





# Image filtering

$$g[m, n] = \sum_{k,l} I(m + k, n + l) * f(k, l)$$

Image  $I$  8x8

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

Kernel  $f$   
3x3

1	2	3
4	5	6
7	8	9

Same position

Register

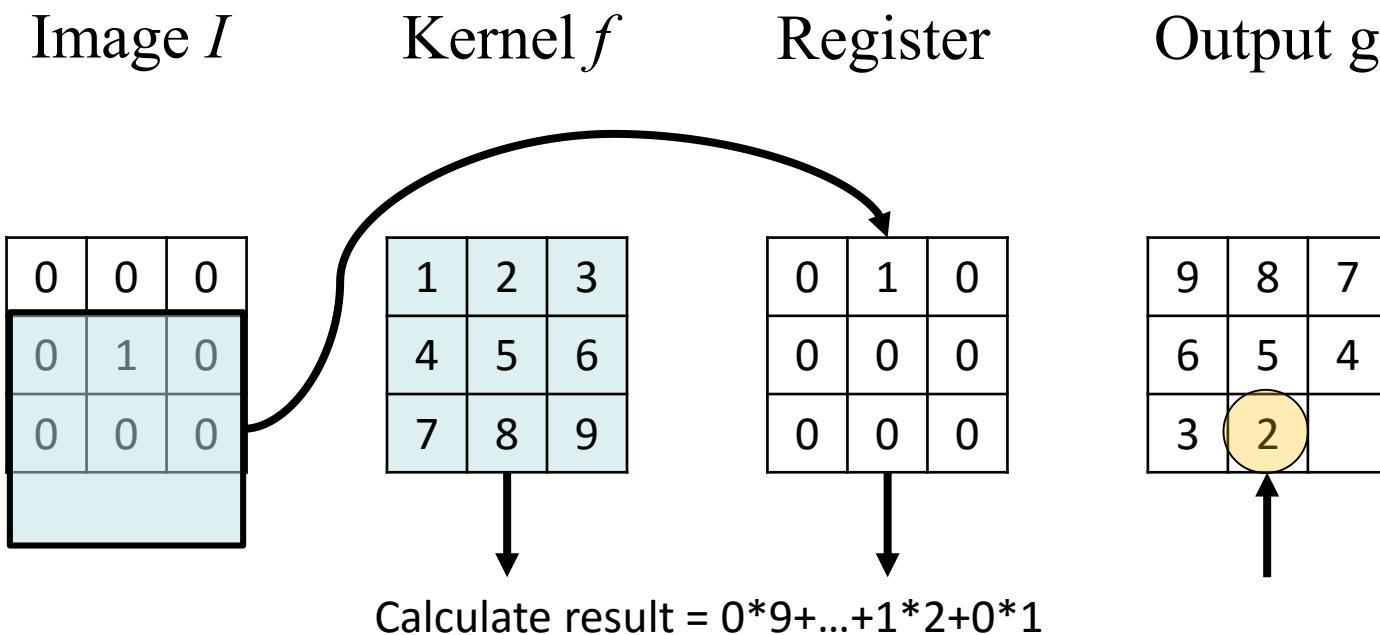
a	b	c
d	e	f
g	h	i

Loop over every pixel

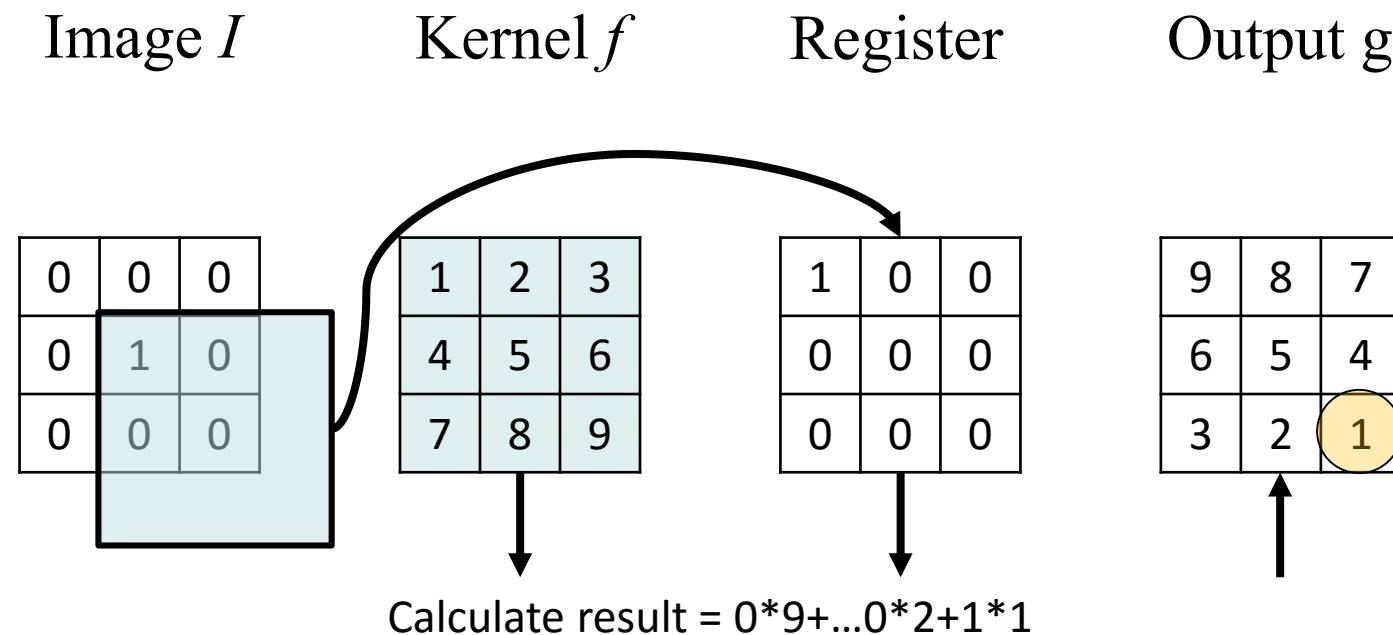
28	39	39	39	39	39	39	39	24
33	45	45	45	45	45	45	45	27
33	45	45	45	45	45	45	45	27
16	21	21	21	21	21	21	21	12
5	6	6	6	6	6	6	6	3
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

Calculate result = a\*1+b\*2+...+i\*9

# Special case: impulse function



# Special case: impulse function



<Note> The output is the kernel flipped left-right, up-down!

# Convolution

- Let  $I$  be an Signal(image), Convolution kernel  $g$ ,

$$f[m, n] = I \otimes g = \sum_{k,l} I[m-k, n-l]g[k, l]$$

# Convolution

- $g[m, n] = I \otimes f = \sum_{k,l} I(m - k, n - l) * f(k, l)$
- Convolution is filtering with kernel flipped

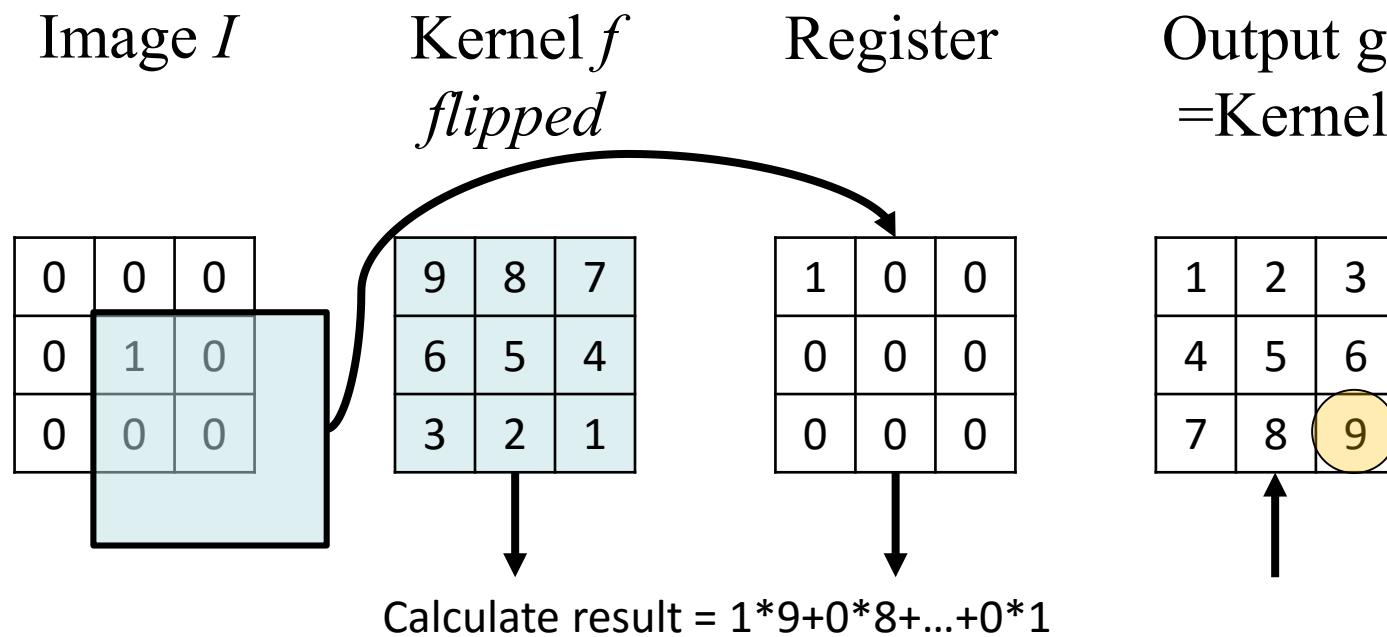


Image  $I$

2	0	0
0	3	0
0	0	0

Kernel  $f$   
*flipped*

9	8	7
6	5	4
3	2	1

Output  $g$

37	32	21
22	17	12
9	6	3

Decompose

1	0	0
0	0	0
0	0	0

\*2

Intermediate

5	4	0
2	1	0
0	0	0

\*2

Add together

0	0	0
0	1	0
0	0	0

\*3

9	8	7
6	5	4
3	2	1

\*3

- Convolution has commutative property  $I \otimes f$

Image  $I$    Kernel  $f$

a	b	c
d	e	f
g	h	i

1	0	0
1	0	0
1	1	0

- Convolution has commutative property  $I \otimes f$

Image  $I$    Kernel  $f$

a	b	c
d	e	f
g	h	i

1	0	0
1	0	0
1	1	0

Kernel  $f'$

0	1	1
0	0	1
0	0	1

(Flipped)

Decompose

- Convolution has commutative property  $I \otimes f$

Image  $I$       Kernel  $f$

a	b	c
d	e	f
g	h	i

1	0	0
1	0	0
1	1	0

Kernel  $f'$

0	1	1
0	0	1
0	0	1

(Flipped)

Decompose



Image  $I$

a	b	c
d	e	f
g	h	i

0	0	0
0	0	0
0	0	1

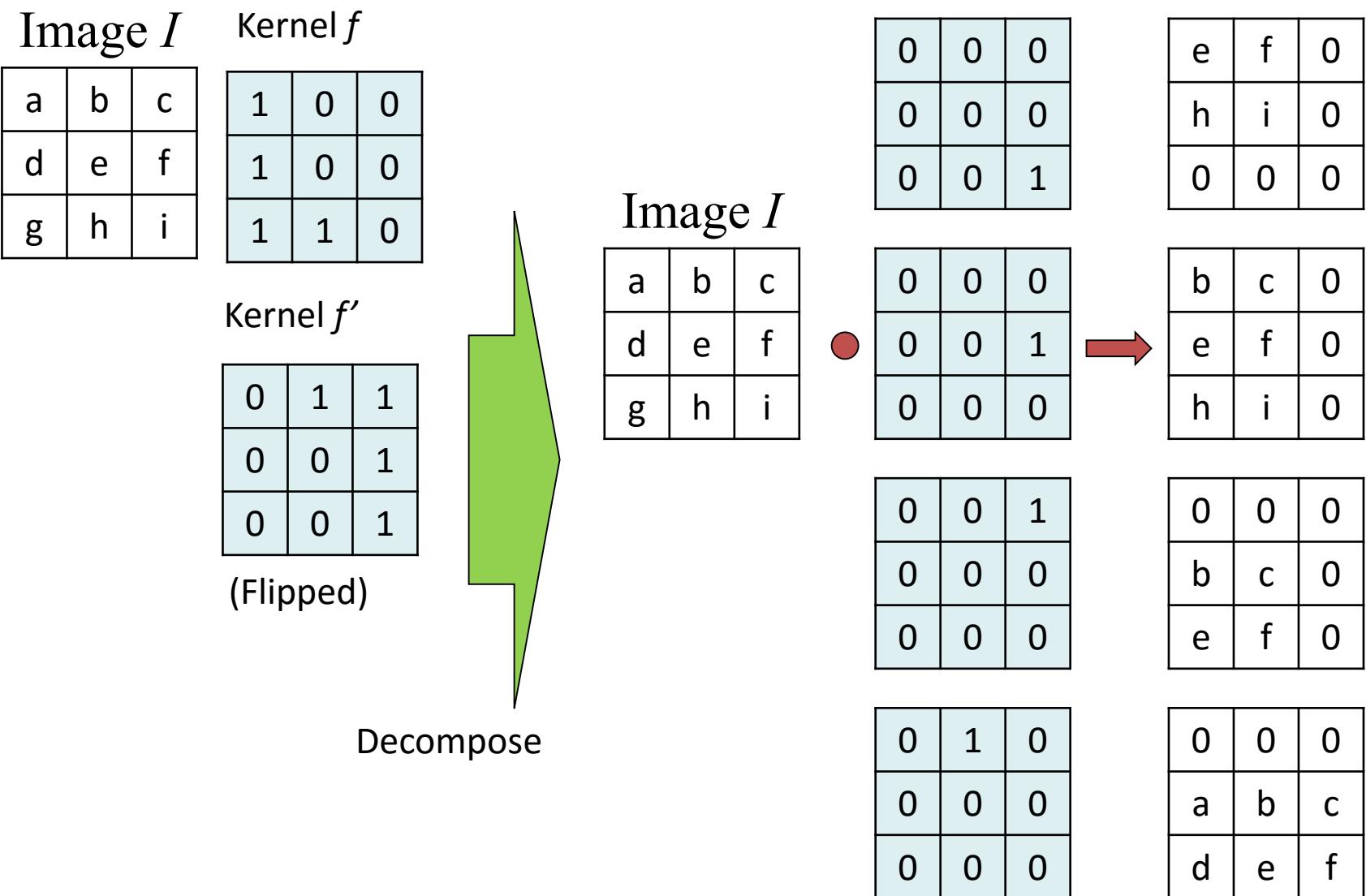


0	0	0
0	0	1
0	0	0

0	0	1
0	0	0
0	0	0

0	1	0
0	0	0
0	0	0

- Convolution has commutative property  $I \otimes f$



- Convolution is commutative  $I \otimes f = f \otimes I$

Image  $I$

a	b	c
d	e	f
g	h	i

Kernel  $f$

1	0	0
1	0	0
1	1	0

Decompose



1	0	0
0	0	0
0	0	0

0	0	0
1	0	0
0	0	0

0	0	0
0	0	0
1	0	0

0	0	0
0	0	0
0	1	0

Image  $I^{flip}$

i	h	g
f	e	d
c	b	a

(Flipped)

e	f	0
h	i	0
0	0	0

b	c	0
e	f	0
h	i	0

0	0	0
b	c	0
e	f	0

0	0	0
a	b	c
d	e	f

- Convolution is commutative  $I \otimes f = f \otimes I$

Image  $I$       Image  $I^{flip}$

a	b	c
d	e	f
g	h	i

i	h	g
f	e	d
c	b	a

Kernel  $f$

1	0	0
1	0	0
1	1	0

Decompose

1	0	0
0	0	0
0	0	0

0	0	0
1	0	0
0	0	0

0	0	0
0	0	0
1	0	0

0	0	0
0	0	0
0	1	0

Image  $I^{flip}$

i	h	g
f	e	d
c	b	a

(Flipped)

e	f	0
h	i	0
0	0	0

b	c	0
e	f	0
h	i	0

b	c	0
e	f	0
h	i	0

a	b	c
d	e	f
h	i	0

# Proof of Commutative property

- $g[m, n] = I \otimes f = f \otimes I$
- $g[m, n] = I \otimes f = \sum_{k,l} I(m - k, n - l) * f(k, l)$
- Let  $k' = m - k, l' = n - l,$   
then  $k = m - k', l = n - l'$
- $g[m, n] = \sum_{k',l'} I(k', l') * f(m - k', n - l') = f \otimes I$

# Impulse functions shift images

Image  $I$

a	b	c
d	e	f
g	h	i

Kernel  $f$

1	0	0
0	0	0
0	0	0

Kernel  $f'$

0	0	0
0	0	0
0	0	1

Result  $I \otimes f$

e	f	0
h	i	0
0	0	0

- In this case the resulting image shifted to the upper left

# Linear independence

Image  $I$

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

5x5

Kernel  $f$

1	0	0
0	1	0
0	0	0

Output  $g = g_1 + g_2$

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

Kernel  $f_1$

1	0	0
0	0	0
0	0	0

Output  $g_1$

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

Output  $g_2$

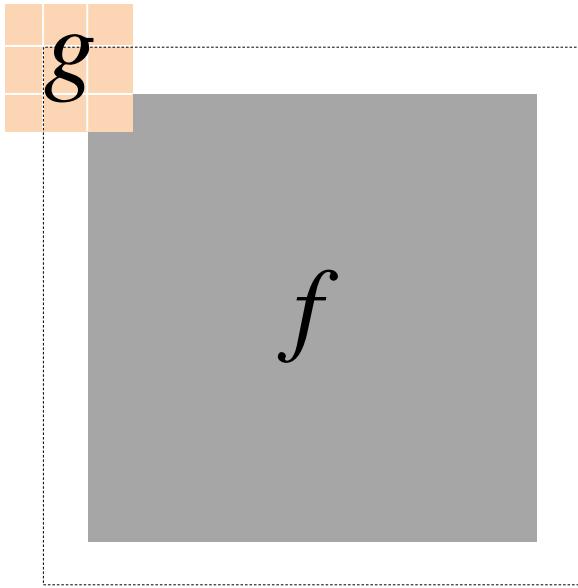
0	1	0	1	0
0	1	0	1	0
0	1	0	1	0
0	1	0	1	0
0	1	0	1	0

Kernel  $f_2$

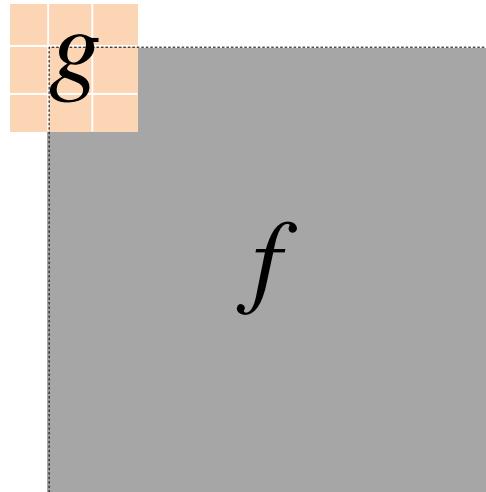
0	0	0
0	1	0
0	0	0

# Output Size of Image Convolution

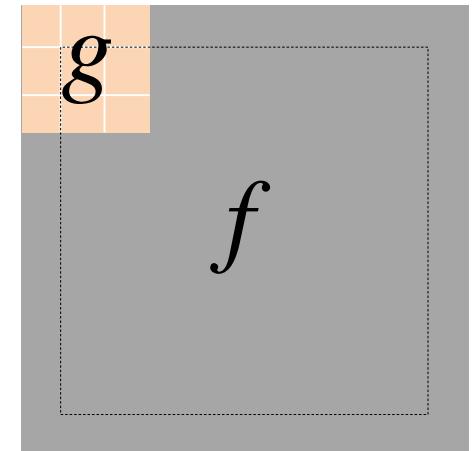
$$f \otimes g$$



Full



Same



Valid

*filter2(g, f, shape)* in MATLAB

Full:  $\text{output\_size} = \text{f\_size} + \text{g\_size} - 1$

Same:  $\text{output\_size} = \text{f\_size}$

Valid:  $\text{output\_size} = \text{f\_size} - (\text{g\_size} - 1)$

# 2D visualization of convolution (full)

Image  $I$

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

8x8

Kernel  $f$

1	2	3
4	5	6
7	8	9

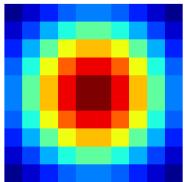
3x3

Output  $g$

1	3	6	6	6	6	6	6	5	3
5	12	21	21	21	21	21	21	16	9
12	27	45	45	45	45	45	45	33	18
12	27	45	45	45	45	45	45	33	18
11	24	39	39	39	39	39	39	28	15
7	15	24	24	24	24	24	24	17	9
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

10x10

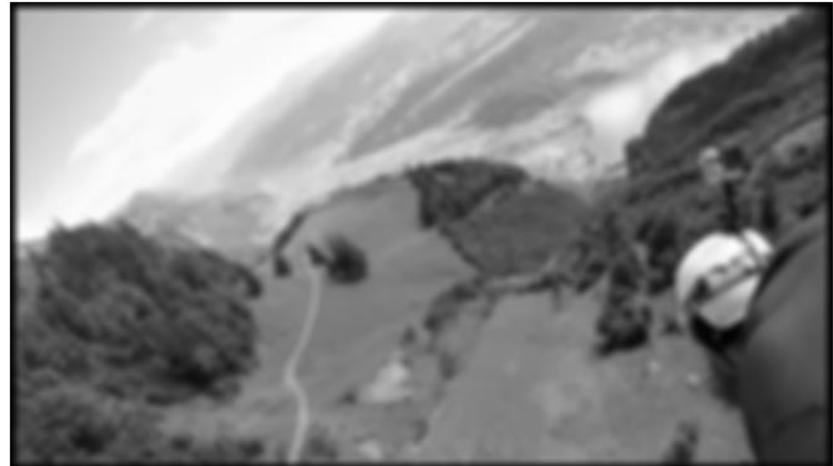
# Output Size of Image Convolution



$g$  :  $10 \times 10$  Gaussian kernel



$f$  :  $640 \times 360$  resolution



Full

`filter2(g, f, shape)` in MATLAB

Full:  $\text{output\_size} = \text{f\_size} + \text{g\_size} - 1$

```
>> full = filter2(g, im, 'full');  
>> size(full)
```

ans =

369 649

# 2D visualization of convolution (same)

Image  $I$

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

8x8

Kernel  $f$

1	2	3
4	5	6
7	8	9

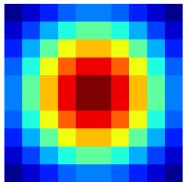
3x3

Output  $g$

12	21	21	21	21	21	21	16
27	45	45	45	45	45	45	33
27	45	45	45	45	45	45	33
24	39	39	39	39	39	39	28
15	24	24	24	24	24	24	17
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

8x8

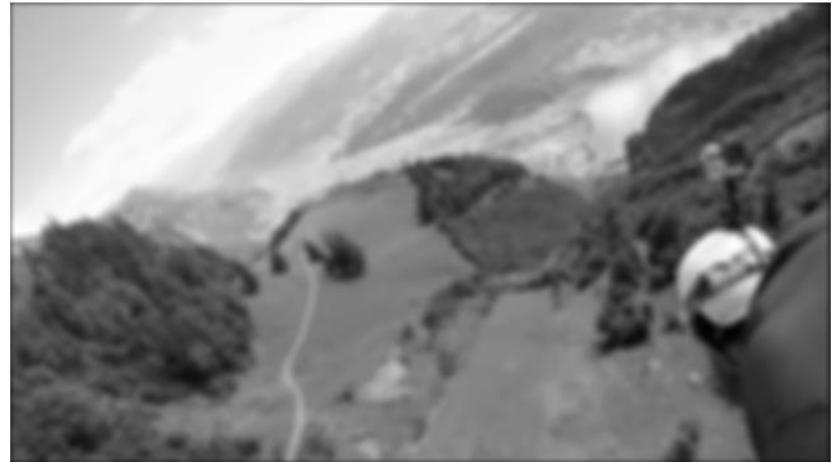
# Output Size of Image Convolution



$g$  :  $10 \times 10$  Gaussian kernel



$f$  :  $640 \times 360$  resolution



Same

`filter2(g, f, shape)` in MATLAB

Full: `output_size = f_size + g_size - 1`

Same: `output_size = f_size`

```
>> same = filter2(g, im, 'same');  
>> size(same)
```

ans =

360 640

# 2D visualization of convolution (valid)

Image  $I$

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

8x8

Kernel  $f$

1	2	3
4	5	6
7	8	9

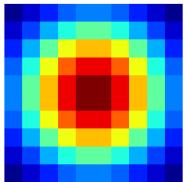
3x3

Output  $g$

45	45	45	45	45	45
45	45	45	45	45	45
39	39	39	39	39	39
24	24	24	24	24	24
0	0	0	0	0	0
0	0	0	0	0	0

6x6

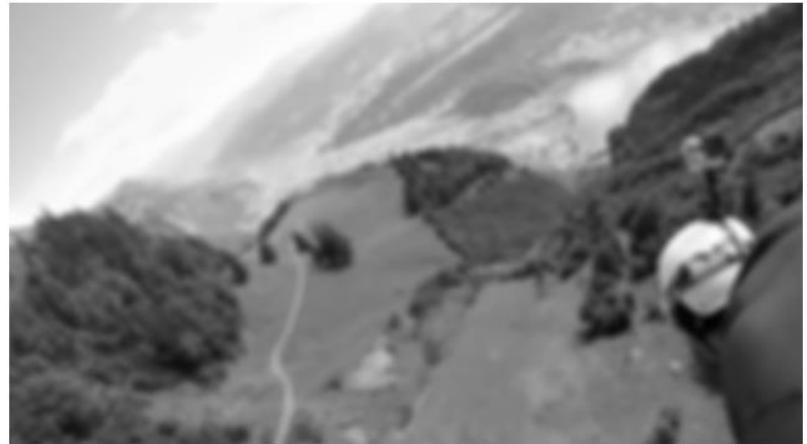
# Output Size of Image Convolution



$g$  :  $10 \times 10$  Gaussian kernel



$f$  :  $640 \times 360$  resolution



Valid

`filter2(g, f, shape)` in MATLAB

Full: `output_size = f_size + g_size - 1`

Same: `output_size = f_size`

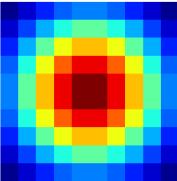
Valid: `output_size = f_size - (g_size - 1)`

```
>> valid = filter2(g, im, 'valid');  
>> size(valid)
```

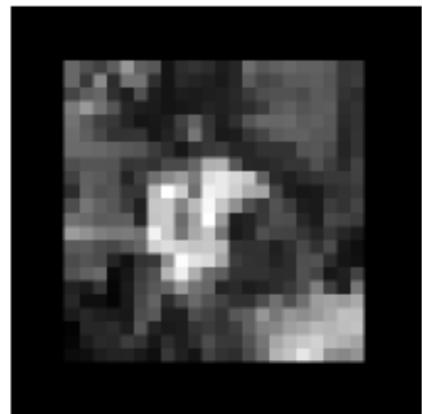
ans =

351 631

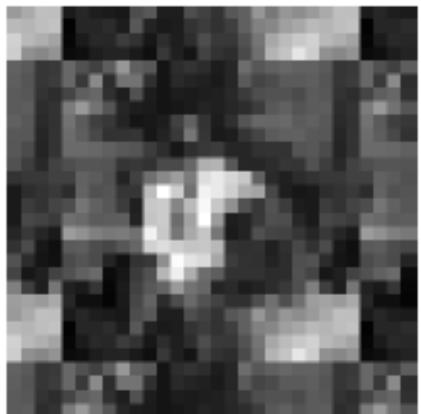
# Image Boundary Effect



The filter window falls off at the edge of image.



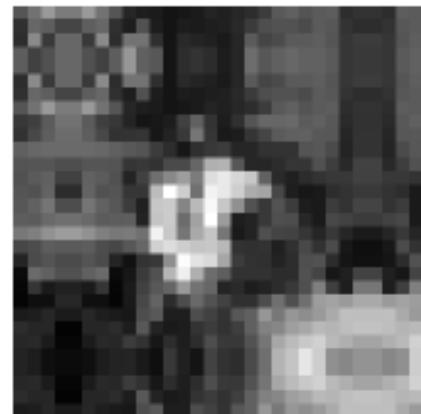
zero



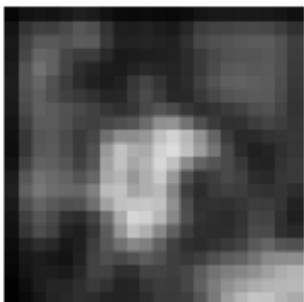
wrap



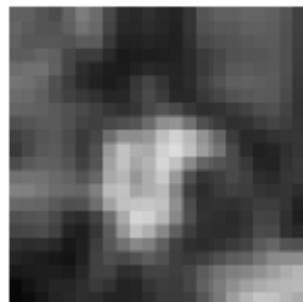
clamp



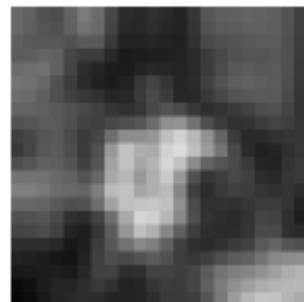
mirror



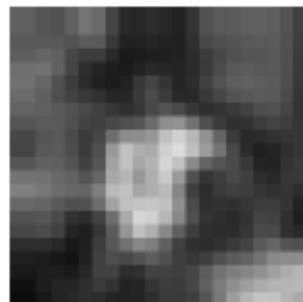
blurred zero



normalized zero



blurred clamp



blurred mirror

# Image Extrapolation (Mirroring)

Code

```
J = imread('image.bmp');  
figure; imshow(J);
```

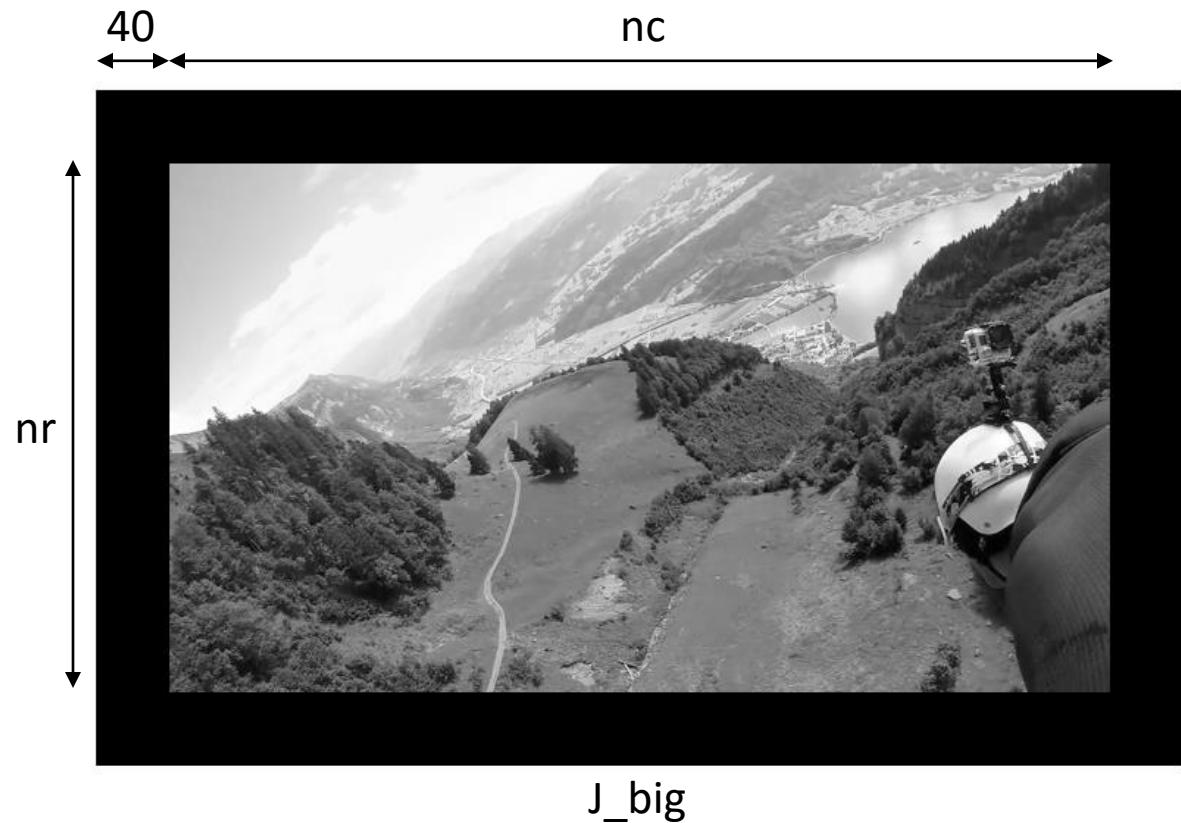


J

# Image Extrapolation (Mirroring)

Code

```
boarder = 40;  
[nr,nc,nb] = size(J);  
J_big = zeros(nr+2*boarder, nc + 2*boarder,nb);  
J_big(boarder+1:boarder+nr,boarder+1:boarder+nc,:) = J;
```

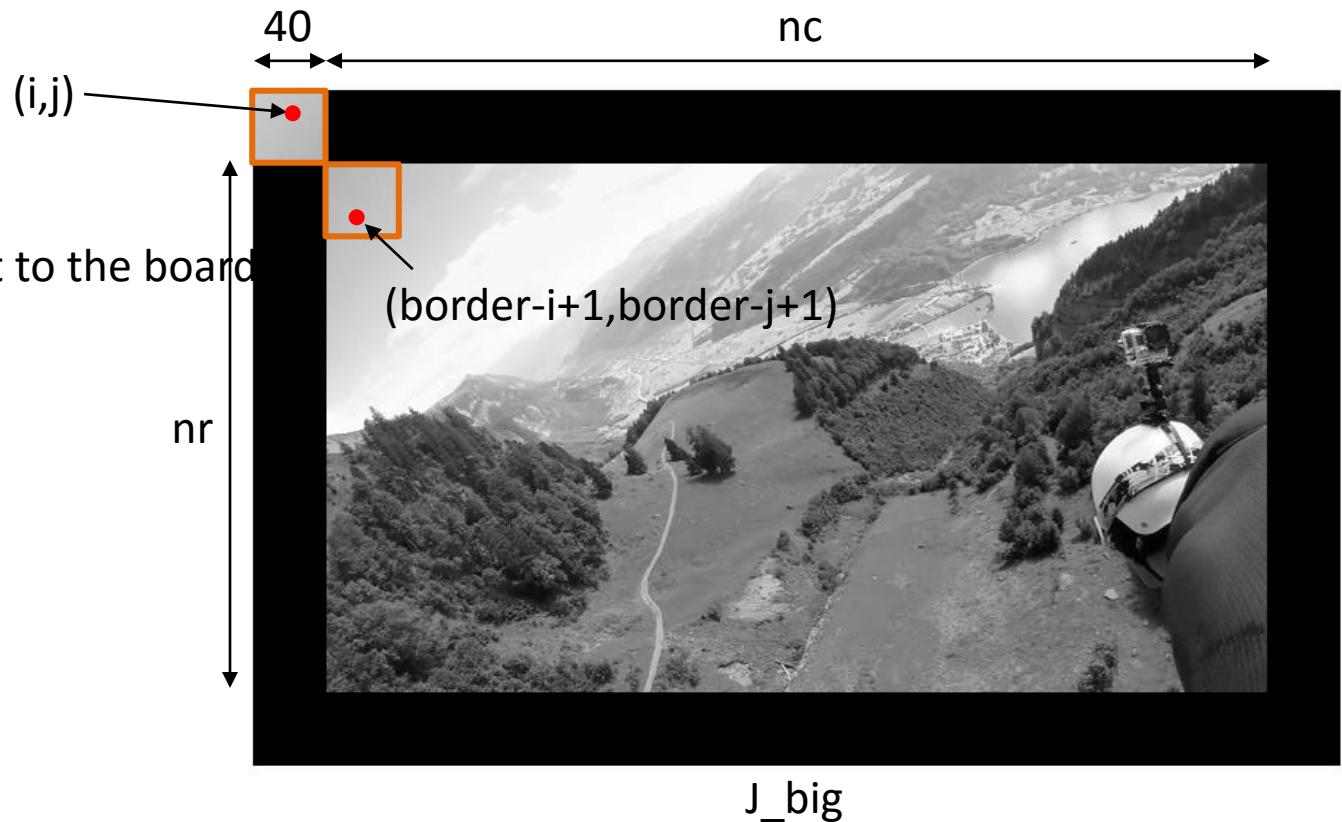


# Image Extrapolation (Mirroring)

Code

```
for i=1:border,  
    for j=1:border,  
        J_big(i,j,:) = J(border-i+1,border-j+1,:);  
    end  
end
```

Mirroring with respect to the board

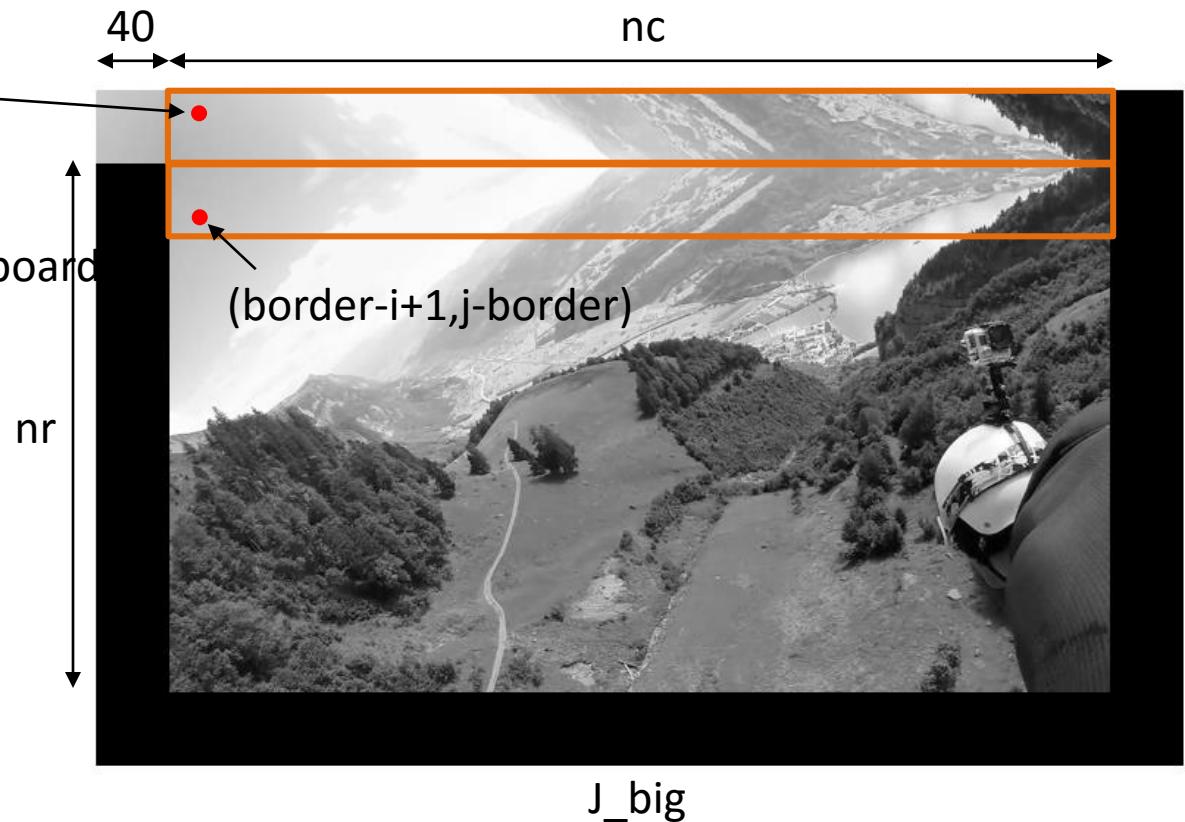


# Image Extrapolation (Mirroring)

Code

```
for i=1:boarder,  
    for j=border+1:border+nc,  
        J_big(i,j,:) = J(border-i+1,j-border,:);  
    end  
end
```

Mirroring with respect to the board

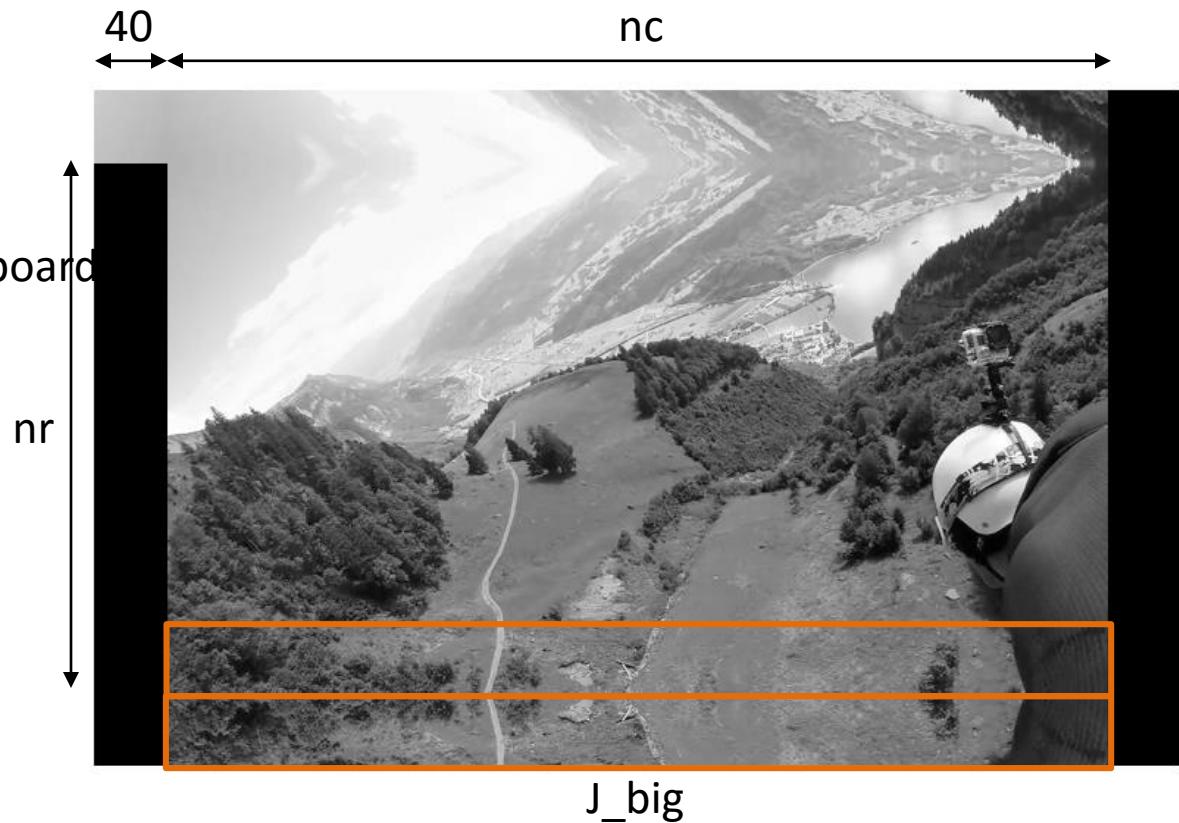


# Image Extrapolation (Mirroring)

Code

```
for i=nr+border+1:border*2+nr,  
    for j=border+1:border+nc,  
        J_big(i,j,:) = J(2*nr-i+border+1,j-border,:);  
    end  
end
```

Mirroring with respect to the board

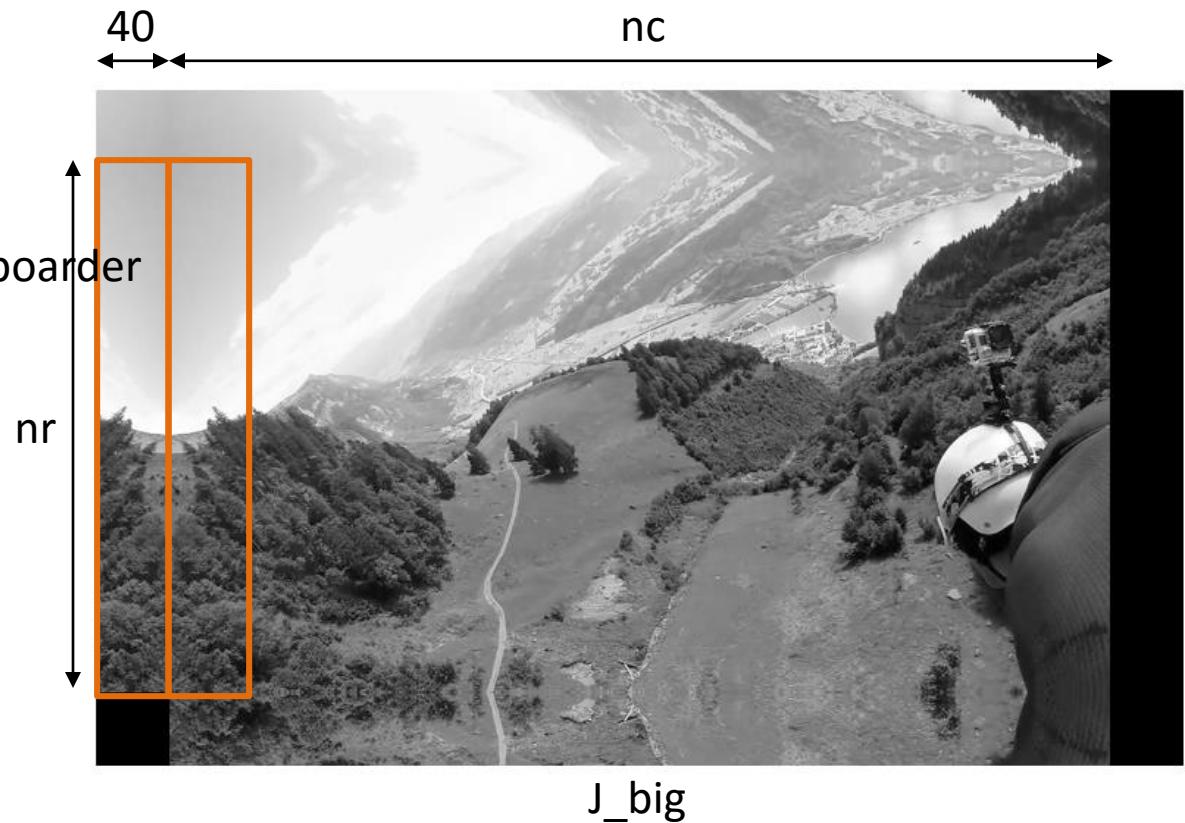


# Image Extrapolation (Mirroring)

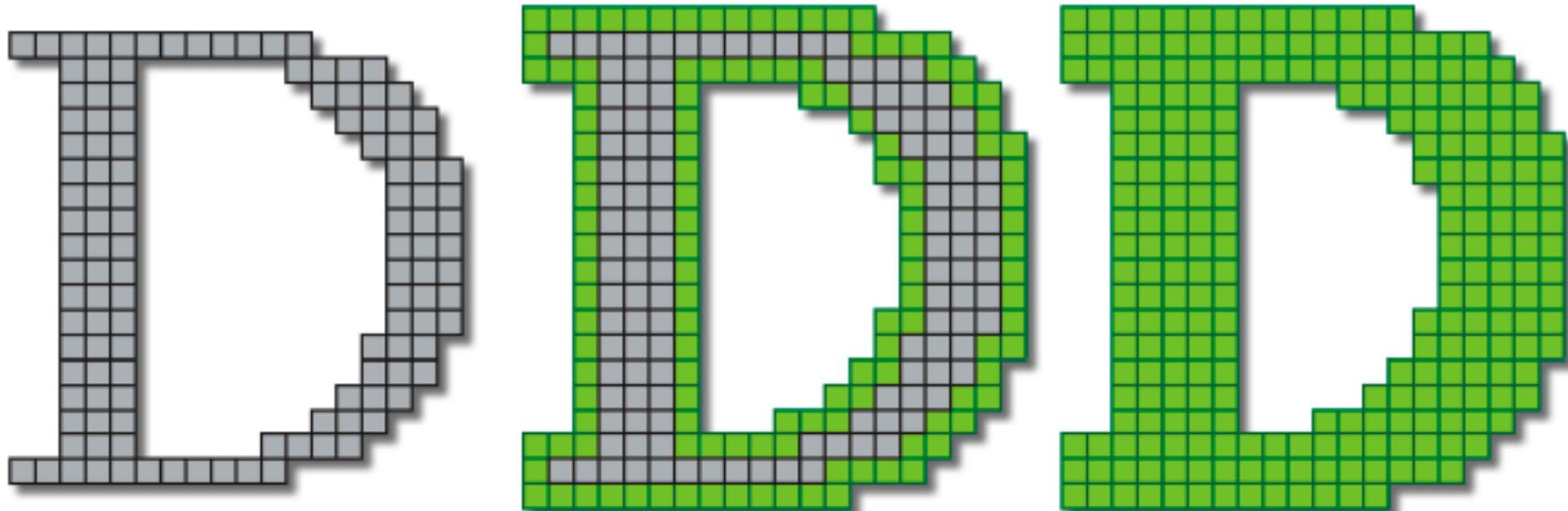
Code

```
for i=border+1:border+nr;
    for j=1:border,
        J_big(i,j,:) = J(i-border,border-j+1,:);
    end
end
```

Mirroring with respect to the border

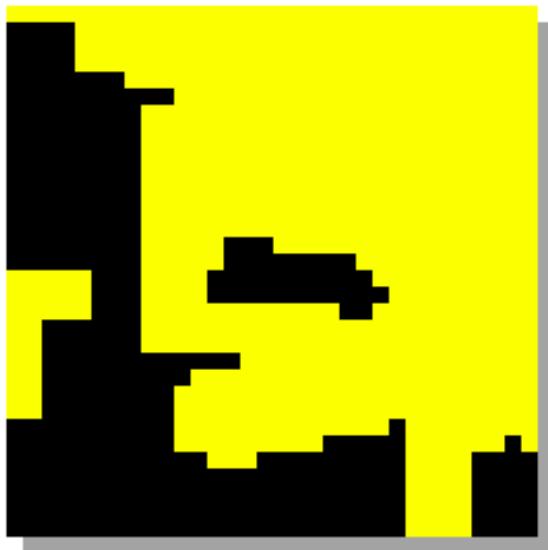


# Dilation

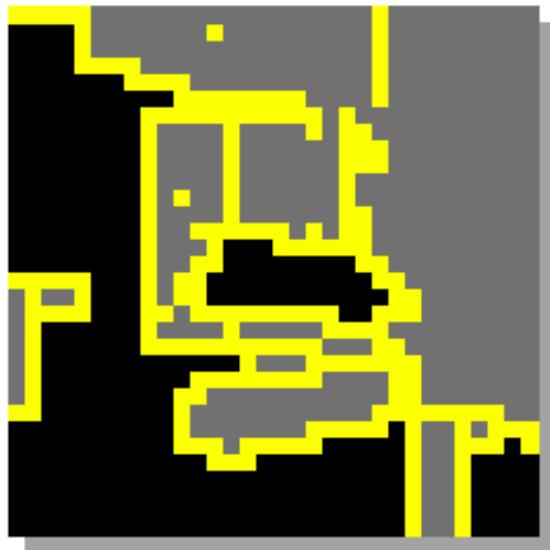


# Dilation

The locus of pixels  $\mathbf{p} \in S_p$  such that  $(\tilde{Z} + \mathbf{p}) \cap I \neq \emptyset$ .



dilated image



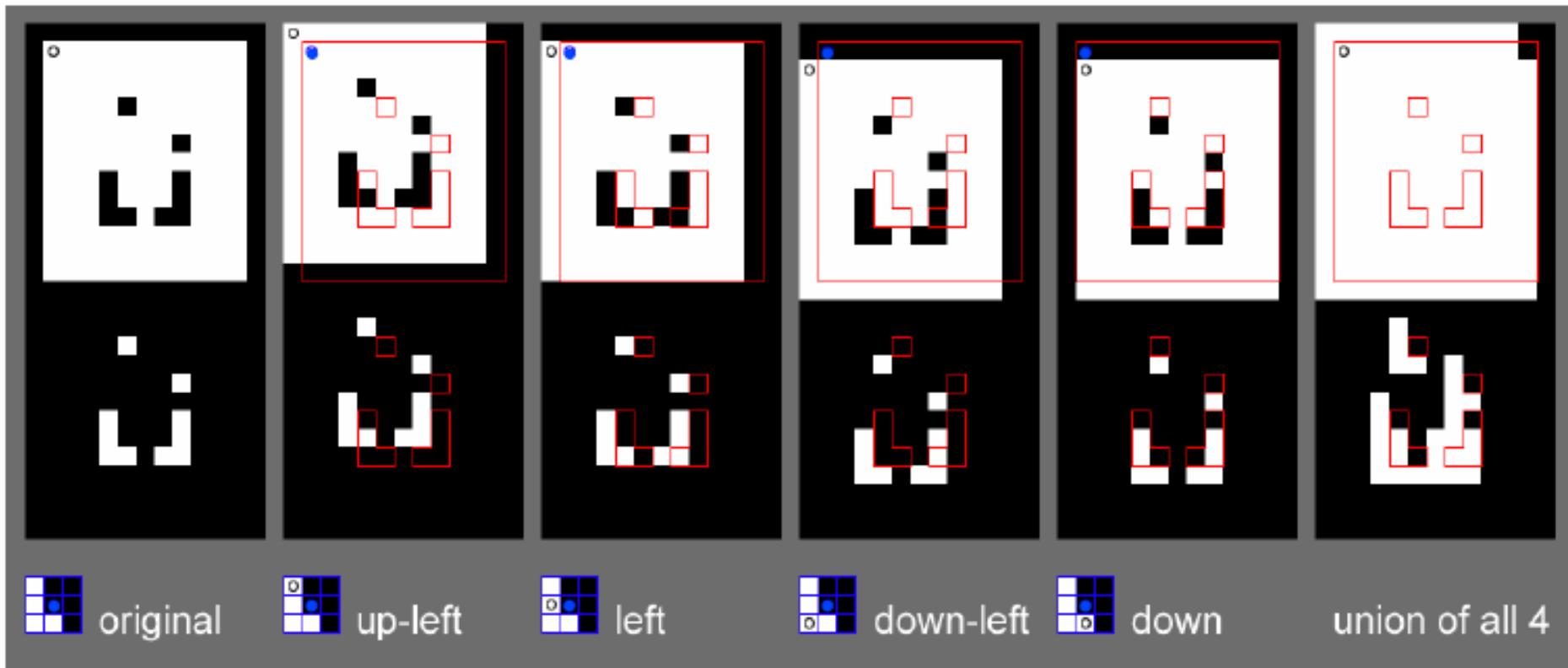
original / dilation



original image

$$SE = Z_8$$

# Dilation through Image Shifting



Examples of image operation as convolution

# Average Filter

- Mask with positive entries, that sum 1.
- Replaces each pixel with an average of its neighborhood.
- If all weights are equal, it is called a BOX filter.

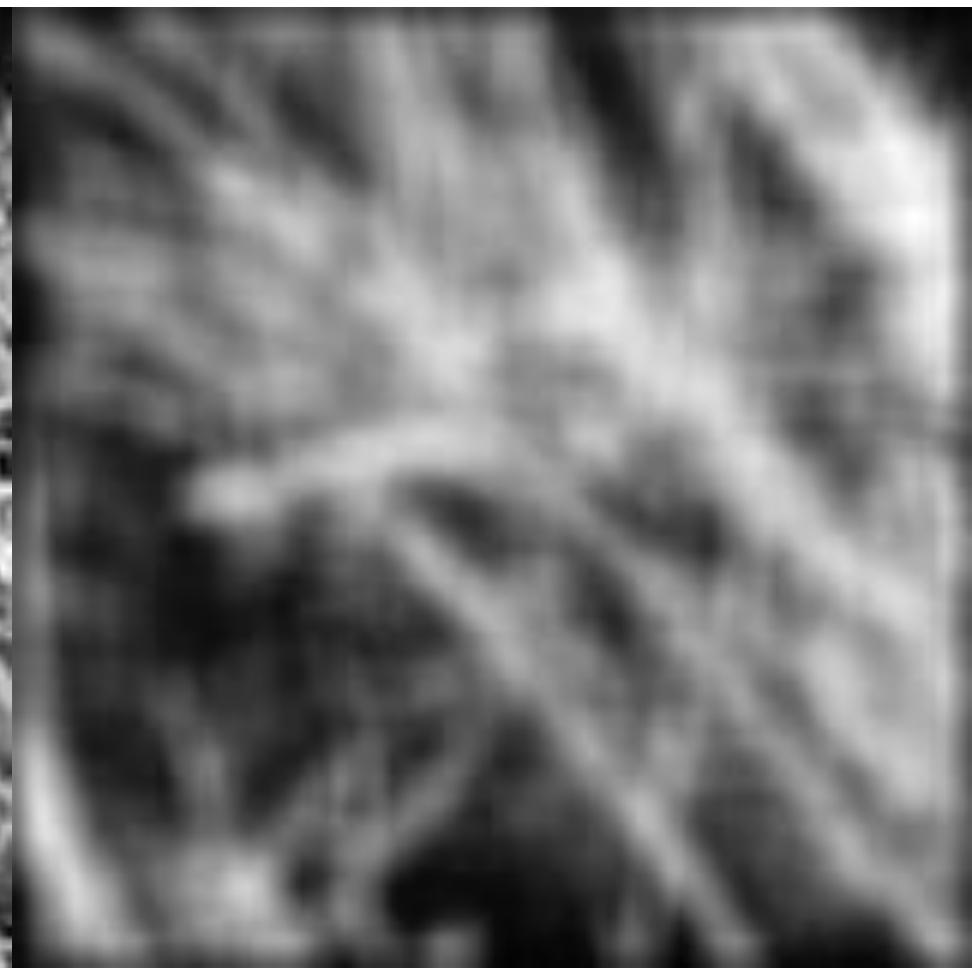
$F$

$1/9$

1	1	1
1	1	1
1	1	1

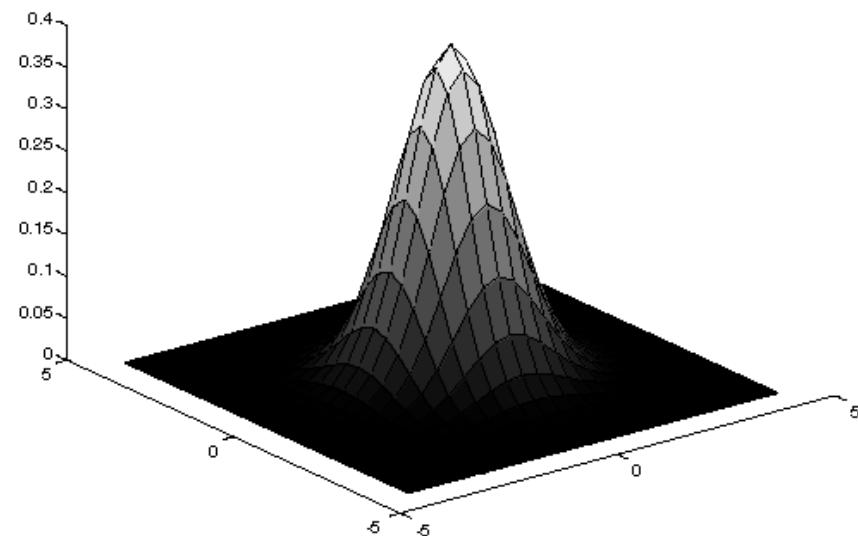
(Camps)

# Example 1: Smoothing by Averaging



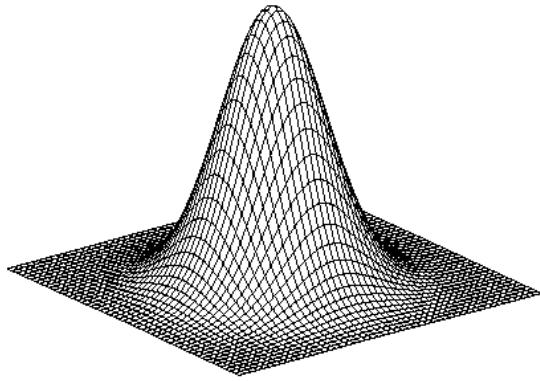
# Gaussian Averaging

- Rotationally symmetric.
- Weights nearby pixels more than distant ones.
  - This makes sense as probabilistic inference.



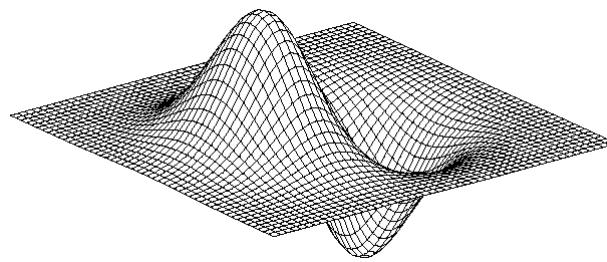
- A Gaussian gives a good model of a fuzzy blob

# 2D filters, more on this later...



Gaussian

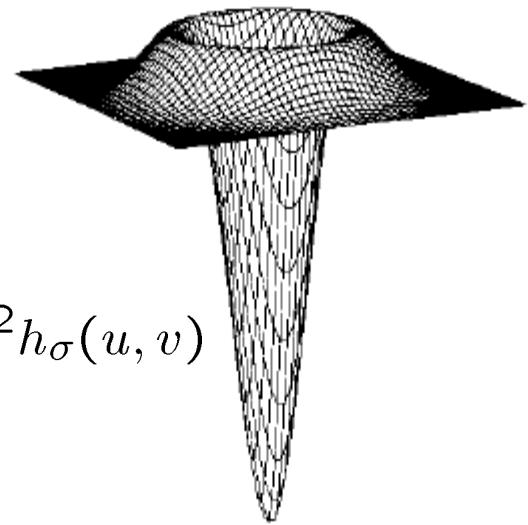
$$h_\sigma(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$



derivative of Gaussian

$$\frac{\partial}{\partial x} h_\sigma(u, v)$$

Laplacian of Gaussian

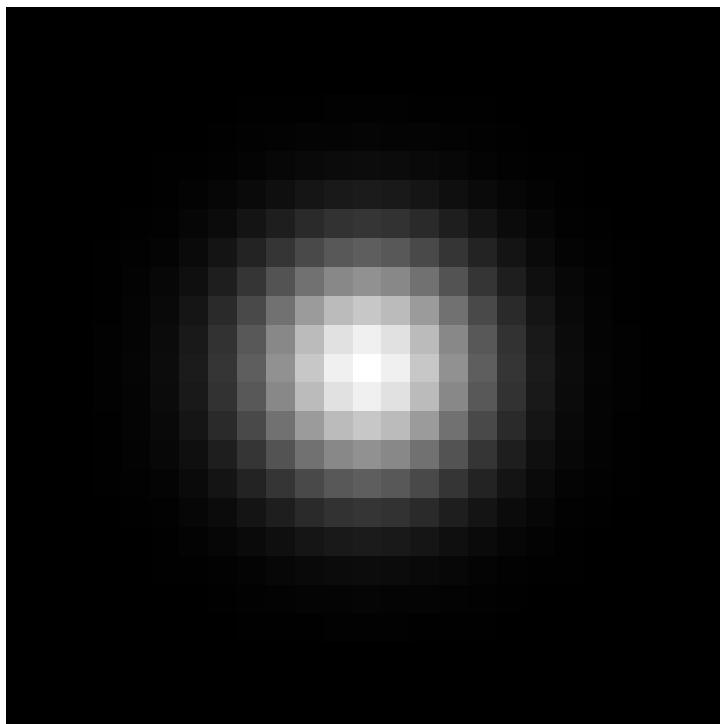


$$\nabla^2 h_\sigma(u, v)$$

- is the **Laplacian** operator:

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

# An Isotropic Gaussian

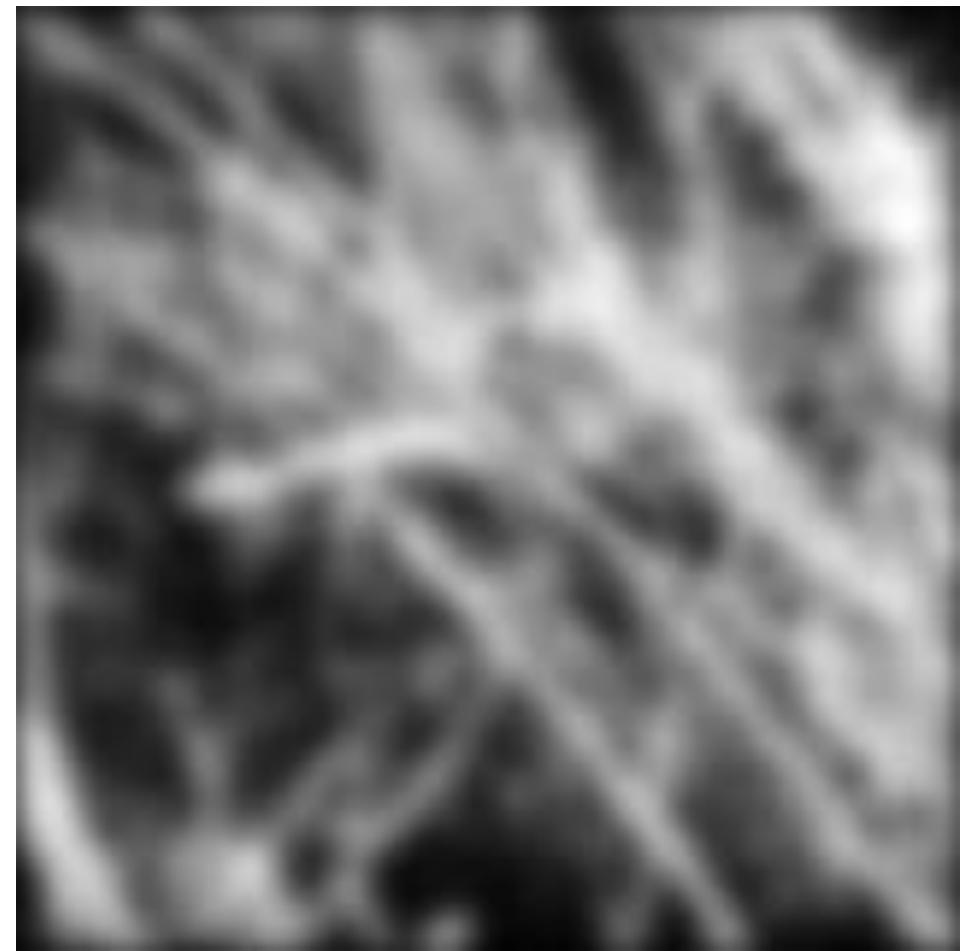


- The picture shows a smoothing kernel proportional to

$$e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- (which is a reasonable model of a circularly symmetric fuzzy blob)

# Smoothing with a Gaussian

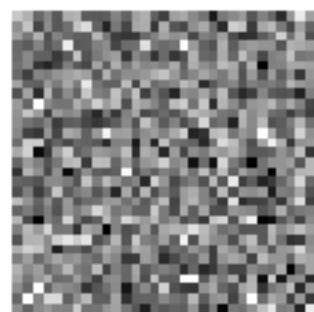
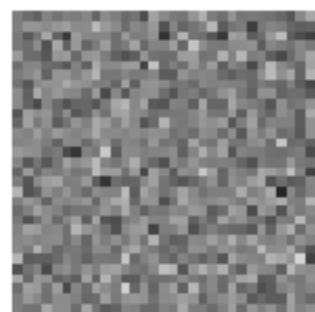
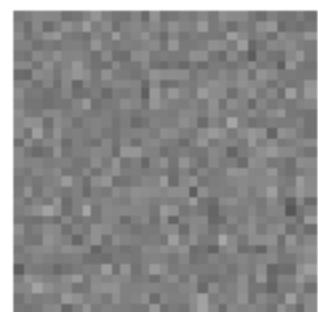


$\sigma=0.05$

$\sigma=0.1$

$\sigma=0.2$

no  
smoothing



$\sigma=1$  pixel



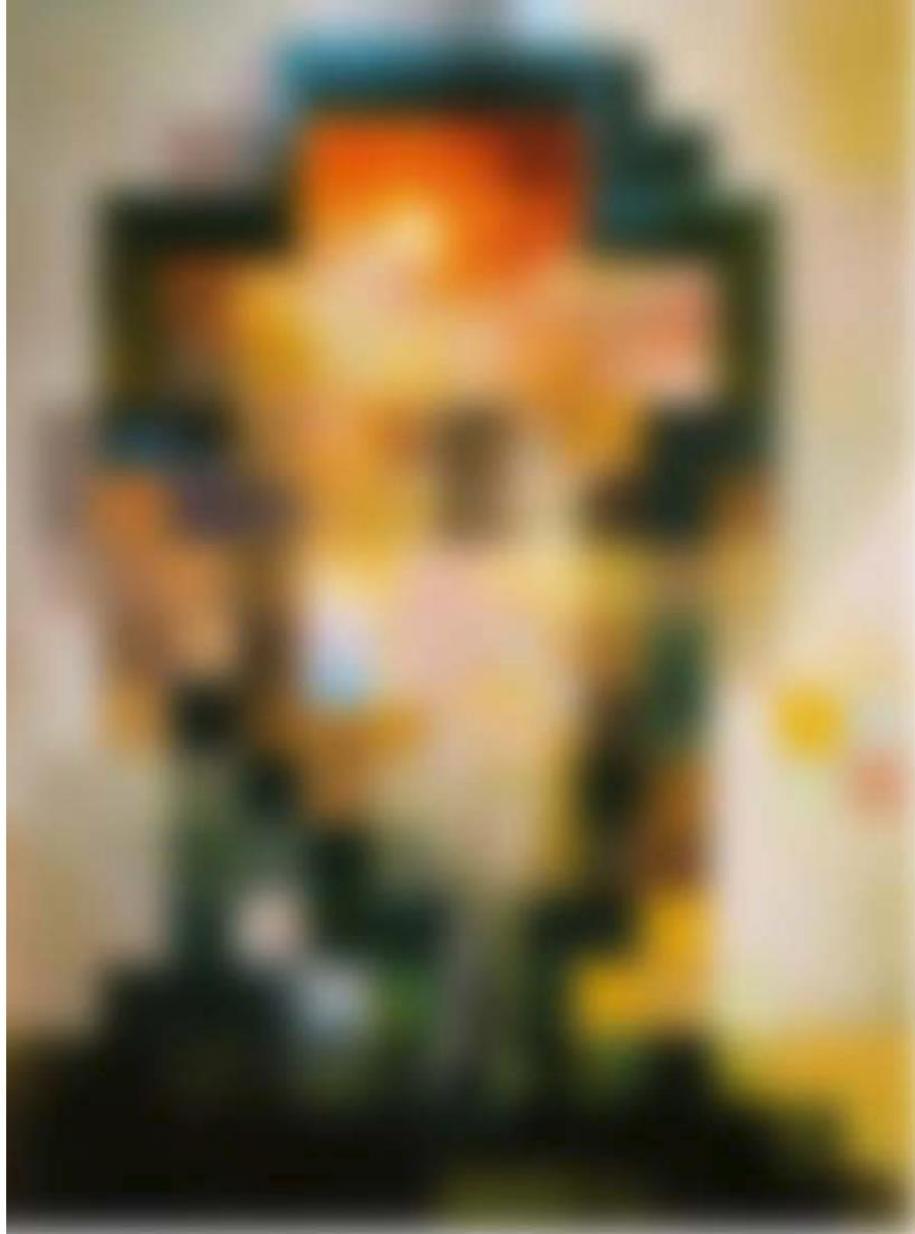
$\sigma=2$  pixels

## The effects of smoothing

Each row shows smoothing with gaussians of different width; each column shows different realizations of an image of gaussian noise.



Salvador Dalí, “*Gala Contemplating the Mediterranean Sea, which at 30 meters becomes the portrait of Abraham Lincoln*”, 1976



Salvador Dali, “*Gala Contemplating the Mediterranean Sea, which at 30 meters becomes the portrait of Abraham Lincoln*”, 1976

**Image smoothing can remove noise, and also ...**





