

# Pixels

- Neighborhood
- Adjacency
- Connectivity
- Paths
- Regions and boundaries

# Neighbors of a Pixel

- Any pixel  $p(x, y)$  has two vertical and two horizontal neighbors, given by  
 $(x+1, y), (x-1, y), (x, y+1), (x, y-1)$
- This set of pixels are called the 4-neighbors of  $P$ , and is denoted by  $N_4(P)$ .
- Each of them are at a unit distance from  $P$ .



# Neighbors of a Pixel (Contd..)

- The four diagonal neighbors of  $p(x,y)$  are given by,  
 $(x+1, y+1), (x+1, y-1), (x-1, y+1), (x-1, y-1)$
- This set is denoted by  $N_D(P)$ .
- Each of them are at Euclidean distance of 1.414 from P.

# Neighbors of a Pixel (Contd..)

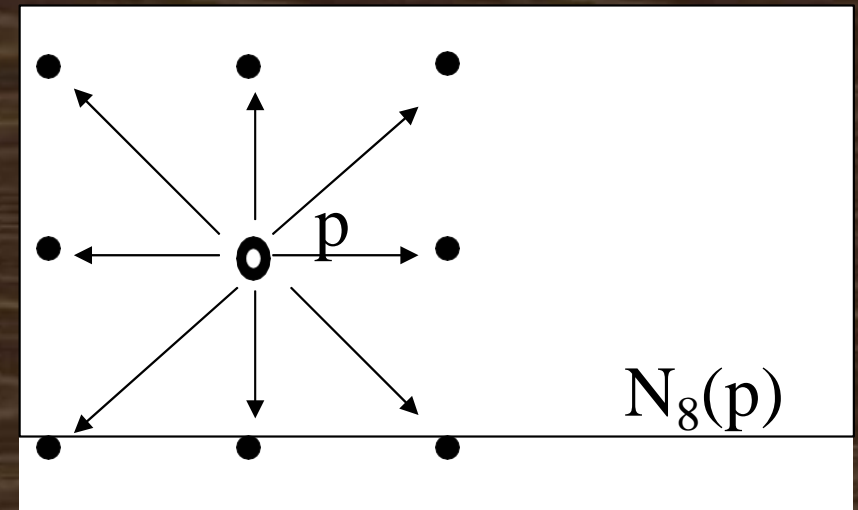
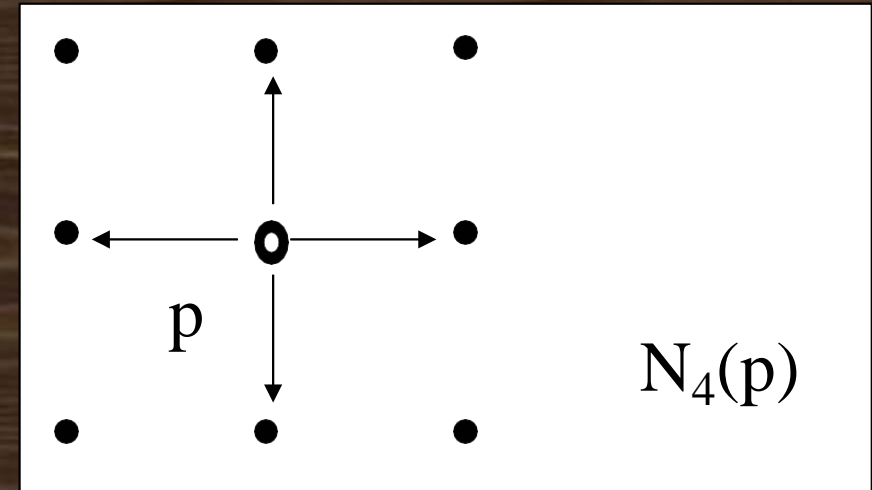
- The points  $N_D(P)$  and  $N_4(P)$  are together known as 8-neighbors of the point  $P$ , denoted by  $N_8(P)$ .
- Some of the points in the  $N_4$ ,  $N_D$  and  $N_8$  may fall outside image when  $P$  lies on the border of image.



# Neighbors of a Pixel (Contd..)

## Neighbors of a pixel

- a. 4-neighbors of a pixel  $p$  are its vertical and horizontal neighbors denoted by  $N_4(p)$
- b. 8-neighbors of a pixel  $p$  are its vertical horizontal and 4 diagonal neighbors denoted by  $N_8(p)$



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$N_D$	$N_4$	$N_D$
$N_4$	P	$N_4$
$N_D$	$N_4$	$N_D$

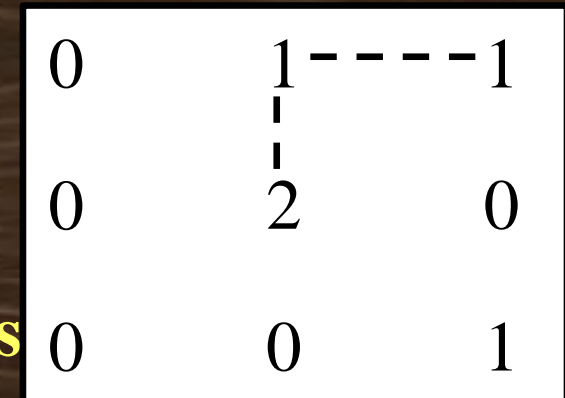
- $N_4$  - 4-neighbors
- $N_D$  - diagonal neighbors
- $N_8$  - 8-neighbors ( $N_4 \cup N_D$ )

## Connectivity :

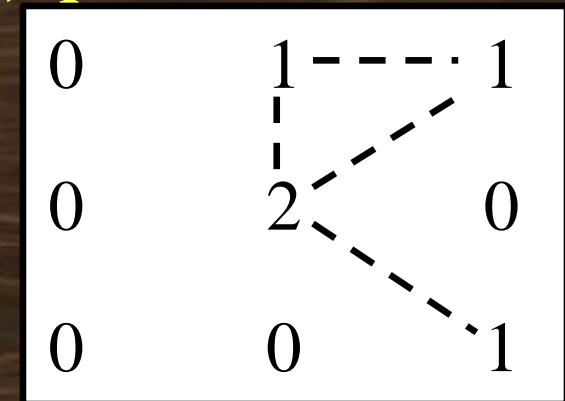
To determine whether the pixels are adjacent in some sense.

Let  $V$  be the set of gray-level values define connectivity; then Two pixels  $p, q$  that have values from the set  $V$  are:

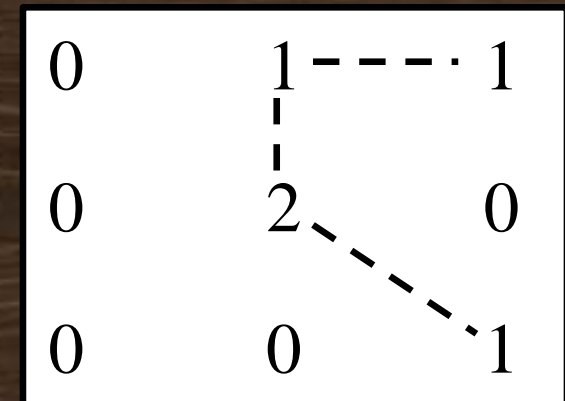
- a. 4-connected, if  $q$  is in the set  $N_4(p)$
- b. 8-connected, if  $q$  is in the set  $N_8(p)$
- c. m-connected, iff
  - i.  $q$  is in  $N_4(p)$  or
  - ii.  $q$  is in  $N_D(p)$  and the set  $N_4(p) \cap N_4(q)$  is empty



a.



b.



c.



# Types of Adjacency

- In this example, we can note that to connect between two pixels (finding a path between two pixels):
  - In 8-adjacency way, you can find multiple paths between two pixels
  - While, in m-adjacency, you can find only one path between two pixels
- So, m-adjacency has eliminated the multiple path connection that has been generated by the 8-adjacency.





- A *path* from pixel  $p$  with coordinates  $(x, y)$  to pixel  $q$  with coordinates  $(s, t)$  is a sequence of distinct pixels with coordinates:

$(x_0, y_0), (x_1, y_1), (x_2, y_2) \dots (x_n, y_n),$

where  $(x_0, y_0) = (x, y)$  and  $(x_n, y_n) = (s, t);$

$(x_i, y_i)$  is adjacent to  $(x_{i-1}, y_{i-1})$   $1 \leq i \leq n$

- Here  $n$  is the *length* of the path.
- We can define 4-, 8-, and m-paths based on type of adjacency used.

- If  $p$  and  $q$  are pixels of an image subset  $S$  then  $p$  is *connected* to  $q$  in  $S$  if there is a path from  $p$  to  $q$  consisting entirely of pixels in  $S$ .
- For every pixel  $p$  in  $S$ , the set of pixels in  $S$  that are connected to  $p$  is called a *connected component* of  $S$ .
- If  $S$  has only one connected component then  $S$  is called *Connected Set*.



# Regions and Boundaries

- A subset  $R$  of pixels in an image is called a *Region* of the image if  $R$  is a connected set.
- The *boundary* of the region  $R$  is the set of pixels in the region that have one or more neighbors that are not in  $R$ .
- If  $R$  happens to be entire Image?



# Distance measures

Given pixels  $p$ ,  $q$  and  $z$  with coordinates  $(x, y)$ ,  $(s, t)$ ,  $(u, v)$  respectively, the distance function  $D$  has following properties:

- a.*  $D(p, q) \geq 0$  [ $D(p, q) = 0$ , iff  $p = q$ ]
- b.*  $D(p, q) = D(q, p)$
- c.*  $D(p, z) \leq D(p, q) + D(q, z)$



# The following are the different Distance measures:

- **Euclidean Distance :**

$$D_e(p, q) = [(x-s)^2 + (y-t)^2]$$

- b. **City Block Distance:**

$$D_4(p, q) = |x-s| + |y-t|$$



		2		
	2	1	2	
2	1	0	1	2
	2	1	2	
		2		

- c. **Chess Board Distance:**

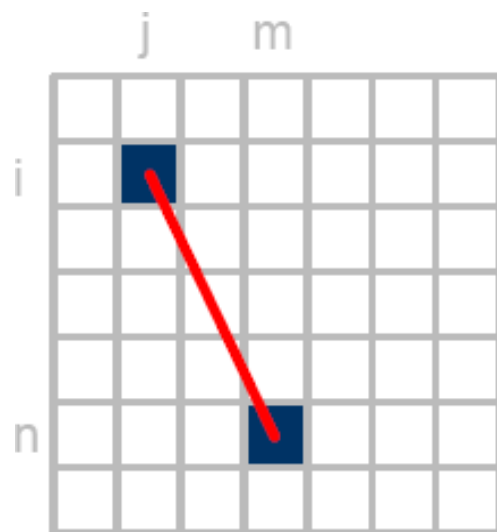
$$D_8(p, q) = \max(|x-s|, |y-t|)$$



2	2	2	2	2
2	1	1	1	2
2	1	0	1	2
2	1	1	1	2
2	2	2	2	2

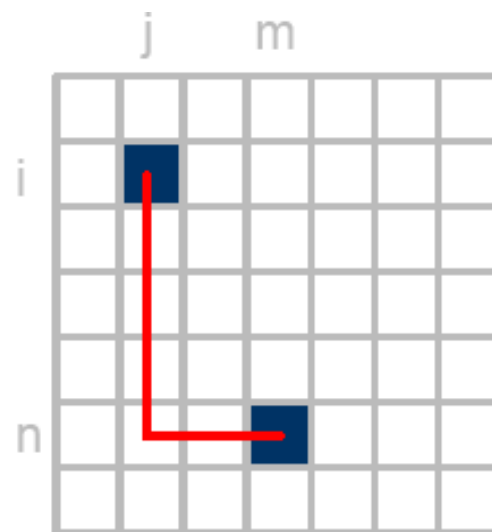
# Distance measures

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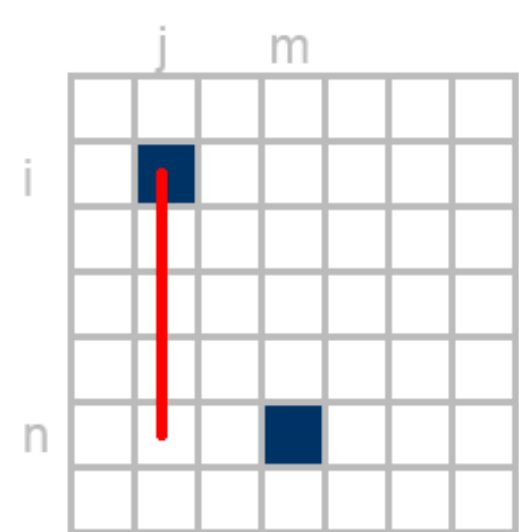
**Euclidean Distance**

$$= \sqrt{(i-n)^2 + (j-m)^2}$$



**City Block Distance**

$$= |i-n| + |j-m|$$



**Chessboard Distance**

$$= \max[ |i-n|, |j-m| ]$$



# Example:

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Compute the distance between the two pixels using the three distances :

q:(1,1)

P: (2,2)

Euclidian distance :  $((1-2)^2 + (1-2)^2)^{1/2} = \text{sqrt}(2)$ .

D4(City Block distance):  $|1-2| + |1-2| = 2$

D8(chessboard distance ) :  $\max(|1-2|, |1-2|) = 1$

(because it is one of the 8-neighbors )

	1	2	3
1	q		
2		p	
3			

# Distance measures

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Example :

Use the city block distance to prove 4-neighbors ?

Pixel A :  $|2-2| + |1-2| = 1$

Pixel B:  $|3-2| + |2-2| = 1$

Pixel C:  $|2-2| + |2-3| = 1$

Pixel D:  $|1-2| + |2-2| = 1$

	1	2	3
1		d	
2	a	p	c
3		b	

Now as a homework try the chessboard distance to proof the 8- neighbors!!!!

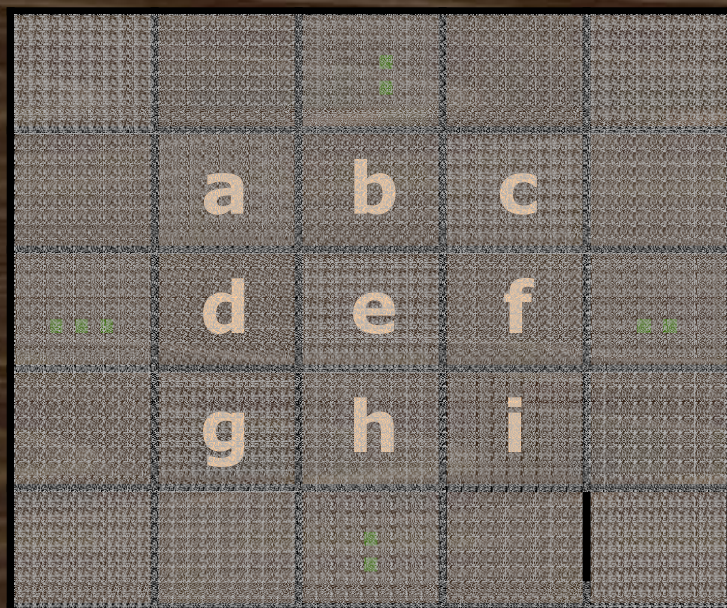
## Arithmetic/Logic Operations:

- **Addition :**  $p + q$
- **Subtraction:**  $p - q$
- **Multiplication:**  $p * q$
- **Division:**  $p / q$
- **AND:**  $p \text{ AND } q$
- **OR :**  $p \text{ OR } q$



## Neighborhood based arithmetic/Logic :

Value assigned to a pixel at position 'e' is a function of its neighbors and a set of window functions.



$$p = (w_1a + w_2b + w_3c + w_4d + w_5e + w_6f + w_7g + w_8h + w_9i)$$
$$= \sum w_i f_i$$

- **Tasks done using neighborhood processing:**

- **Smoothing / averaging**
- **Noise removal / filtering**
- **Edge detection**
- **Contrast enhancement**

# What is convolution?

- Convolution is a general purpose filter effect for images.
- Is a matrix applied to an image and a mathematical operation comprised of integers
- It works by determining the value of a central pixel by adding the weighted values of all its neighbors together
- The output is a new modified filtered image



# The process of image convolution

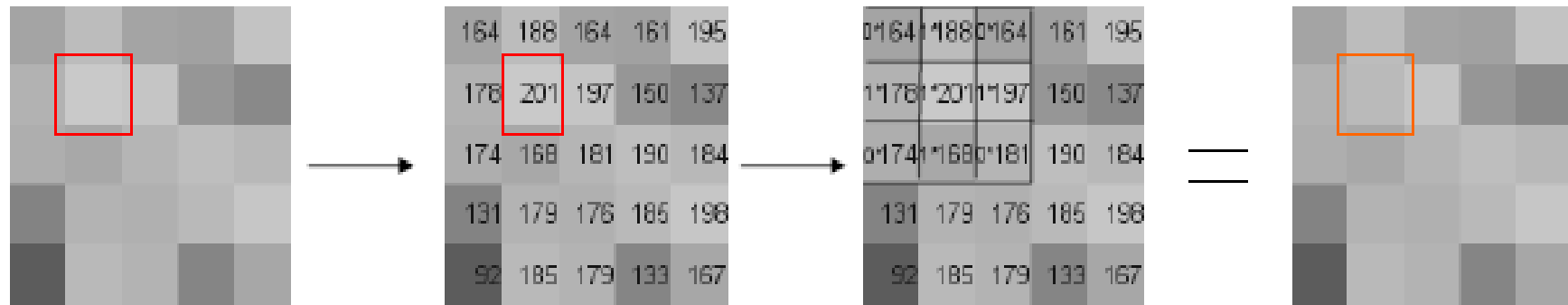
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- ❑ A convolution is done by multiplying a pixel's and its neighboring pixels color value by a matrix
- ❑ **Kernel:** A kernel is a (usually) small matrix of numbers that is used in image convolutions.
  - Differently sized kernels containing different patterns of numbers produce different results under convolution.
  - The size of a kernel is arbitrary but 3x3 is often used

Example kernel:

0	1	0
1	1	1
0	1	0

# Example



Original image

Image with color values placed over it

Image with 3x3 kernel placed over it

Output image

164	188	164
178	201	197
174	168	181

Color values



0	1	0
1	1	1
0	1	0

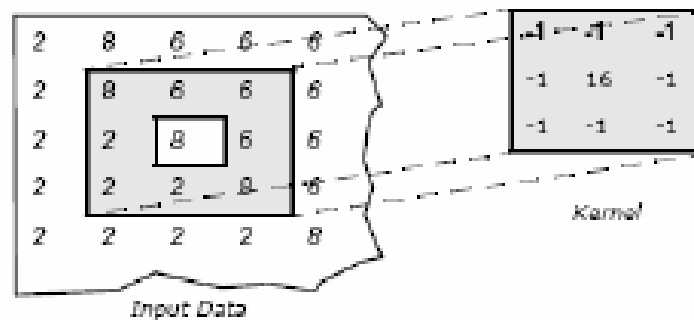
Kernel

Divided by the sum of the kernel

$932 \div 5 = \text{new pixel color}$

# More examples

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```
integer [(-1 × 8) + (-1 × 6) + (-1 × 6) + (-1 × 2) + (16 × 8) +
(-1 × 6) +
(-1 × 2) + (-1 × 2) + (-1 × 8) ÷ (-1 + -1 + -1 + -1 + 16 + -1 +
-1 + -1 + -1)]
= int [(128-40) / (16-8)]
= int (88 / 8) = int (11) = 11
```



## Some other kernel examples

1	1	1
1	1	1
1	1	1

Unweighted 3x3 smoothing kernel

0	1	0
1	4	1
0	1	0

Weighted 3x3 smoothing kernel with Gaussian blur

0	-1	0
-1	5	-1
0	-1	0

Kernel to make image sharper

-1	-1	-1
-1	9	-1
-1	-1	-1

Intensified sharper image



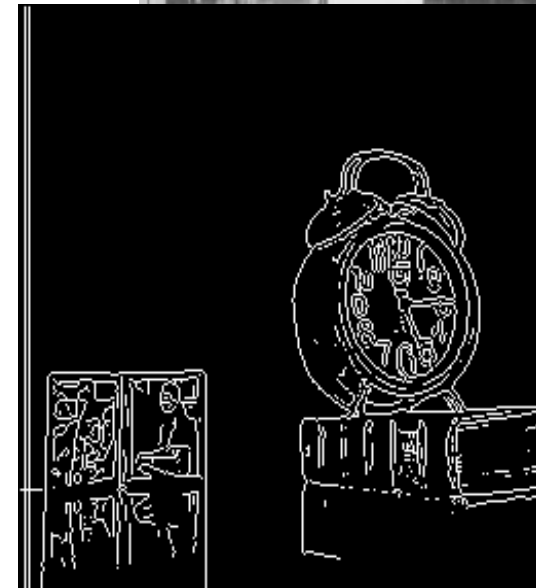
Gaussian Blur



Sharpened image

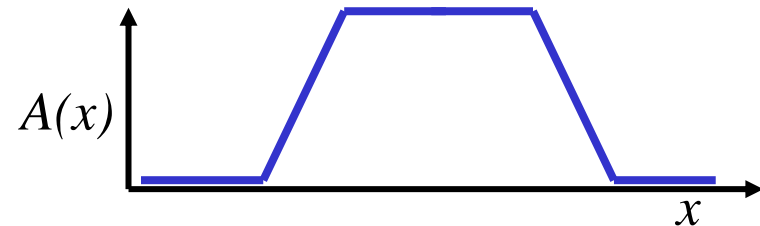
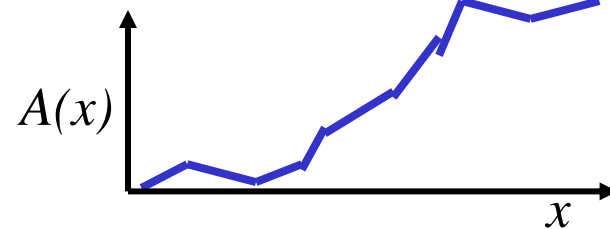
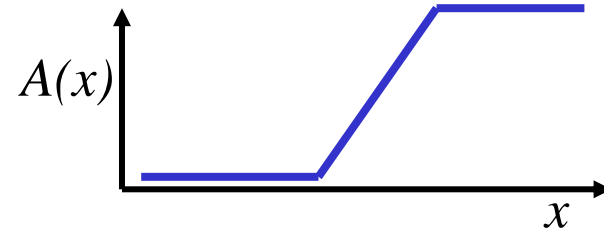
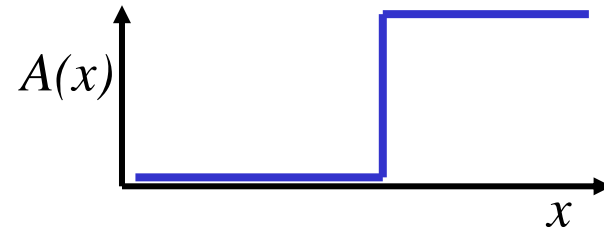
# What are edges ?

- Change, or discontinuity, in image brightness between two reasonably smooth regions.
- Fundamentally important primitive image characteristics.
- Only information in most black and white images.



# What are edges?

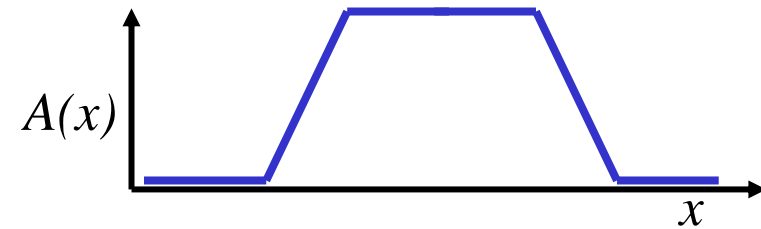
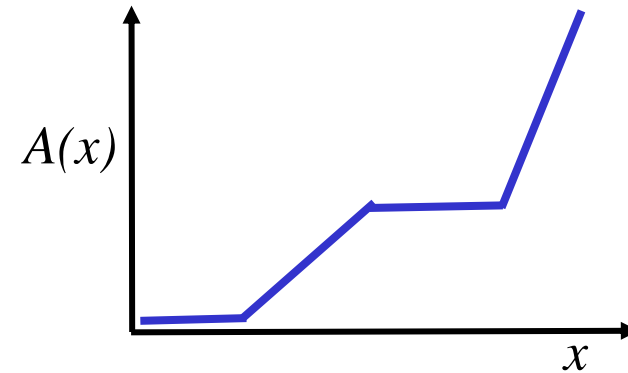
- Ideal edge
- It is usually *ramped* because of sensor processing during capture
- Noisy edge
- Line





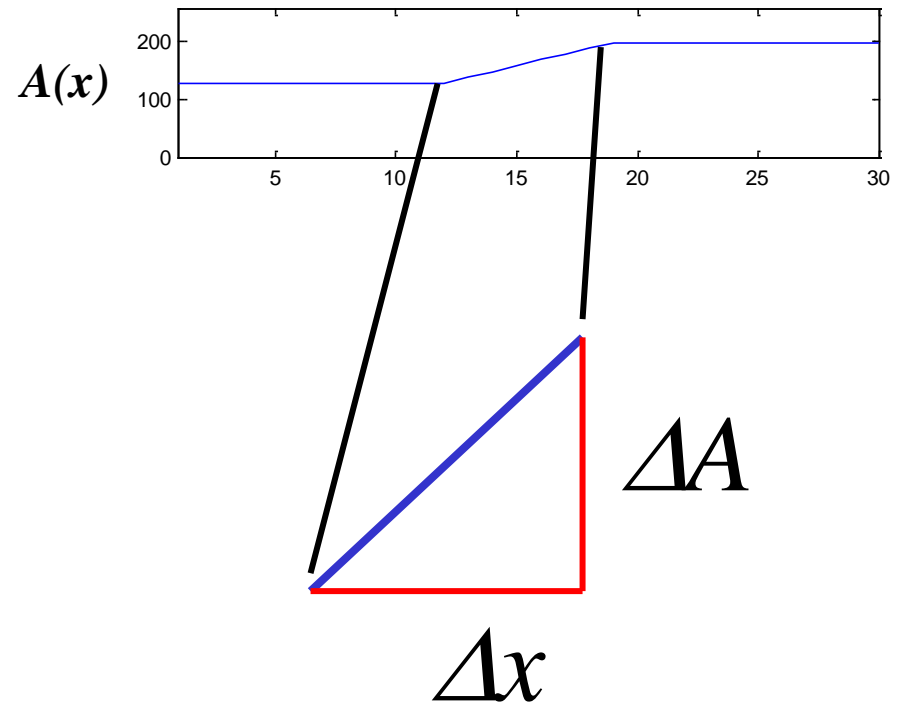
# Edge Properties

- Edge has two properties:
  - how steep it is
  - direction, ie, is it pointing towards the left or right?



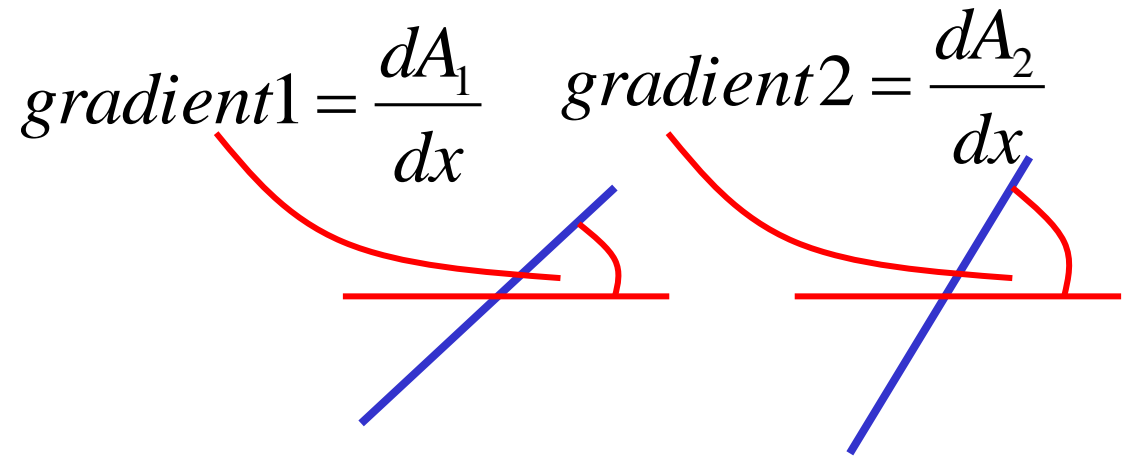
# Edge Properties- gradient

- Consider a 1-d continuous image of an edge, denoted by  $A(x)$
- Edge properties can be obtained from the gradient =  $\Delta A / \Delta x$
- gradient =  $dA/dx$  as  $\Delta x \rightarrow 0$ .



# Edge Properties

- Gradient has two properties
  - magnitude
  - direction
- Magnitude, or steepness, given by  $|dA/dx|$
- Direction, left or right, given by sign of  $dA/dx$



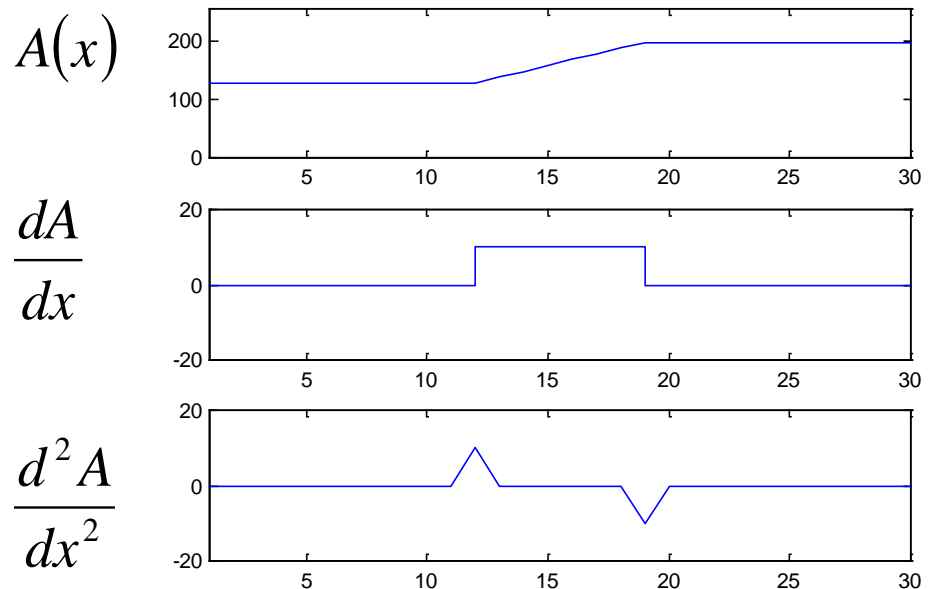
$$\left| \frac{dA_2}{dx} \right| > \left| \frac{dA_1}{dx} \right|$$

$$\text{sgn}\left(\frac{dA_2}{dx}\right) = \text{sgn}\left(\frac{dA_1}{dx}\right)$$



# Edge Properties- gradient

- Gradient given by first derivative  $dA/dx$ .
- Second derivative,  $d^2A/dx^2$ , generates two peaks at beginning and end of edge.
- Called ‘ringing’.



# Edge Properties-discrete gradient

$$A(x) = A_i$$

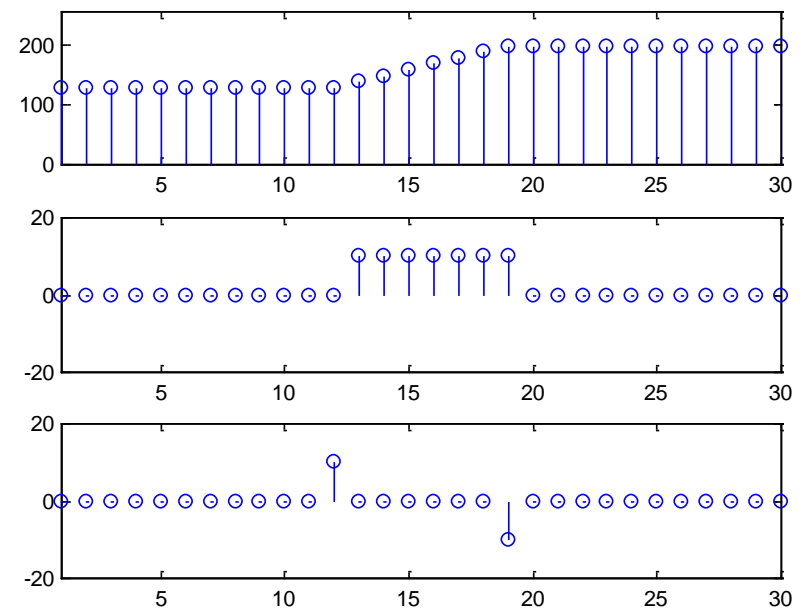
$$\mathbf{B} = [-1 \ 1]$$

$$\frac{dA}{dx} \approx A_{i+1} - A_i = \Delta A_i$$

$$\frac{d^2 A}{dx^2} \approx \Delta A_{i+1} - \Delta A_i$$

$$= A_{i+2} - A_{i+1} - (A_{i+1} - A_i) \quad \mathbf{B} = [1 \ -2 \ 1]$$

$$= A_{i+2} - 2A_{i+1} + A_i = \Delta^2 A_i$$



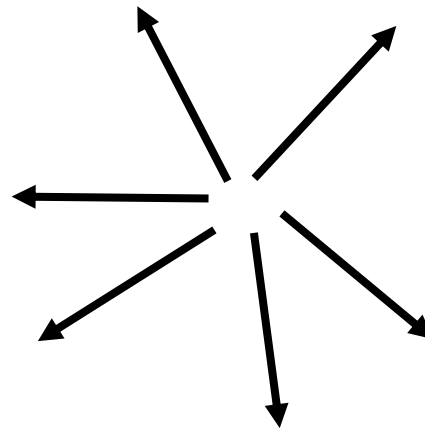
# Neighbourhood Operators

- First derivative can be calculated by convolving with mask  $B = [-1 \ 1]$ .
- Second derivative can be calculated by convolving with mask  $B = [1 \ -2 \ 1]$ .



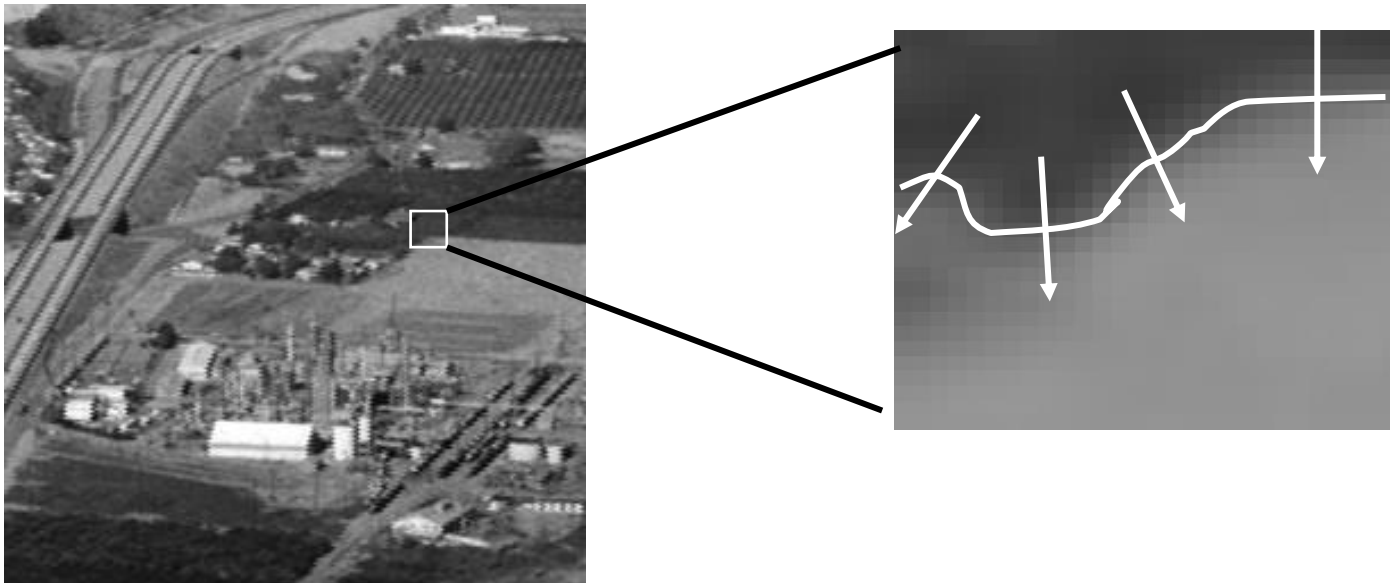
# Edges in 2-D Images

- Edge properties are provided by gradient of image brightness  $A(x,y)$
- 1-d case the gradient direction is either  $\rightarrow$  or  $\leftarrow$
- 2-d gradient has a magnitude and orientation

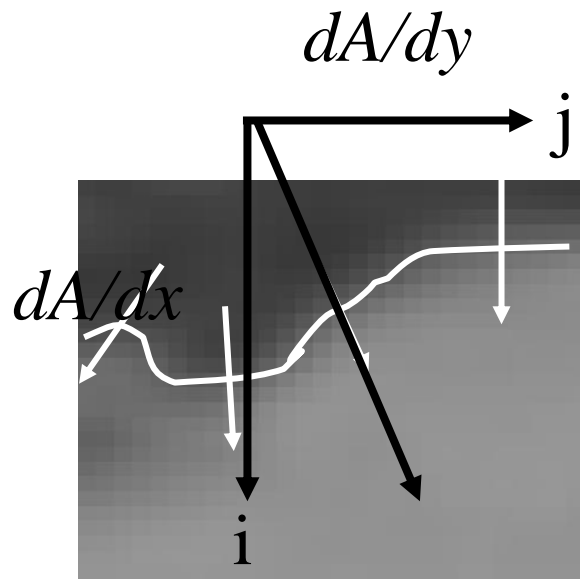


# Edges in 2-D Images

- Direction of gradient at any point is the direction of maximum change.



# 2-d Gradient Operator



$$\Delta A = \frac{dA}{dx} \mathbf{i} + \frac{dA}{dy} \mathbf{j}$$

$$\text{Magnitude} = \sqrt{\left(\frac{dA}{dx}\right)^2 + \left(\frac{dA}{dy}\right)^2}$$

$$\text{Orientation } n = \tan^{-1} \left( \frac{dA/dy}{dA/dx} \right)$$



# Discrete 2-d gradient operator

$$A(x, y) = A_{i,j}$$

$$\frac{\partial A}{\partial x} \approx A_{i+1,j} - A_{i,j} = \Delta_i A_{i,j}$$

$$\frac{\partial A}{\partial y} \approx A_{i,j+1} - A_{i,j} = \Delta_j A_{i,j}$$

$$\Delta A_{i,j} = \Delta_i A_{i,j} \mathbf{i} + \Delta_j A_{i,j} \mathbf{j}$$



Neighbour hood  
operators

$$B_i = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

$$B_j = \begin{bmatrix} -1 & 1 \end{bmatrix}$$

# Neighbourhood Operators

$$A(x, y) = A_{i,j}$$

$$\begin{aligned}\frac{\partial^2 A}{\partial x^2} &\approx \Delta_i A_{i+1,j} - \Delta_i A_{i,j} = \Delta_i^2 A_{i,j} \\ &= A_{i+2,j} - A_{i+1,j} - (A_{i+1,j} - A_{i,j}) \\ &= A_{i+2,j} - 2A_{i+1,j} + A_{i,j}\end{aligned}$$



$$\Delta_i^2 \mathbf{A} = \mathbf{A} * \mathbf{B}_i$$

$$\mathbf{B}_i = \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$$

$$\begin{aligned}\frac{\partial^2 A}{\partial y^2} &\approx \Delta_j A_{i,j+1} - \Delta_j A_{i,j} = \Delta_j^2 A_{i,j} \\ &= A_{i,j+2} - A_{i,j+1} - (A_{i,j+1} - A_{i,j}) \\ &= A_{i,j+2} - 2A_{i,j+1} + A_{i,j}\end{aligned}$$

$$\Delta_j^2 \mathbf{A} = \mathbf{A} * \mathbf{B}_j$$

$$\mathbf{B}_j = \begin{bmatrix} 1 & -2 & 1 \end{bmatrix}$$

# Neighbourhood Operators

$$\begin{aligned}\Delta^2 \mathbf{A} &= \Delta_i^2 \mathbf{A} + \Delta_j^2 \mathbf{A} \\ &= \mathbf{A} * \mathbf{B}_i + \mathbf{A} * \mathbf{B}_j \\ &= \mathbf{A} * (\mathbf{B}_i + \mathbf{B}_j) \\ &= \mathbf{A} * \mathbf{B}\end{aligned}$$

$$\mathbf{B} = \mathbf{B}_i + \mathbf{B}_j = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

# Laplacian Image

$$\mathbf{L} = -\Delta^2 \mathbf{A}$$

$$\mathbf{B} = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

