

# Image Gradients

Computational Photography (CSCI 3240U)

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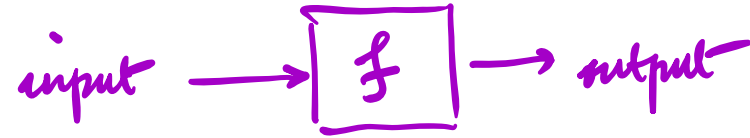
<http://vclab.science.ontariotechu.ca>



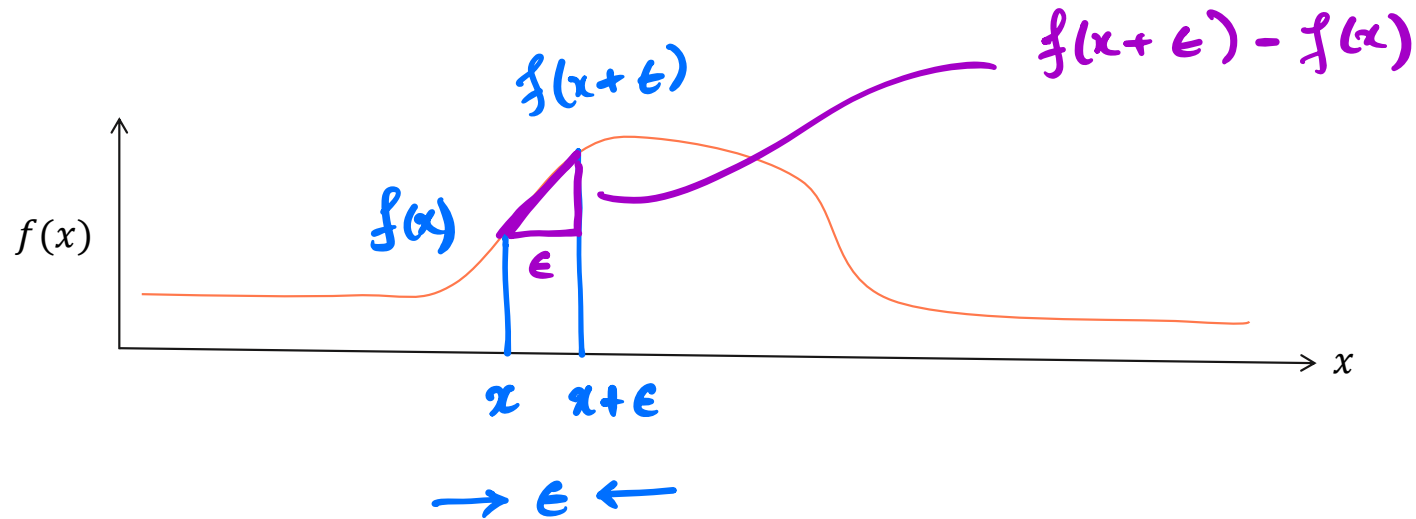
# Today's lecture

- Why do we care about image gradients?
- Computing image gradients
- Sobel filters
- Gradient magnitude and directions
- Visualizing image gradients

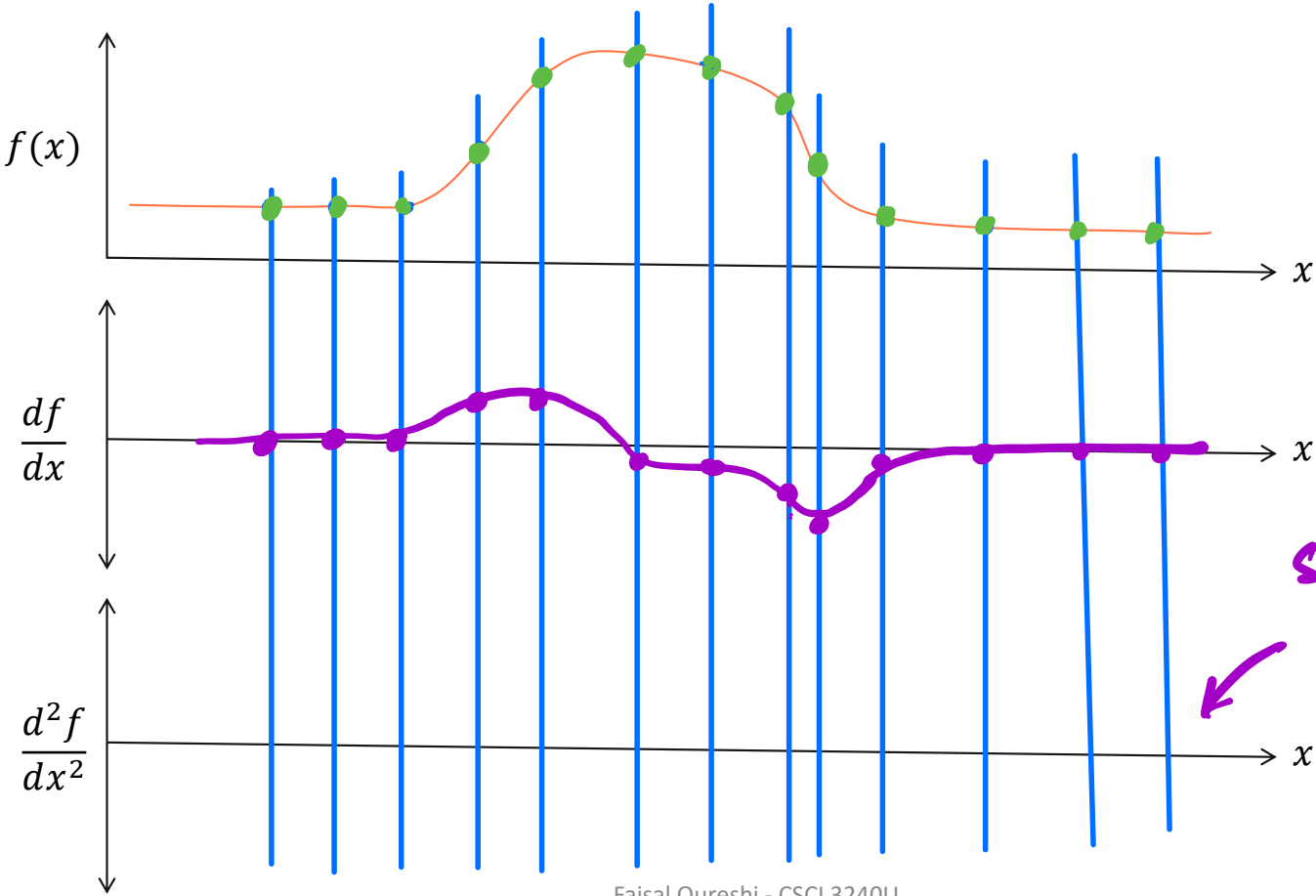
# Derivative



$$\frac{df}{dx} = \lim_{\epsilon \rightarrow 0} \frac{f(x + \epsilon) - f(x)}{\epsilon}$$



# Derivative



SELF - STUDY

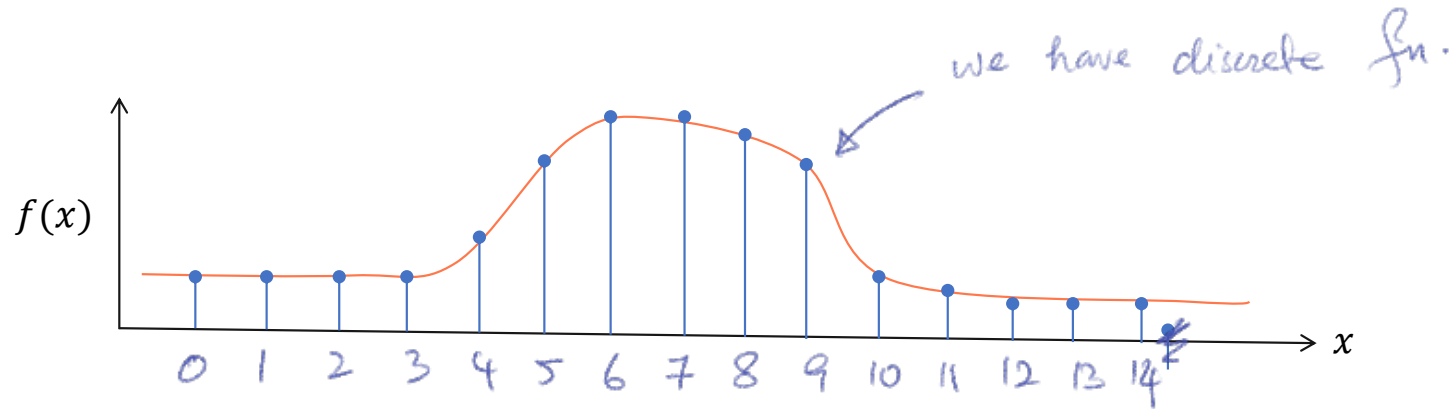


# Derivative

$$\frac{df}{dx} = \lim_{\epsilon \rightarrow 0} \frac{f(x + \epsilon) - f(x)}{\epsilon}$$

$$f(x) = x^2 \sin(x)$$

$$f'(x) = 2x \sin(x) + x^2 \cos(x)$$

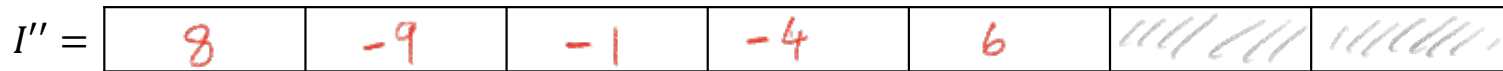
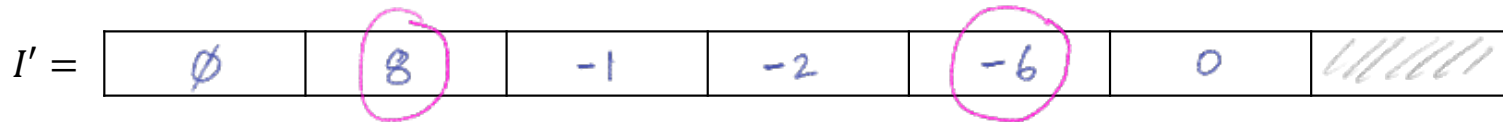
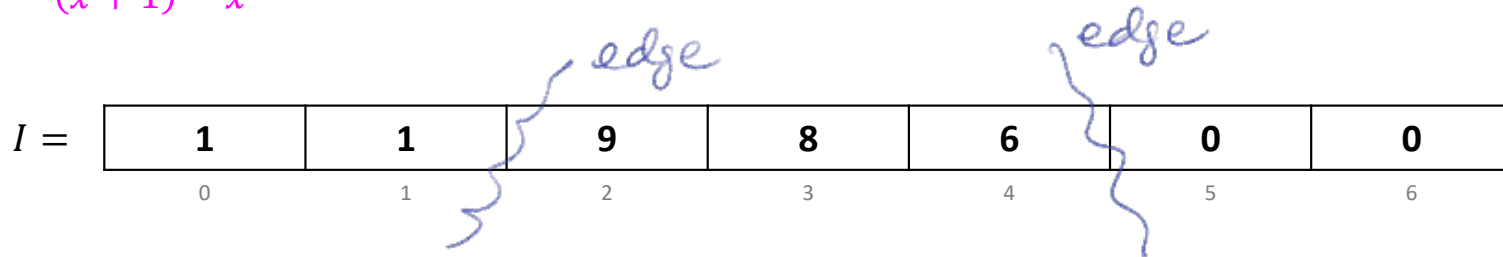


Finite-difference approximation

$$\frac{df}{dx} \approx \frac{\Delta f}{\Delta x} = \frac{f(x+1) - f(x)}{(x+1) - x} = f(x+1) - f(x)$$

# Use finite difference approximation to compute image derivatives

$$\frac{df}{dx} \approx \frac{\Delta f}{\Delta x} = \frac{f(x+1) - f(x)}{(x+1) - x} = f(x+1) - f(x)$$



Observation: (1) derivative magnitude correspond to edges.  
(2) sign tells going up or down

# Use finite difference approximation to compute image derivatives

$$\frac{df}{dx} \approx \frac{\Delta f}{\Delta x} = \frac{f(x+1) - f(x)}{(x+1) - x} = f(x+1) - f(x)$$

*I \* [1,1,1] ~> Image blur*  
*I \* G<sub>σ</sub> ~> Gaussian blur*  
**POWER OF LINEAR FILTERING**

$I =$	<b>1</b>	<b>1</b>	<b>9</b>	<b>8</b>	<b>6</b>	<b>0</b>	<b>0</b>
	0	1	2	3	4	5	6

$I' =$	<b>0</b>	<b>8</b>	<b>-1</b>	<b>-2</b>	<b>-6</b>	<b>0</b>	<b>?</b>
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*signal* → *Filter* →  
 $I * [1, -1] =$   
 ↑  
*convolution*

$I * [1, -1] =$	0	8	-1	-2	-6	0	//////
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# Partial derivatives

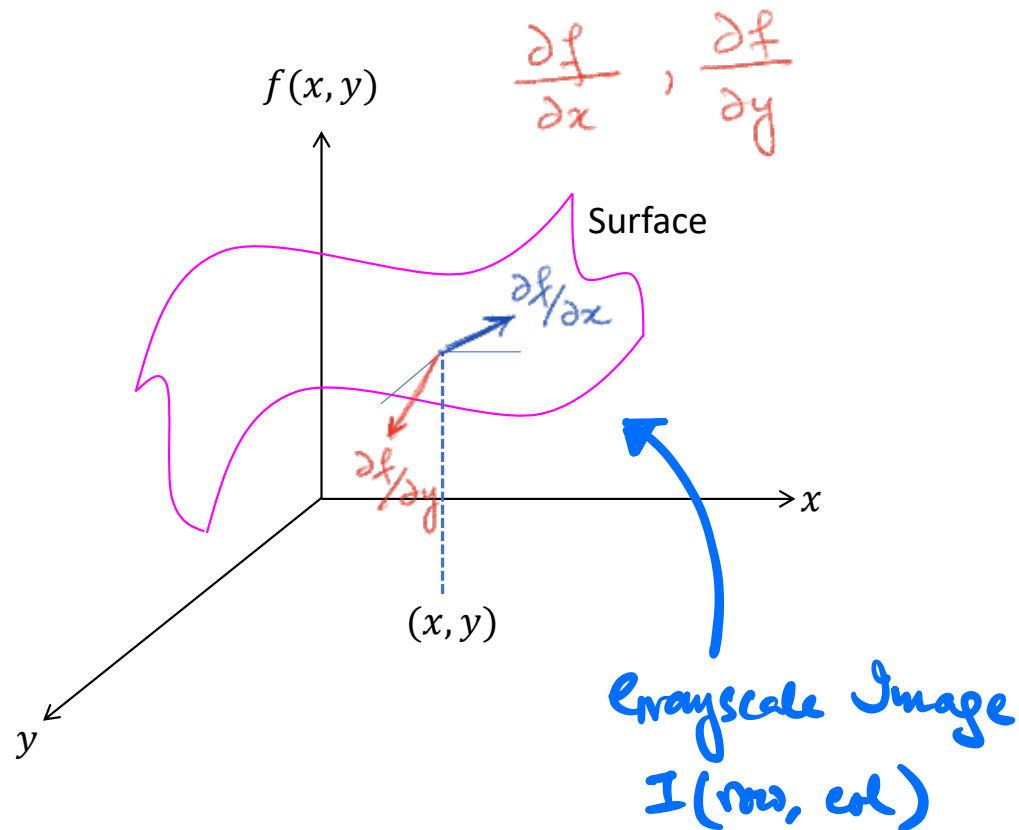
Grayscale:  $I(x, y)$

Color image (RGB):  $I(x, y, c)$

Hyperspectral image:  $I(x, y, \lambda_1, \lambda_2, \dots, \lambda_n)$

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ASIDE:  $f(x, y; \theta)$





# Image derivatives in $x$ and $y$ directions

$I =$

1	1	9	8	1
8	8	8	8	8
1	3	5	8	1
5	3	2	8	6

*This is a 2D fn.*

$$\frac{\partial I}{\partial x}$$



$$I_x = I * [1, -1] =$$

0	8	-1	-7	
0	0	0	0	
2	2	3	-7	
-2	-1	6	-2	

$$\frac{\partial I}{\partial y}$$



$$I_y = I * [1, -1]^T =$$


# Image gradient $\nabla I$

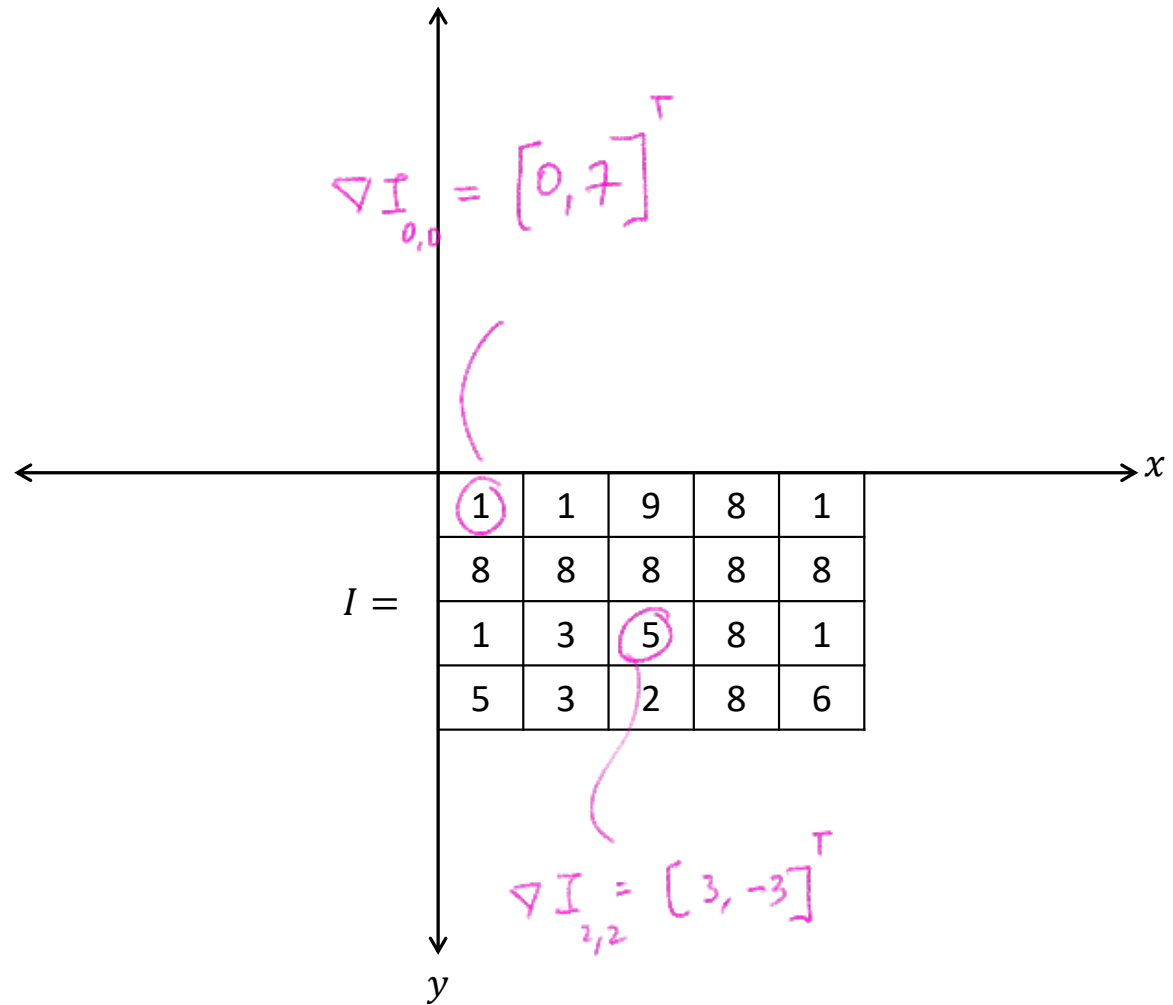
$$\nabla I = \left[ \frac{\partial I(x, y)}{\partial x}, \frac{\partial I(x, y)}{\partial y} \right]$$

$$I_x =$$

0	8	-1	-7	/
0	0	0	0	/
2	2	3	-7	/
-2	-1	6	-2	/

$$I_y =$$

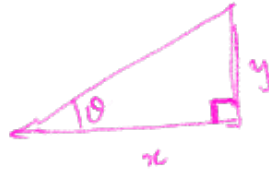
7	7	-1	0	7
-7	-5	-3	0	7
4	0	-3	0	5
/	/	/	/	/



# Gradient direction and magnitude

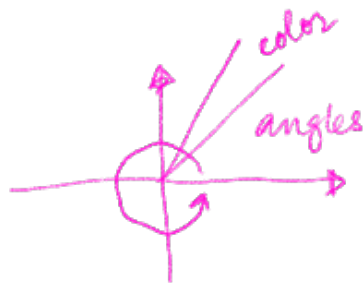
$$\|\nabla I\| = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2}$$

$$\theta = \tan^{-1}\left(\frac{\partial I / \partial y}{\partial I / \partial x}\right)$$



$$\nabla I_{2,2} = \begin{bmatrix} 3 \\ -3 \end{bmatrix}$$

$$\|\nabla I_{2,2}\| = \sqrt{9+9} = \sqrt{18}$$



# Filters for computing image derivatives

**Sobel**



$$H_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

$$H_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

**Prewire**

$$H_x = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}$$

$$H_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

**Roberts**

$$H_x = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

$$H_y = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

# Image noise and gradients

$I$  Goal:  $I'$

$\nabla * I$  poor result

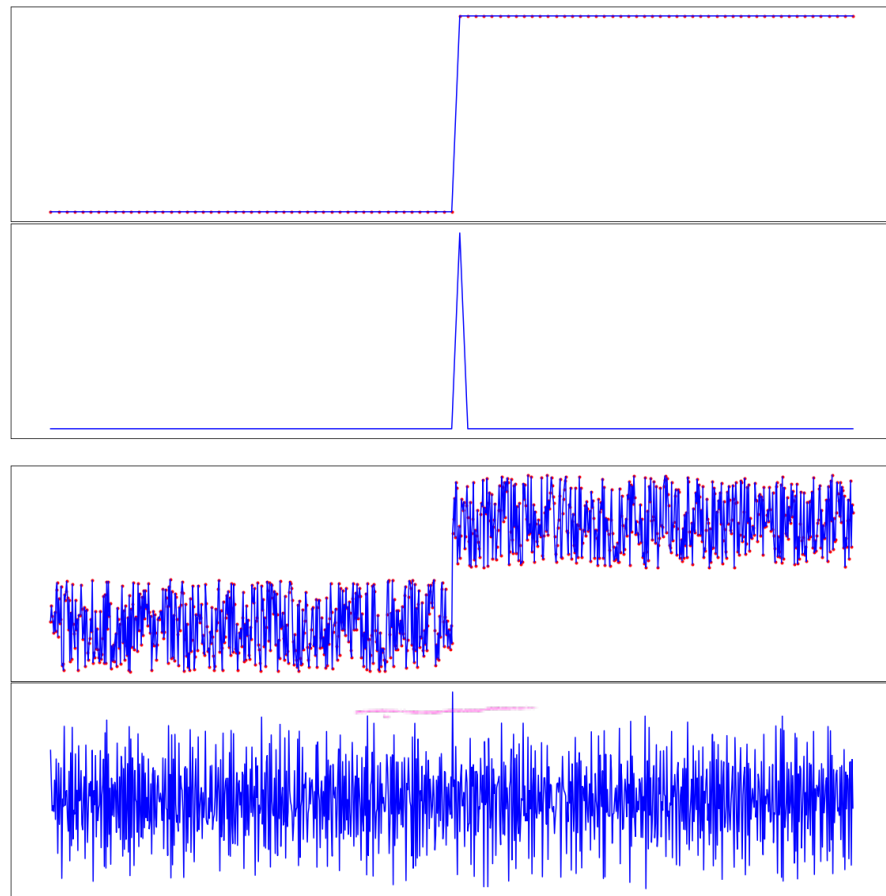
↑  
some filter for computing derivatives

$\nabla * (G_6 * I)$  better results

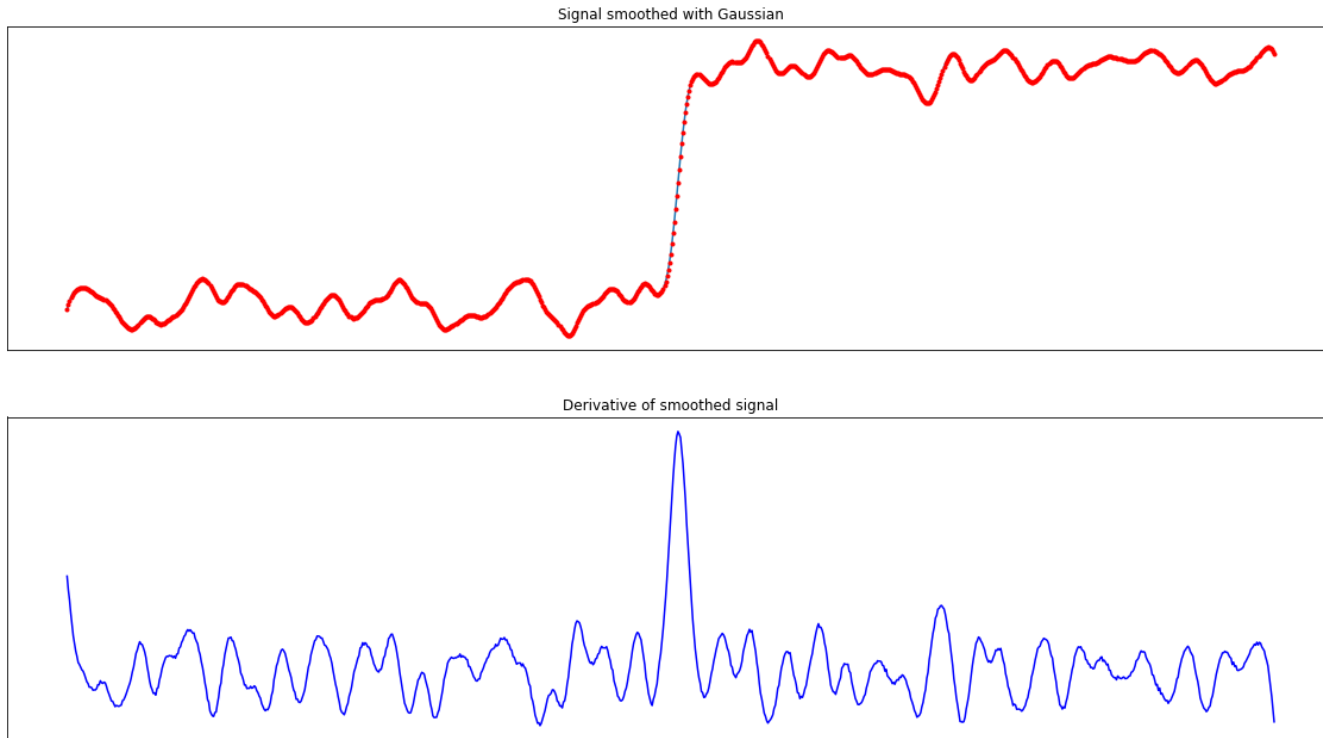
blur it first

re-write

$(\nabla * G_6) * I$



# Image noise and gradients



# Summary

- Image gradients
- Finite-difference approximation filters
- Gradient magnitude and direction
- Image noise and gradients