



# Perception | Correlation & Convolution

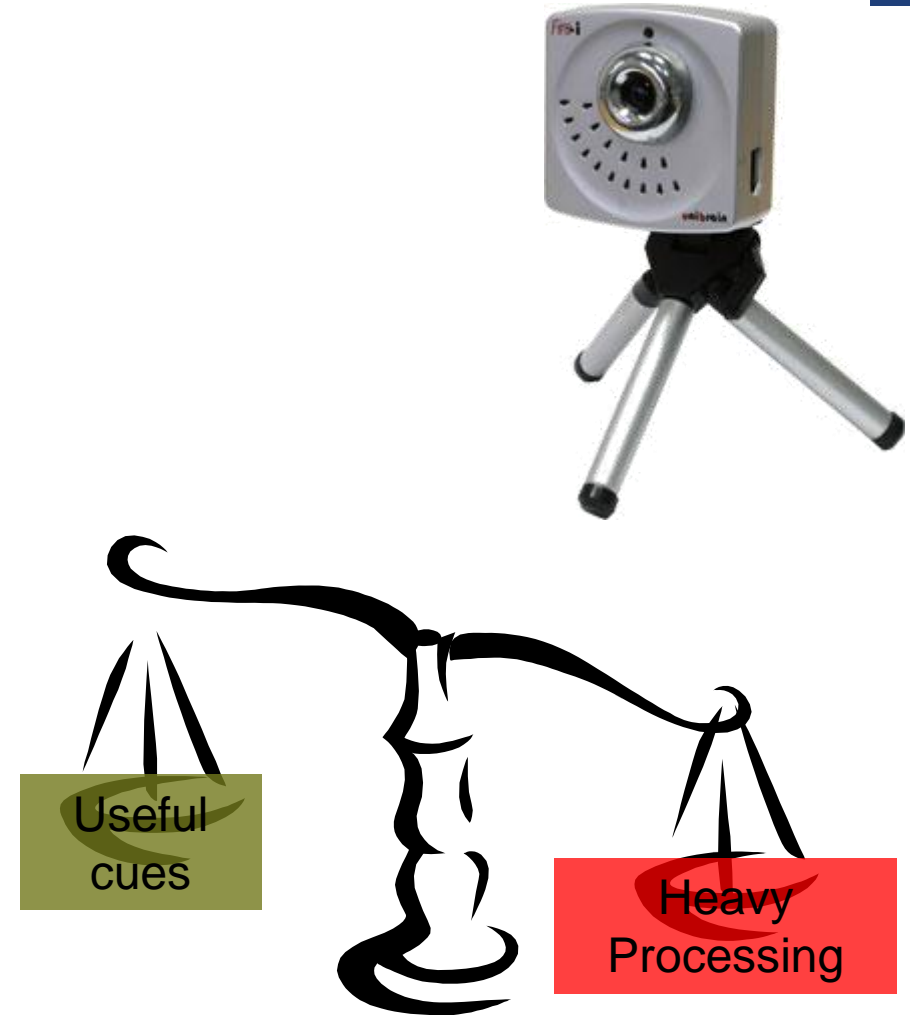
## Autonomous Mobile Robots

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# Image Saliency | data reduction

- Monochrome image  $\Rightarrow$  matrix of intensity values
  - Typical sizes:
    - 320 x 240 (QVGA)
    - 640 x 480 (VGA)
    - 1280 x 720 (HD)
  - Intensities sampled to 256 grey levels  $\Rightarrow$  8 bits
  - Images capture a lot of information
- $\Rightarrow$  Reduce the amount of input data:  
preserving useful info & discarding redundant info

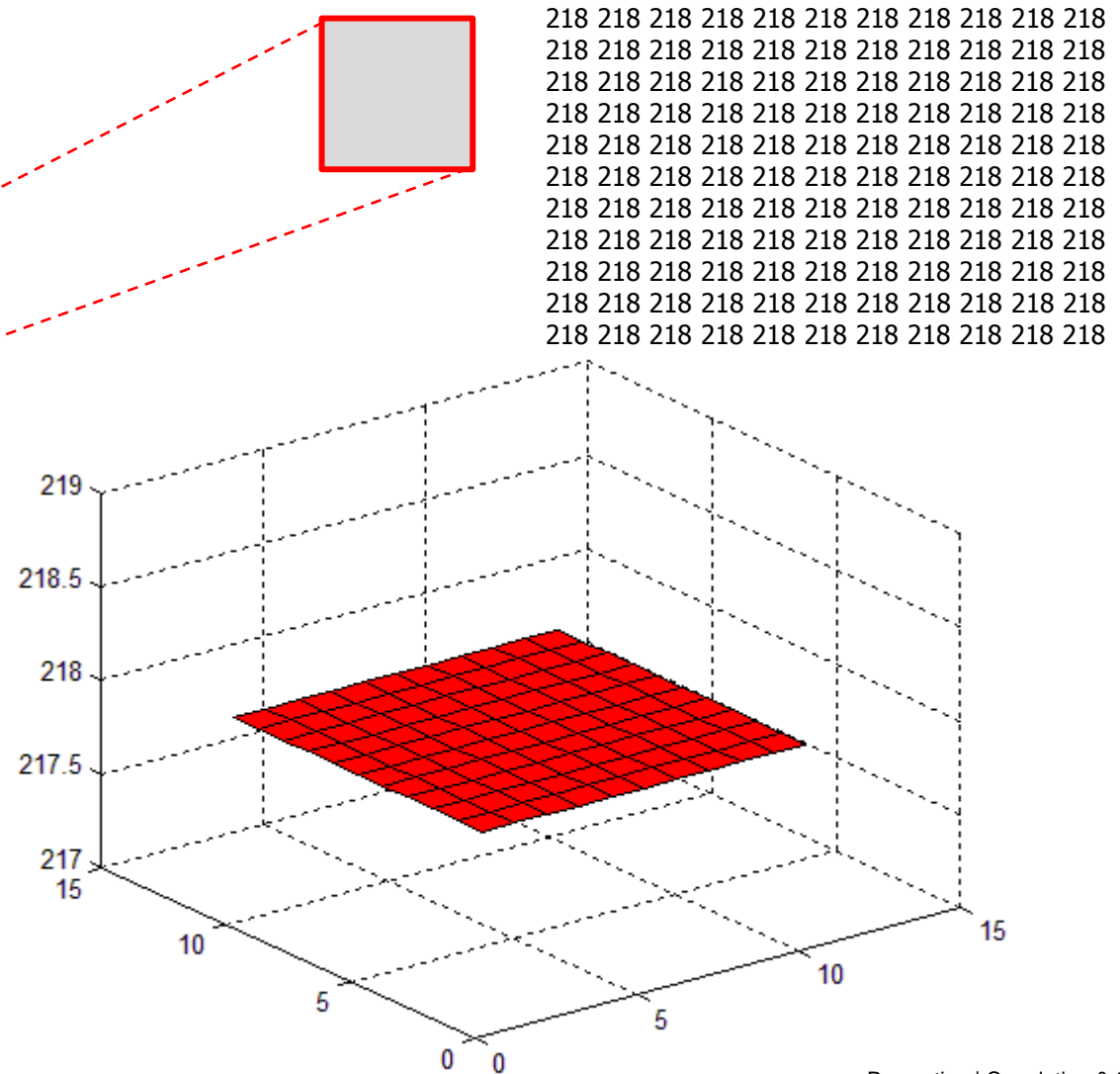


# Image Saliency | what is USEFUL, what is REDUNDANT ?



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# Image Saliency | what is USEFUL, what is REDUNDANT ?



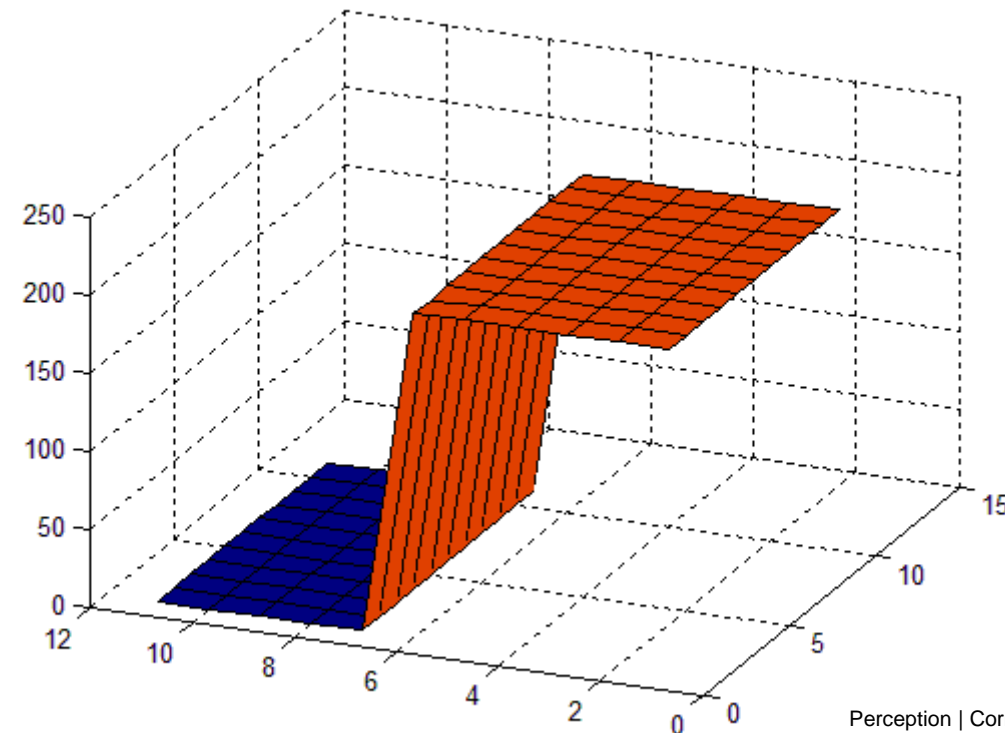
'Slightly confusing signs' by Dan McKay, <http://www.flickr.com/photos/mukluk/241256203/>.  
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## Autonomous Mobile Robots

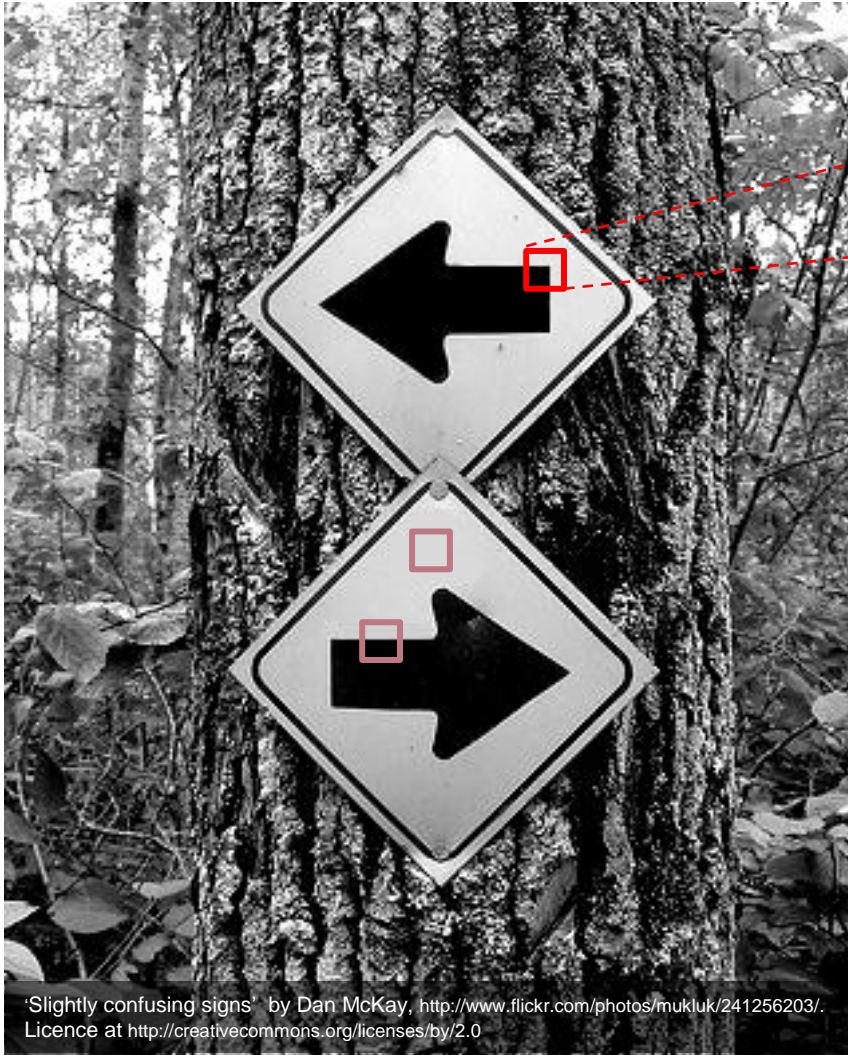
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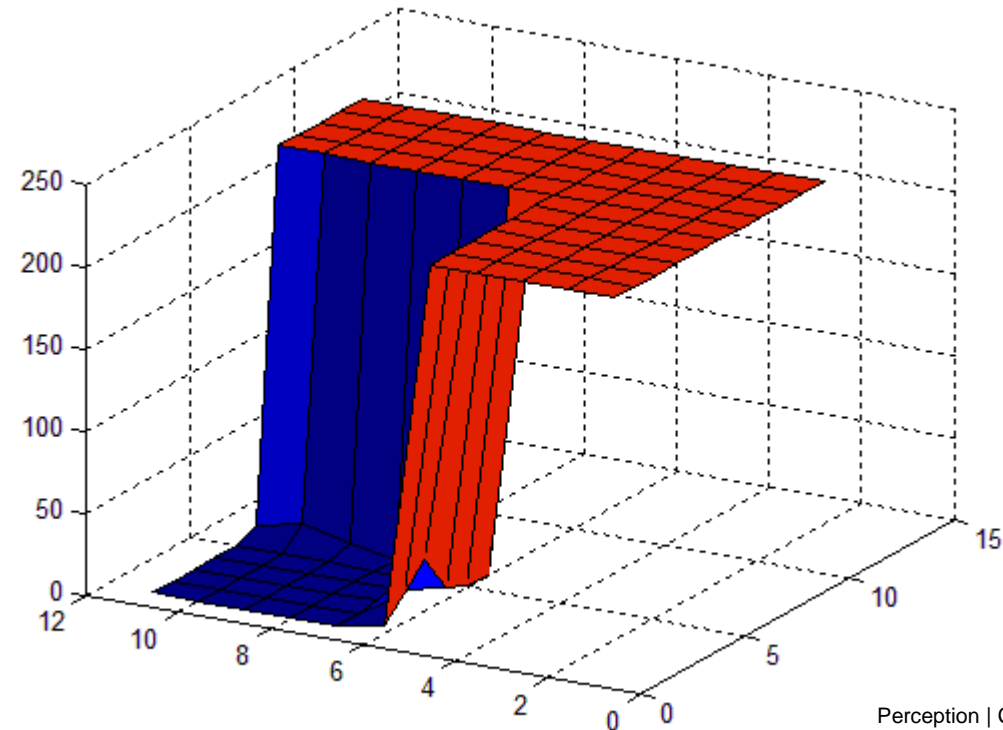
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# Image Saliency | what is USEFUL, what is REDUNDANT ?



229	229	229	229	229	229	229	229	229	229	229	229
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229	229	229	229	229	229	229	229	229	229	229	229
229	229	229	229	229	229	230	229	229	229	229	229
5	17	31	7	1	0	229	229	229	229	229	229
0	0	1	0	0	0	229	229	229	229	229	229
0	0	0	0	0	0	229	229	229	229	229	229
0	0	0	0	1	4	229	229	229	229	229	229
0	0	0	0	0	11	229	229	229	229	229	229
0	0	0	0	0	5	229	229	229	229	229	229





# Image filtering | spatial filters

- “filtering”: accept / reject certain components
- $S_{xy}$  : neighborhood of pixels around the point  $(x,y)$  in an image  $I$
- Spatial filtering operates on  $S_{xy}$  to generate a new value for the corresponding pixel at output image  $J$

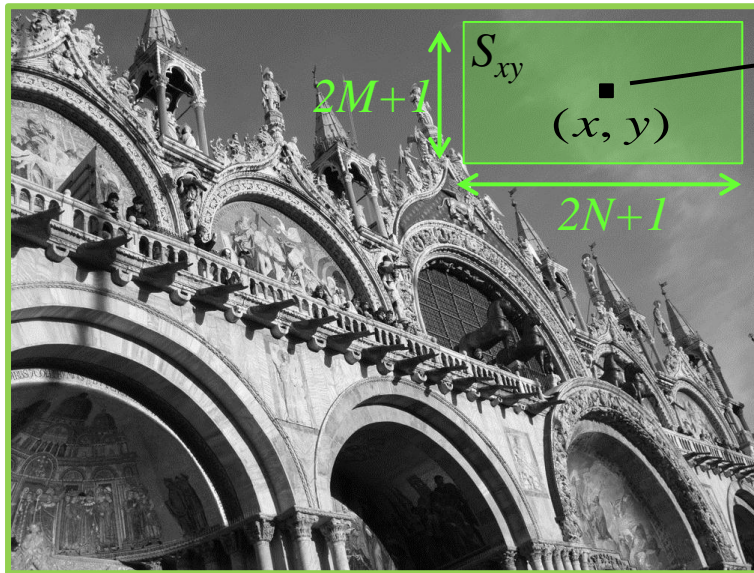


Image  $I$



Filtered Image  $J = F(I)$

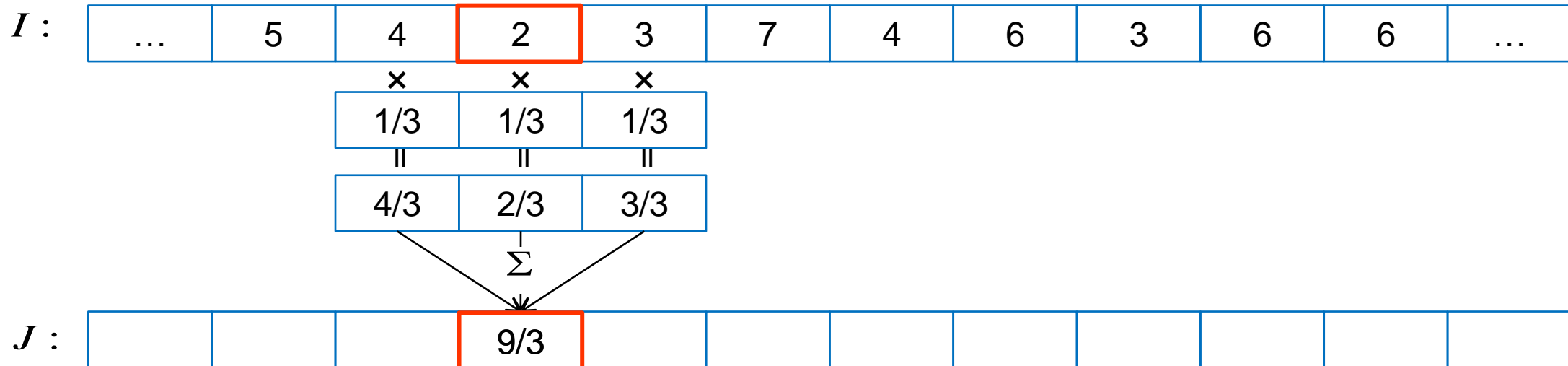
- For example, an averaging filter is: 
$$J(x, y) = \frac{\sum_{(r,c) \in S_{xy}} I(r, c)}{(2M + 1)(2N + 1)}$$

# Image filtering | linear, shift-invariant filters

- **Linear:** every pixel is replaced by a linear combination of its neighbors
- **Shift-invariant:** the same operation is performed on every point on the image
- Basic & very useful filtering operations:
  - Correlation
  - Convolution
- Brief study of these filters in the simplest case of 1D images (i.e. a row of pixels) & their extension to 2D

# Image filtering | correlation

- An averaging filter

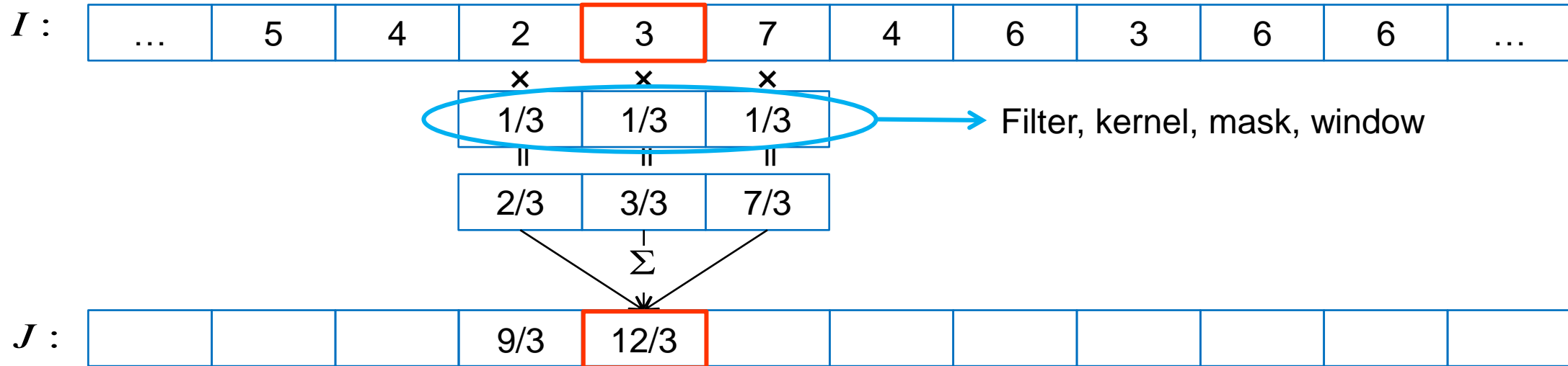


- How to handle boundaries?
  - Ignore filtered values at boundaries
  - Pad image with zeros
  - Pad image with first/last image values



# Image filtering | correlation

- An averaging filter



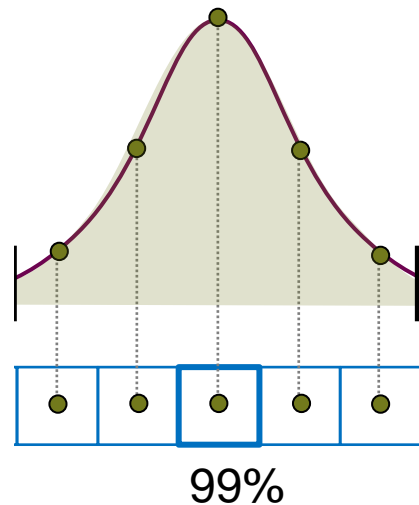
- Formally, Correlation is  $J(x) = F \circ I(x) = \sum_{i=-N}^N F(i)I(x+i)$

- In this smoothing example  $F(i) = \begin{cases} 1/3, & i \in [-1,1] \\ 0, & i \notin [-1,1] \end{cases}$

Other examples of smoothing filters?

# Image filtering | constructing filter from a continuous $f^n$

- Common practice for image smoothing:  
use a Gaussian



Normalize filter so that values always add up to 1

$$G(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

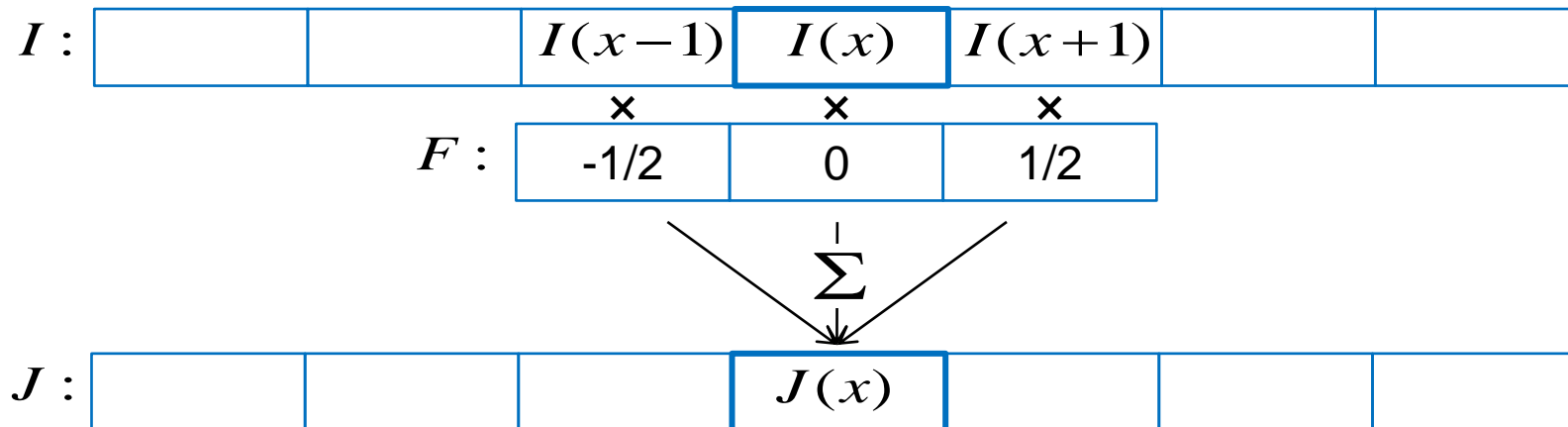
$$\mu = 0$$

$\sigma$  : controls the amount of smoothing

- Near-by pixels have a bigger influence on the averaged value rather than more distant ones

# Image filtering | taking derivatives with correlation

- Derivative of an image: quantifies how quickly intensities change (along the direction of the derivative)
- Approximate a derivative operator:



$$J(x) = \frac{I(x+1) - I(x-1)}{2}$$

# Image filtering | matching using correlation

- Find locations in an image that are similar to a **template**
- Filter = template 

3	8	3
---	---	---

  
⇒ test it against all image locations

$I :$

3	2	4	1	3	8	4	0	3	8	7	7
---	---	---	---	---	---	---	---	---	---	---	---

- Similarity measure: Sum of Squared Differences (**SSD**) – minimize

$$\sum_{i=-N}^N (F(i) - I(x+i))^2 = \sum_{i=-N}^N (F(i))^2 + \sum_{i=-N}^N (I(x+i))^2 - 2 \sum_{i=-N}^N (F(i)I(x+i))$$

$J :$

26	37	21	50	54	1	50	65	59	16	42	17
----	----	----	----	----	---	----	----	----	----	----	----



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---	---	---	---	---	---	---	---	---	---	---	---

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Correlation

$J$  : 

26	37	21	50	54	1	50	65	59	16	42	17
----	----	----	----	----	---	----	----	----	----	----	----

- Similarity measure: Correlation? – maximize

$J$  : 

30	37	41	29	51	85	56	21	48	86	101	77
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# Image filtering | NCC: Normalized Cross Correlation

- Find locations in an image that are similar to a **template**
- Filter = template 

3	8	3
---	---	---

  
⇒ test it against all image locations

$I :$

3	2	4	1	3	8	4	0	3	8	7	7
---	---	---	---	---	---	---	---	---	---	---	---

- Correlation value is affected by the magnitude of intensities
- Similarity measure: Normalized Cross Correlation (**NCC**) – maximize

$$\frac{\sum_{i=-N}^{i=N} (F(i)I(x+i))}{\sqrt{\sum_{i=-N}^{i=N} (F(i))^2} \sqrt{\sum_{i=-N}^{i=N} (I(x+i))^2}}$$

$J :$

0.919	0.759	0.988	0.628	0.655	0.994	0.691	0.464	0.620	0.860	0.876	0.859
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# Image filtering | ZNCC: Zero-mean Normalized Cross Correlation

- Find locations in an image that are similar to a **template**
- Filter = template 

3	8	3
---	---	---

  
⇒ test it against all image locations

$I$  : 

3	2	4	1	3	8	4	0	3	8	7	7
---	---	---	---	---	---	---	---	---	---	---	---

- For better invariance to intensity changes, try to eliminate all absolute effects on intensities  
Similarity measure: Zero-mean Normalized Cross Correlation (**ZNCC**) – maximize

$$\frac{\sum_{i=-N}^{i=N} (F(i) - \mu_F)(I(x+i) - \mu_{I_x})}{\sqrt{\sum_{i=-N}^{i=N} (F(i) - \mu_F)^2} \sqrt{\sum_{i=-N}^{i=N} (I(x+i) - \mu_{I_x})^2}}$$

where

$$\begin{cases} \mu_F = \frac{\sum_{i=-N}^N F(i)}{2N+1} \\ \mu_{I_x} = \frac{\sum_{i=-N}^N I(x+i)}{2N+1} \end{cases}$$

# Image filtering | 2D Gaussian smoothing

- Correlation in 2D:  $F \circ I(x, y) = \sum_{j=-M}^M \sum_{i=-N}^N F(i, j) I(x + i, y + j)$

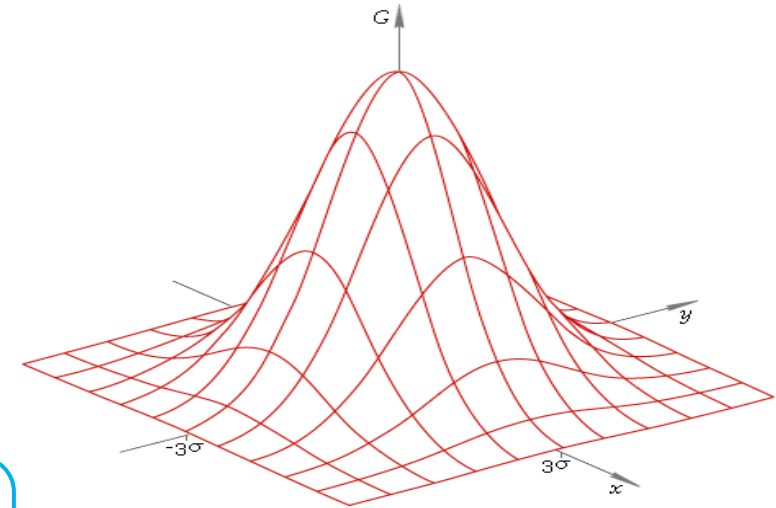
- A general, 2D Gaussian  $G(x, y) = \frac{1}{2\pi|S|^{1/2}} e^{-\frac{1}{2} \begin{pmatrix} x \\ y \end{pmatrix}^T S^{-1} \begin{pmatrix} x \\ y \end{pmatrix}}$

- We usually want to smooth by the same amount in both  $x$  and  $y$  directions  $S = \begin{bmatrix} \sigma^2 & 0 \\ 0 & \sigma^2 \end{bmatrix}$

- So this simplifies to:

$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} = \underbrace{\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}}_{G_{\sigma}(x)} \cdot \underbrace{\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{y^2}{2\sigma^2}}}_{G_{\sigma}(y)}$$

- A “separable” filter





# Image filtering | convolution

- Convolution is **equivalent** to Correlation with a flipped filter before correlating

- CONVOLUTION:  $J(x) = F * I(x) = \sum_{i=-N}^N F(i)I(x-i)$

- CORRELATION:  $J(x) = F \circ I(x) = \sum_{i=-N}^N F(i)I(x+i)$

So if  $F = \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}$   
 $F' = \begin{bmatrix} 3 & 2 & 1 \end{bmatrix}$   
Then,  $J(x) = J'(x)$

- Likewise, in 2D we flip the filter both horizontally & vertically

$$J(x, y) = F * I(x, y) = \sum_{j=-M}^M \sum_{i=-N}^N F(i, j)I(x-i, y-j)$$

- Key difference with correlation: **convolution is associative**:  $F * (G * I) = (F * G) * I$
- Very useful!
- Example: smooth an image & take its derivative  $\Rightarrow$  convolve the Derivative filter with the Gaussian filter & convolve the resulting filter with the Image