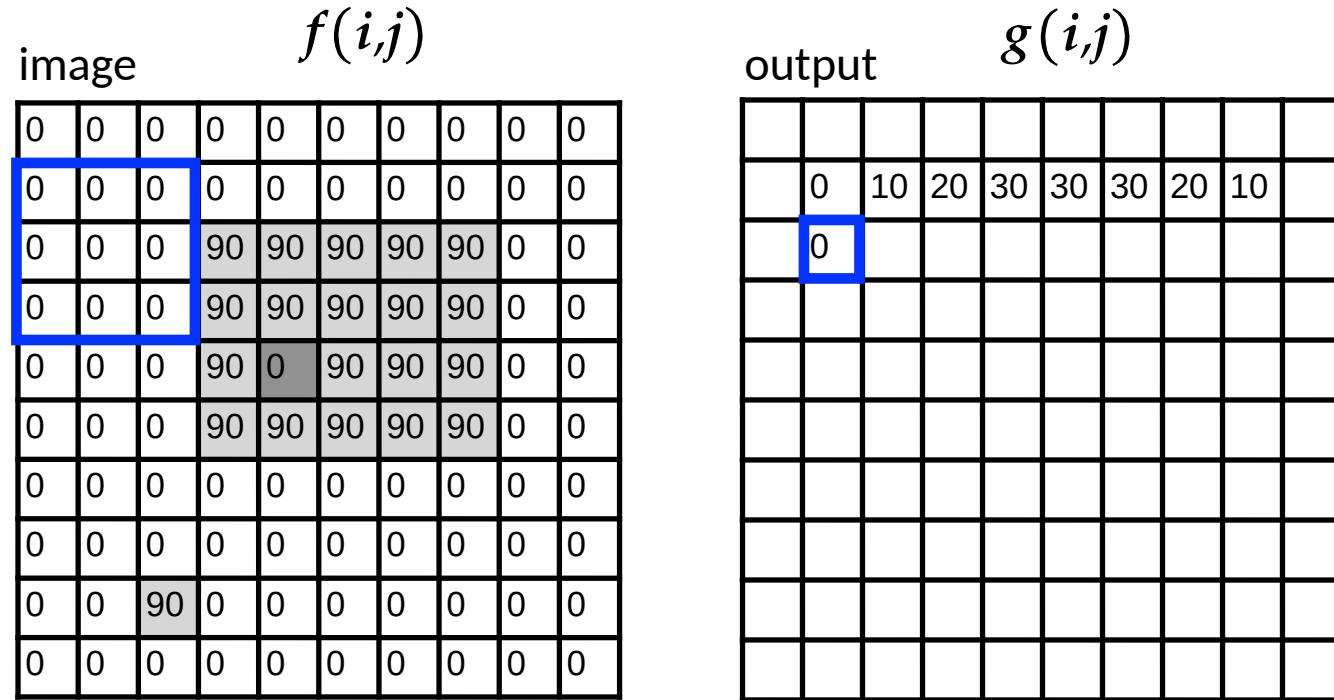
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

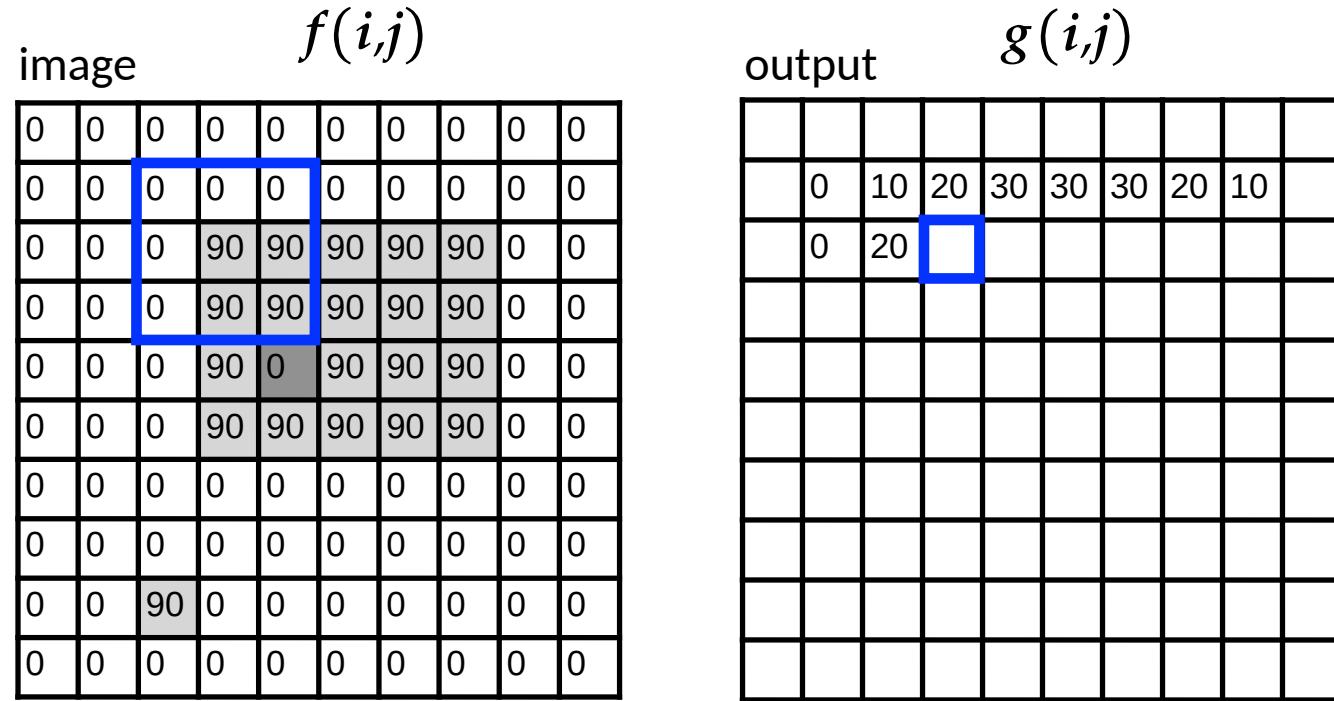
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

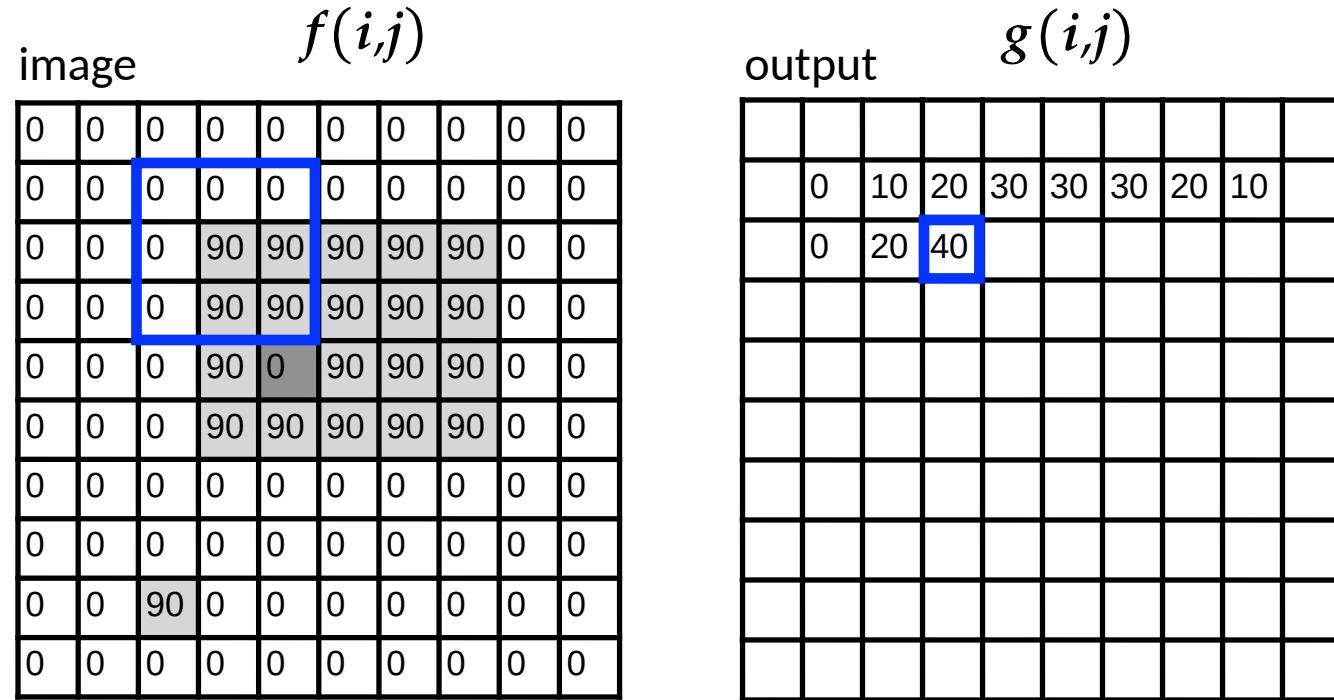
"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1



$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

1	1	1
1	1	1
1	1	1

kernel

$$g[i, j] = \sum_{m=1}^M \sum_{n=1}^N f[m, n] h[i - m, j - n]$$

"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9} \begin{array}{|c|c|c|} \hline & \text{kernel} & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

$$g[i, j] = \sum_{m=1}^M \sum_{n=1}^N f[m, n] h[i - m, j - n]$$

"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1

image										$f(i,j)$								output								$g(i,j)$							
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	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	90	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	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0					
0	0	0	90	0	90	90	90	90	90	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	90	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0					
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	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	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				

$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

"Mask," "Kernel," "Filter"

Let's run the box filter

$$h(i,j) = \frac{1}{9}$$

kernel

1	1	1
1	1	1
1	1	1

image	$f(i,j)$	output	$g(i,j)$
0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 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 90 90 90 90 90 0	0 0 0 30 50 80 80 90 60	0 0 0 20 40 60 60 40 20
0 0 0 90 90 90 90 90 0	0 0 0 90 90 90 90 90 0	0 0 0 30 50 80 80 90 60	0 0 0 20 40 60 60 40 20
0 0 0 90 0 90 90 90 90	0 0 0 90 0 90 90 90 90	0 0 0 30 50 80 80 90 60	0 0 0 20 30 50 50 60 40 20
0 0 0 90 90 90 90 90 0	0 0 0 90 90 90 90 90 0	0 0 0 10 20 30 30 30 20 10	0 0 0 10 10 10 10 0 0 0
0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0	0 0 0 10 10 10 10 0 0 0	0 0 0 10 10 10 10 0 0 0
0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0
0 0 90 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 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0

$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[i-m, j-n]$$

"Mask," "Kernel," "Filter"

... and the result is

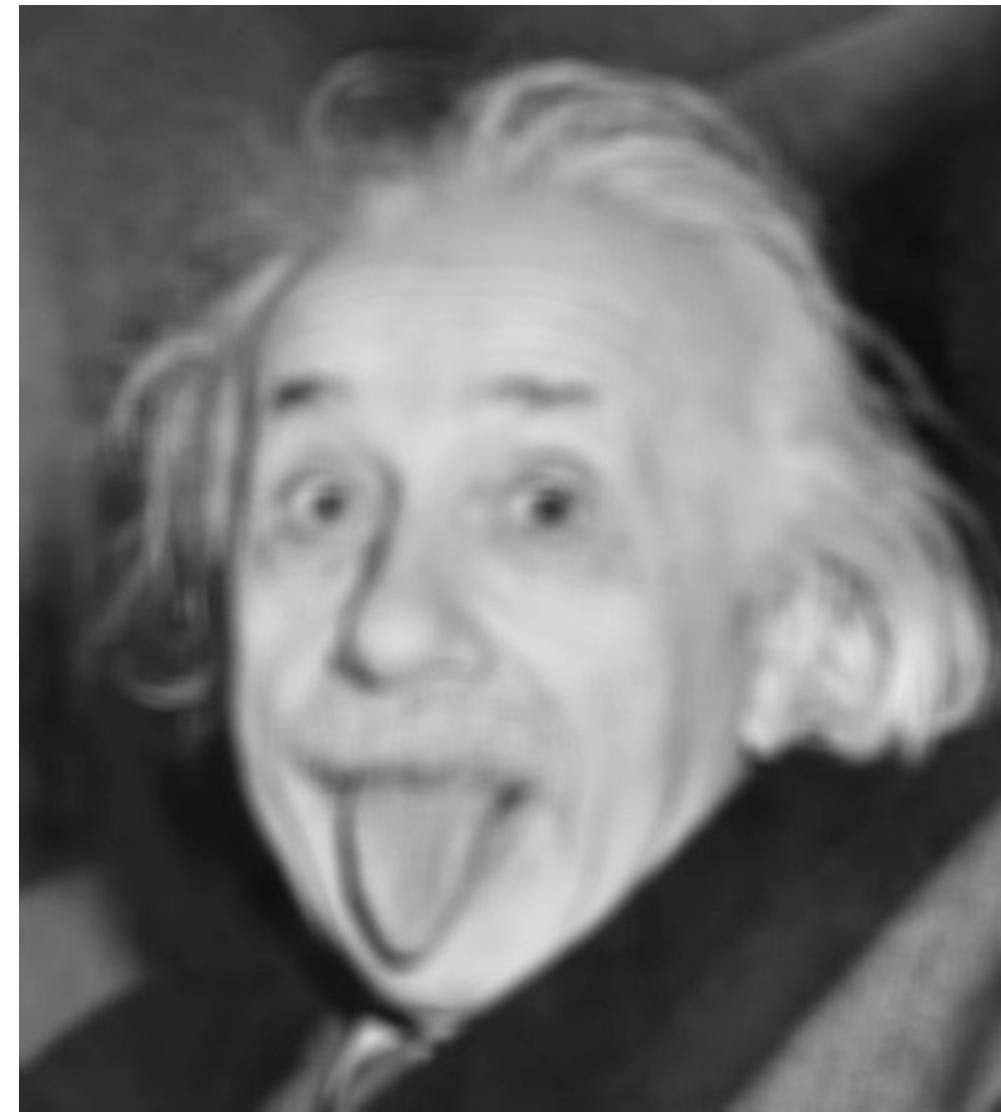
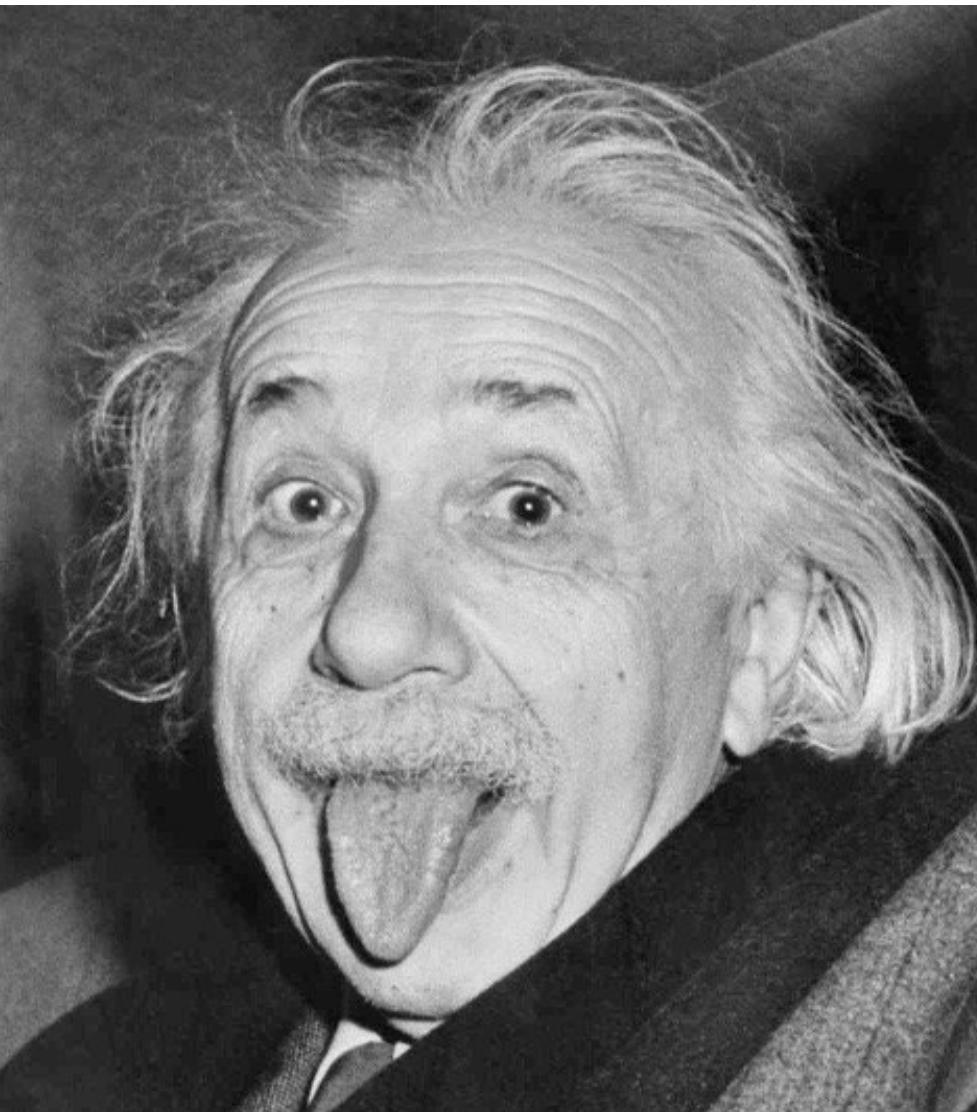
$$h(i,j) = \frac{1}{9} \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$

image	$f(i,j)$	output	$g(i,j)$
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 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 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			

$$g[i,j] = \sum_{m=1}^M \sum_{n=1}^N f[m,n] h[\underline{i-m, j-n}]$$

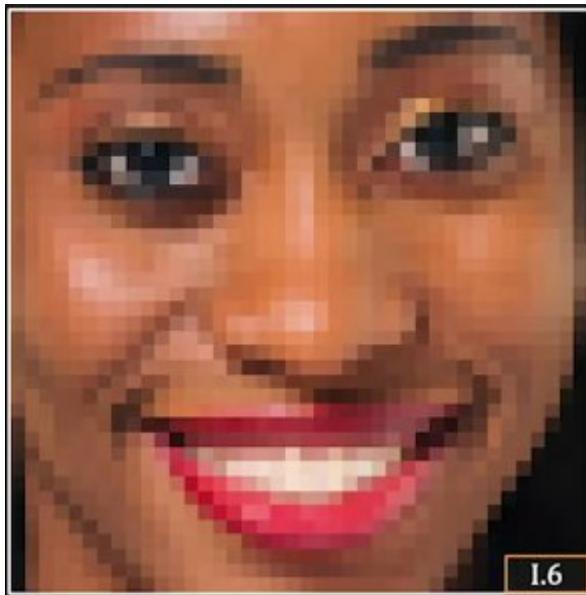
"Mask," "Kernel," "Filter"

Example: the box filter



Example: the impulse filter

Input



Output

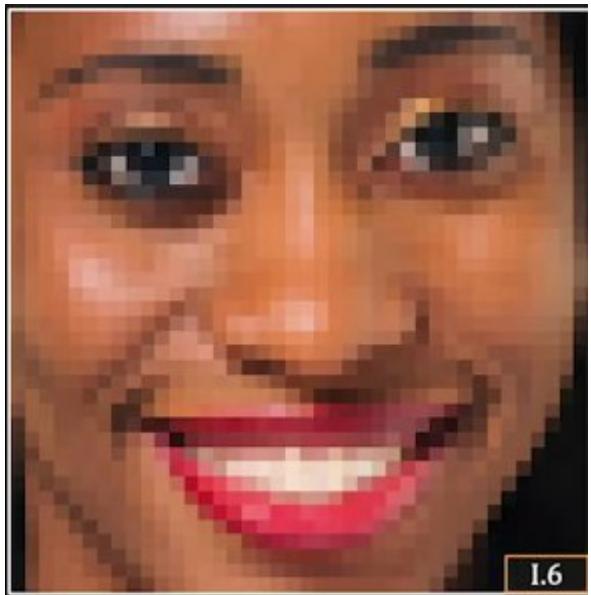
$$* \begin{array}{|c|c|} \hline & \blacksquare \\ \hline \blacksquare & \\ \hline \end{array} =$$

$f(x, y)$

$\delta(x, y)$

Example: the impulse filter

Input



$f(x, y)$

$$* \quad \begin{matrix} & & & \\ & & \blacksquare & \\ & & & \\ & & & \end{matrix} =$$

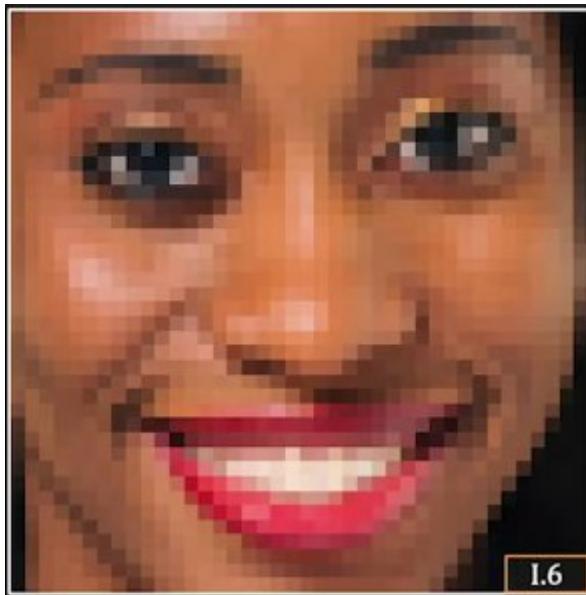
Output



$f(x, y)$

Example: the impulse filter

Input



Output

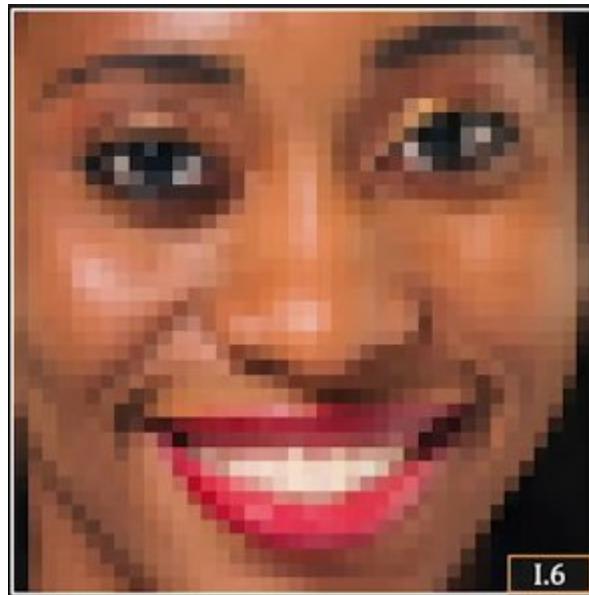
$$f(x, y) * \delta(x - u, y - v) =$$
A 5x5 grid of black squares, with a single white square located at the bottom-right corner. This represents the impulse filter $\delta(x - u, y - v)$.

$f(x, y)$

$\delta(x - u, y - v)$

Example: Image shift

Input



$$* \quad \begin{matrix} & & \\ & & \\ & & \\ & & \\ & & \end{matrix} =$$

Output



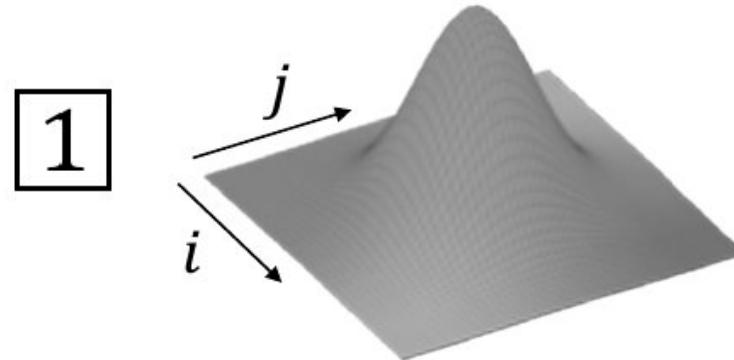
$$f(x, y)$$

$$\delta(x - u, y - v)$$

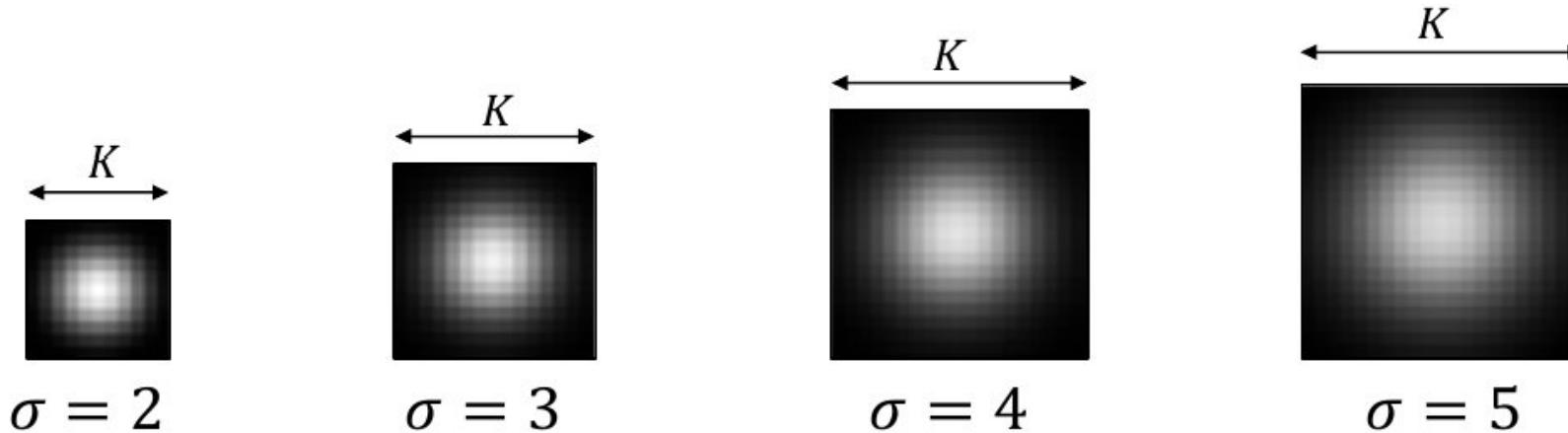
$$f(x - u, y - v)$$

Smoothing With the Gaussian Filter

$$n_{\sigma}[i,j] = \frac{1}{2\pi\sigma^2} e^{-\frac{1}{2}\left(\frac{i^2+j^2}{\sigma^2}\right)}$$



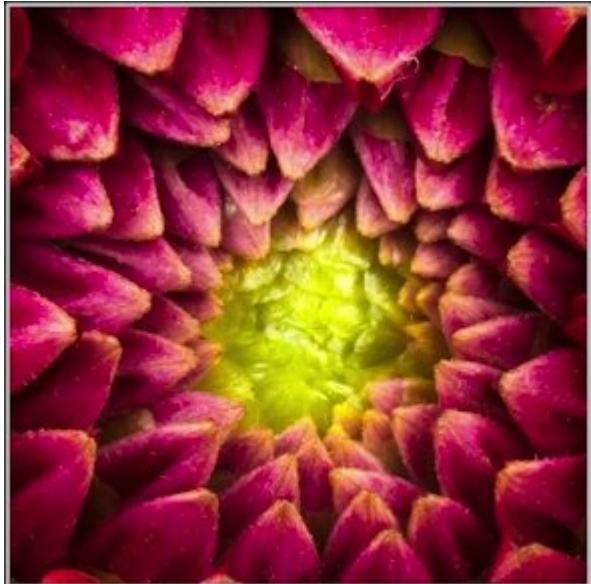
σ^2 : Variance



Rule of thumb: Set kernel size $K \approx 2\pi\sigma$

Smoothing With the Gaussian Filter

Input

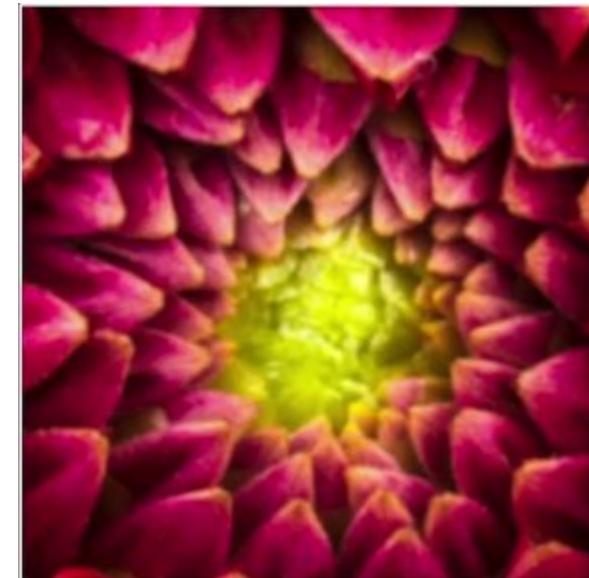


$$f(x, y)$$

$$\ast \quad \begin{matrix} \bullet \\ \text{---} \end{matrix} =$$

$$\sigma = 4$$

Output



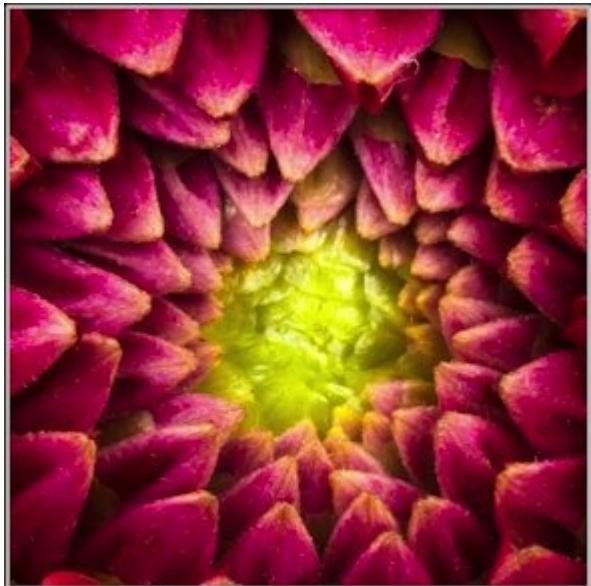
$$n_4(x, y)$$

$$g(x, y)$$

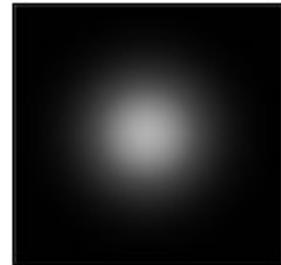
Larger the kernel (or σ), more the blurring

Smoothing With the Gaussian Filter

Input



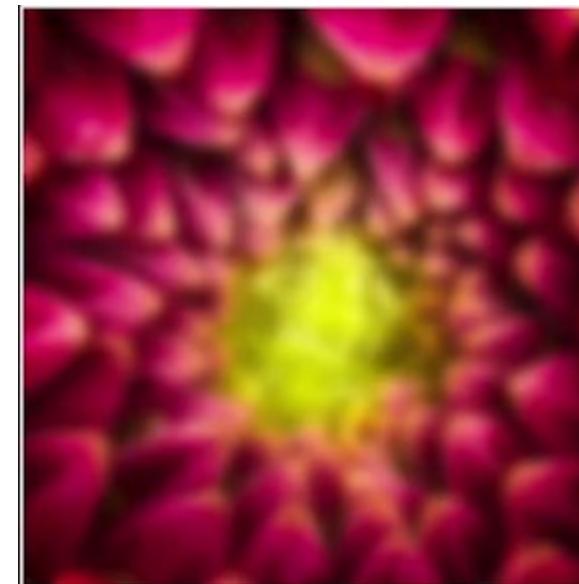
*



=

$$\sigma = 16$$

Output



$$f(x, y)$$

$$n_4(x, y)$$

$$g(x, y)$$

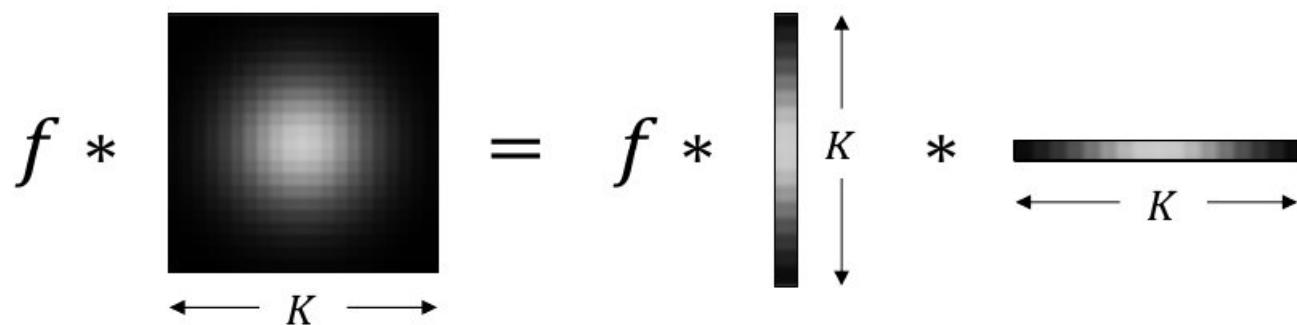
Larger the kernel (or σ), more the blurring

Gaussian Smoothing is Separable

$$g[i, j] = \frac{1}{2\pi\sigma^2} \sum_{m=1}^K \sum_{n=1}^K e^{-\frac{1}{2}\left(\frac{m^2+n^2}{\sigma^2}\right)} f[i - m, j - n]$$

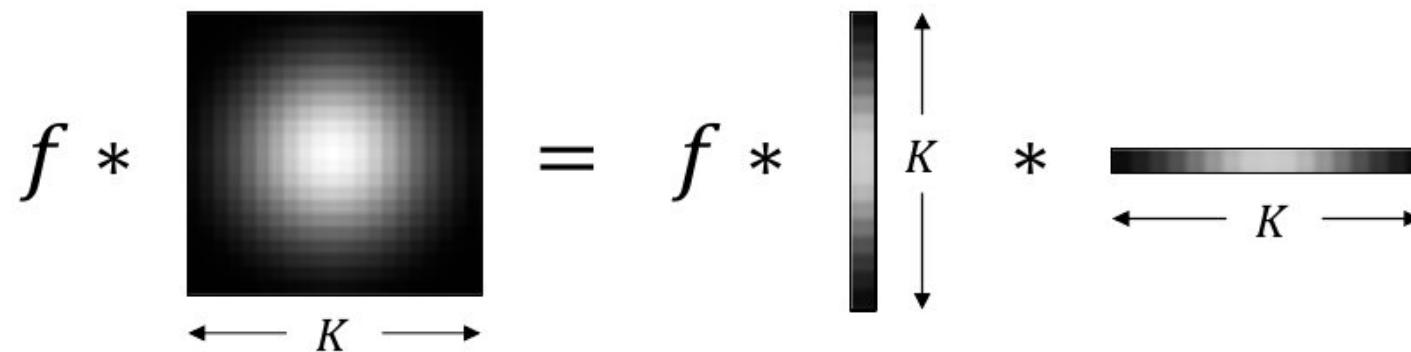
$$g[i, j] = \frac{1}{2\pi\sigma^2} \sum_{m=1}^K e^{-\frac{1}{2}\left(\frac{m^2}{\sigma^2}\right)} \cdot \sum_{n=1}^K e^{-\frac{1}{2}\left(\frac{n^2}{\sigma^2}\right)} f[i - m, j - n]$$

Using One 2D Gaussian Filter \equiv Using Two 1D Gaussian Filters



Gaussian Smoothing is Separable

Using One 2D Gaussian Filter \equiv Using Two 1D Gaussian Filters



Which one is faster? Why?

K^2 Multiplications

$K^2 - 1$ Additions

$2K$ Multiplications

$2(K - 1)$ Additions

Other filters

input



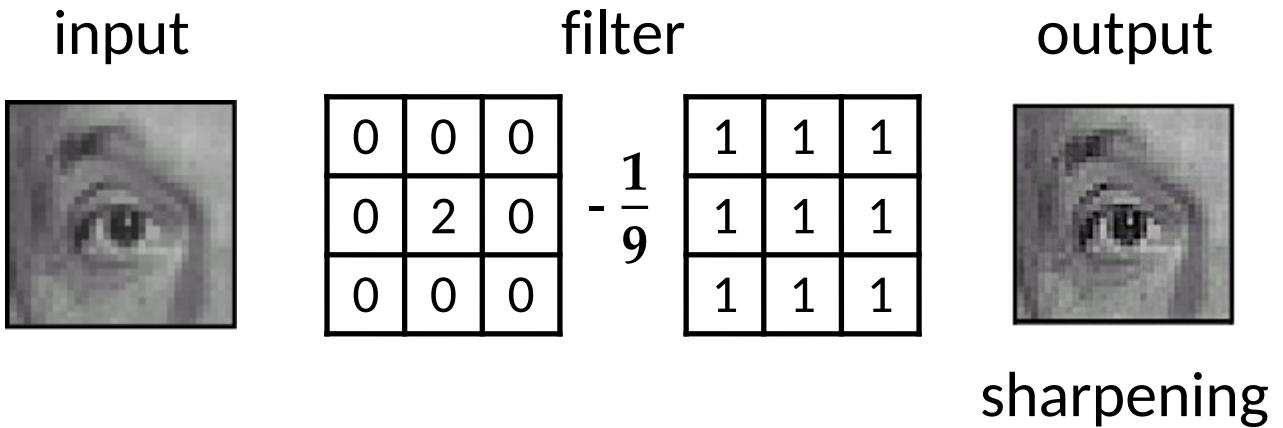
filter

$$\begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 0 & 2 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array} - \frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

output

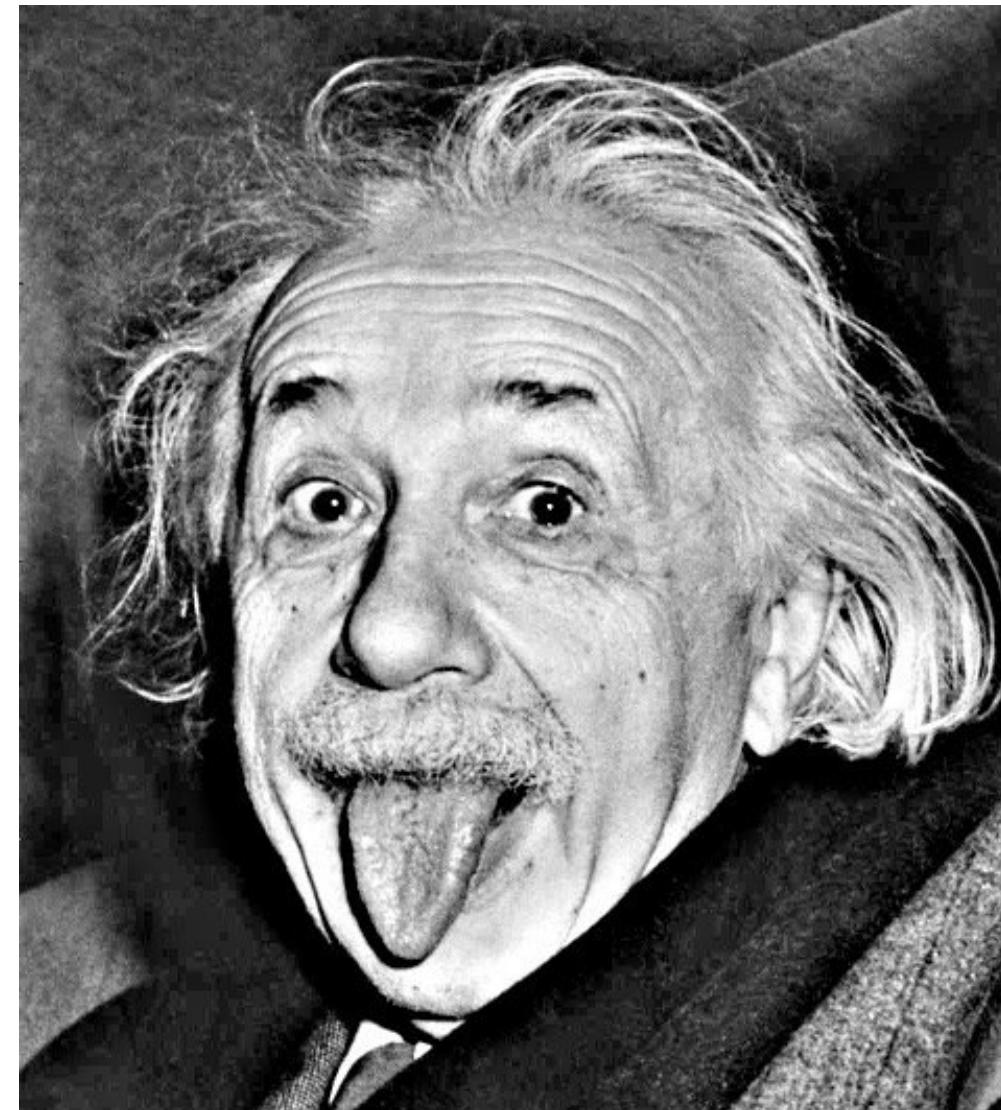
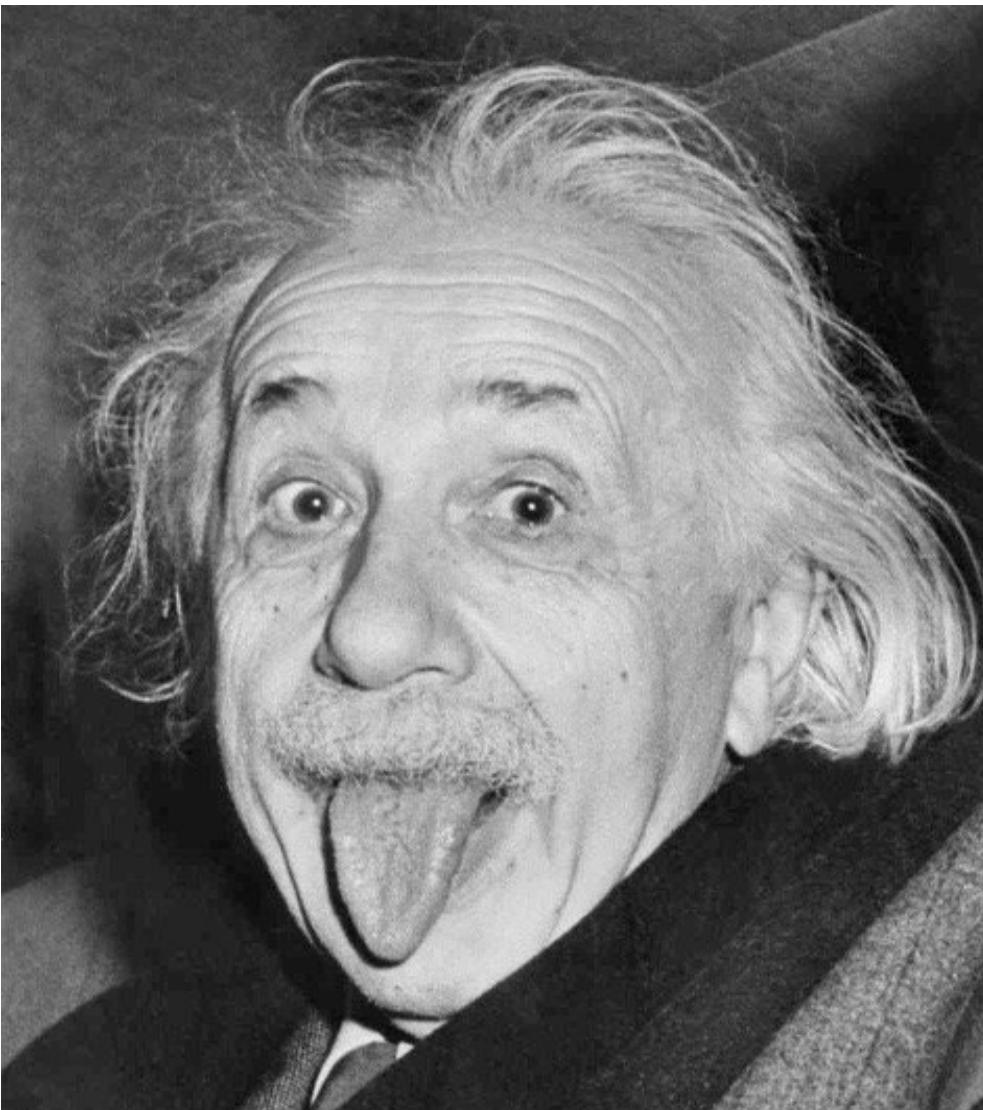
?

Sharpening filter



- do nothing for flat areas (no change where intensity is constant)
- stress intensity peaks (enhance edges and sharp transitions)

Sharpening examples



Sharpening examples



Sharpening examples

