# EE 046746 - Technion - Computer Vision

## Tutorial 02 - Edge and Line Detection

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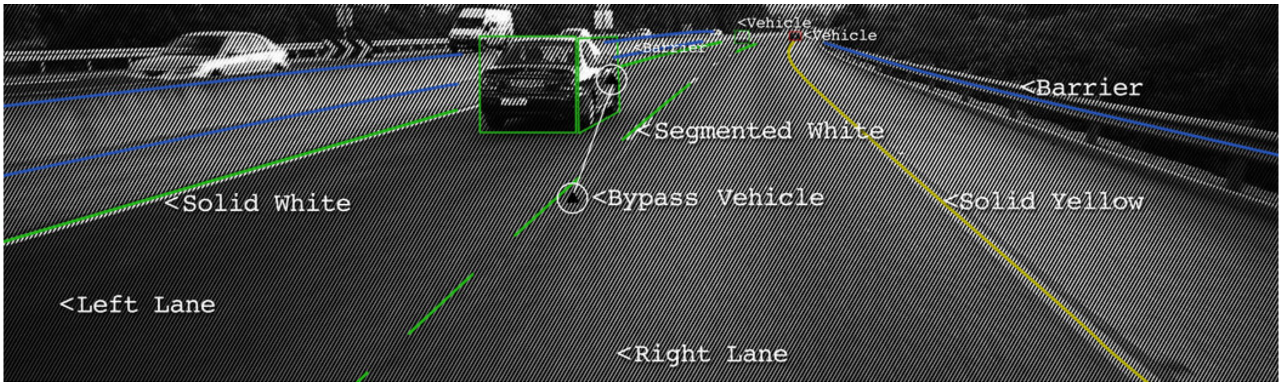


* Image source

## Agenda

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* Why Do We Need Edge Detection?
* Edge Detection
  * Derivatives and Edges
  * What is a Good Edge Detector?
  * Canny Edge Detection
* Line Fitting
  * Hough Transform
  * RANSAC
  * SCNN
* Recommended Videos
* Credits

In [1]:

```python
# imports for the tutorial
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image
import cv2
from scipy import signal
%matplotlib inline
```

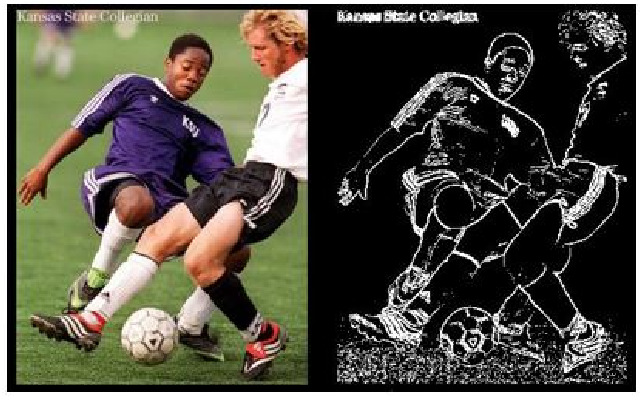
In [2]:

```python
# plot images function
def plot_images(image_list, title_list, subplot_shape=(1,1), axis='off', fontsize=30, figsize=(4,4), cmap
    plt.figure(figsize=figsize)
    for ii, im in enumerate(image_list):
        c_title = title_list[ii]
        if len(cmap) > 1:
            c_cmap = cmap[ii]
        else:
            c_cmap = cmap[0]
        plt.subplot(subplot_shape[0], subplot_shape[1],ii+1)
        plt.imshow(im, cmap=c_cmap)
        plt.title(c_title, fontsize=fontsize)
```

```
        plt.axis(axis)
        if cbar:
            plt.colorbar()
```

## Corners For Features, Edges For What?

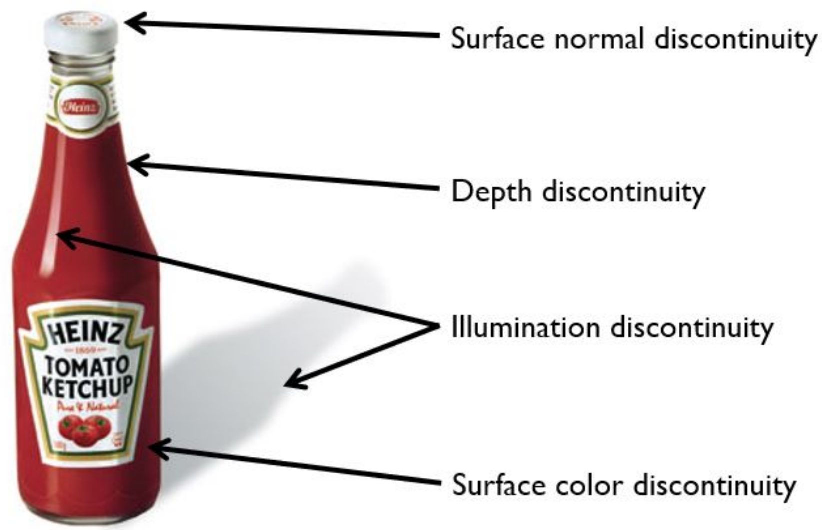
- We know edges are special
- Human visual system is based on edges
- Given an image that contains only edges we can identify objects without any additional information




## Edge Detection Goal

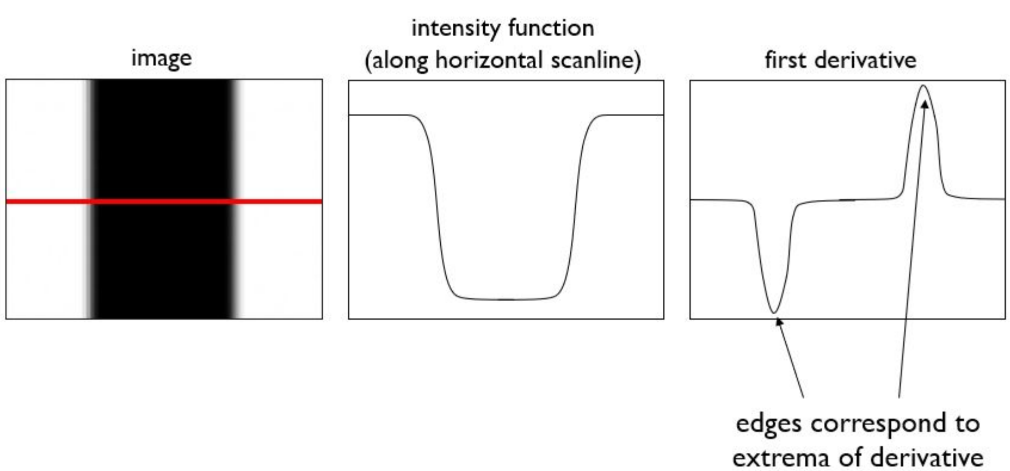
- **Goal**: Map image from 2d array of pixels to a set of curves, line segments, or contours.
    - Most semantic and shape information from the image can be encoded in the edges
    - A more compact representation than a complete image
- **Ideal**: Artist's Line drawing (but artists use prior knowledge)

### What can cause an edge?

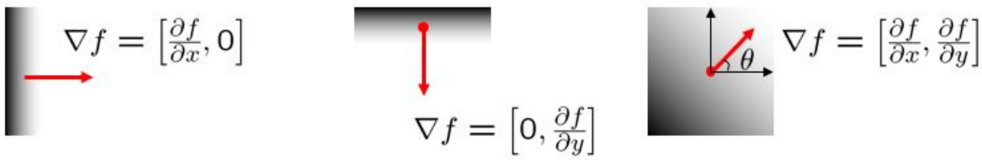

## Derivatives and Edges

- An edge is a place of rapid change in the image intensity function.



### Image Gradient

- The gradient of an image: $\nabla f = [\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}]$
- The gradient points in the direction of most rapid change in intensity




- The gradient direction (orientation of edge normal) is given by: $\theta = tan^{-1}(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x})$
- The edge strength is given by the gradient magnitude $||\nabla f|| = \sqrt{(\frac{\partial f}{\partial y})^2 + (\frac{\partial f}{\partial x})^2}$

### Differentiation and Convolution

- For 2D function, f(x,y), the partial derivative is:

$$\frac{\partial f(x,y)}{\partial x} = lim_{\epsilon \to 0} \frac{f(x+\epsilon, y) - f(x,y)}{\epsilon}$$

- For discrete data, we can approximate using finite differences:

$$\frac{\partial f(x,y)}{\partial x} = \frac{f(x+1,y) - f(x,y)}{\Delta x}$$

- To implement above as convolution, what would be the associated filter?

| | |
|---|---|
| -1 | 1 |

### Assorted Finite Difference Filters

**Prewitt:** $M_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$ ; $M_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$

**Sobel:** $M_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$ ; $M_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$

**Roberts:** $M_x = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ ; $M_y = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$

In [3]:

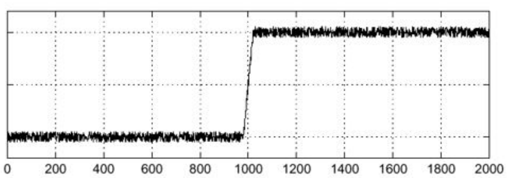
```python
im = cv2.imread('assets/sobel_bulding.jpg')
im = cv2.cvtColor(im, cv2.COLOR_BGR2GRAY)
ksize = 3
im_x = np.abs(cv2.Sobel(im, cv2.CV_64F, 1, 0, ksize=ksize))
im_y = np.abs(cv2.Sobel(im, cv2.CV_64F, 0, 1, ksize=ksize))

plot_images([im,im_x,im_y], ['','',''], subplot_shape=(1,3), figsize=(12,4))
```

- Which show changes with respect to $x$? $y$?

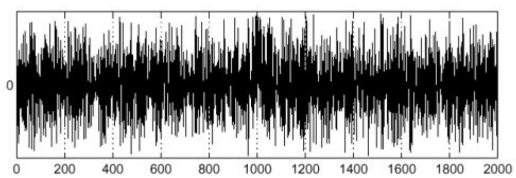
## Effects of Noise

- Consider a single row or column of the image
- Plotting intensity as a function of position gives a signal:

$f(x)$




$\frac{d}{dx}f(x)$



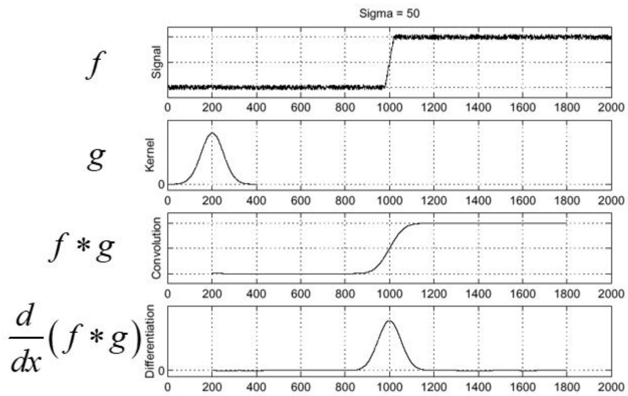

- Where is the edge?

- Finite difference filters respond strongly to noise

  - Image noise results in pixels that look very different from their neighbors
  - Generally, the larger the noise the stronger the response
- What can be done?

- Smoothing the image should help! – it forces pixels to look more like their neighbors

## Solution: Smooth First




- Where is the edge?
  - Look for peaks in $\frac{\partial}{\partial x}(f * g)$

## Derivative Theorem of Convolution

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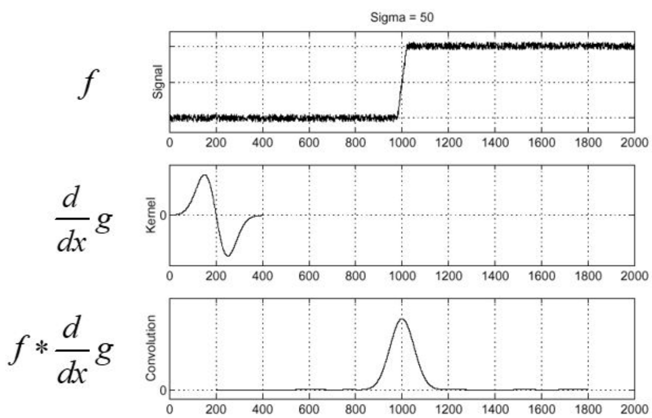
Differentiation property of convolution: $\frac{\partial}{\partial x}(f * g) = f * \frac{\partial}{\partial x} g$




## Derivative of Gaussian Filter

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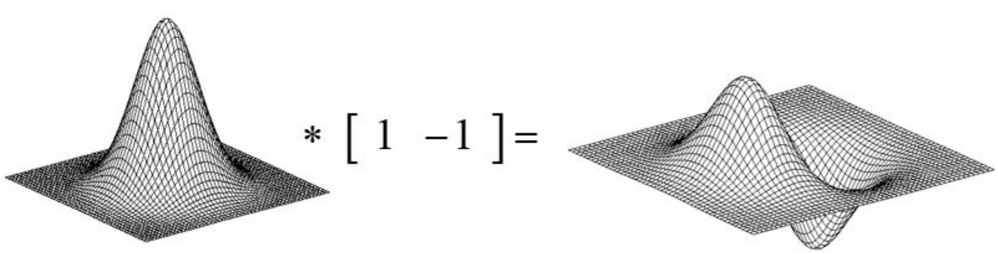
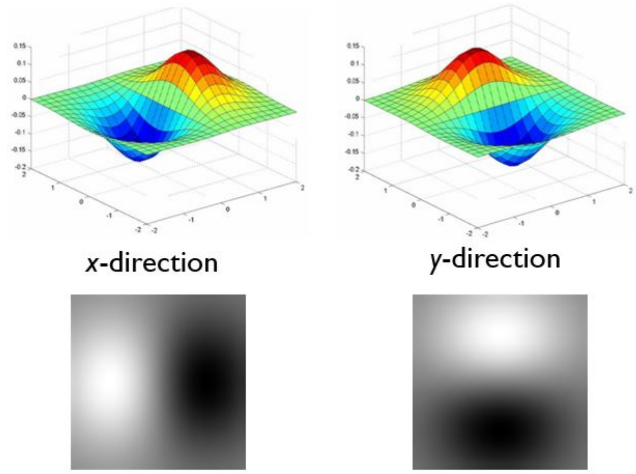
- Is this a separable filter?



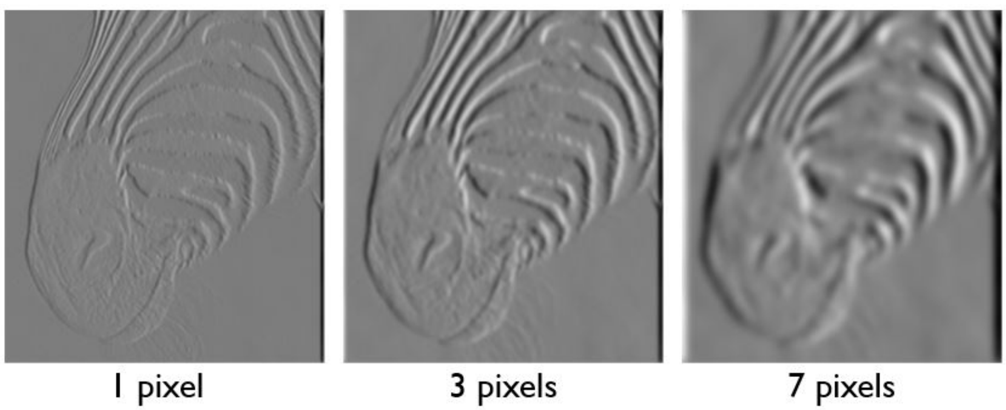

- Yes, we can split it into two filters in which their order does not matter
- Median is a non-separable filter

## Derivative of Gaussian Filter



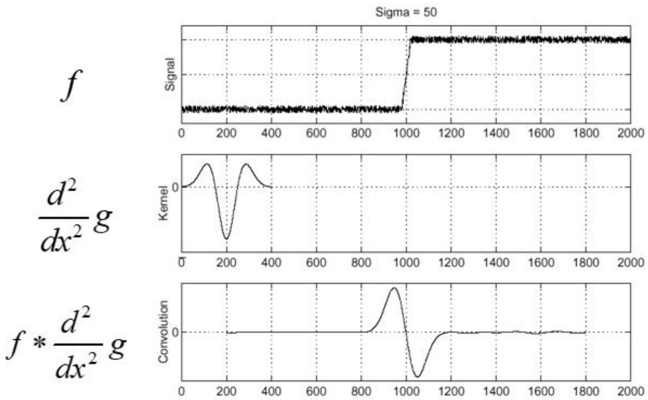

- Which one finds horizontal/vertical edges?

## Smoothing Tradeoffs



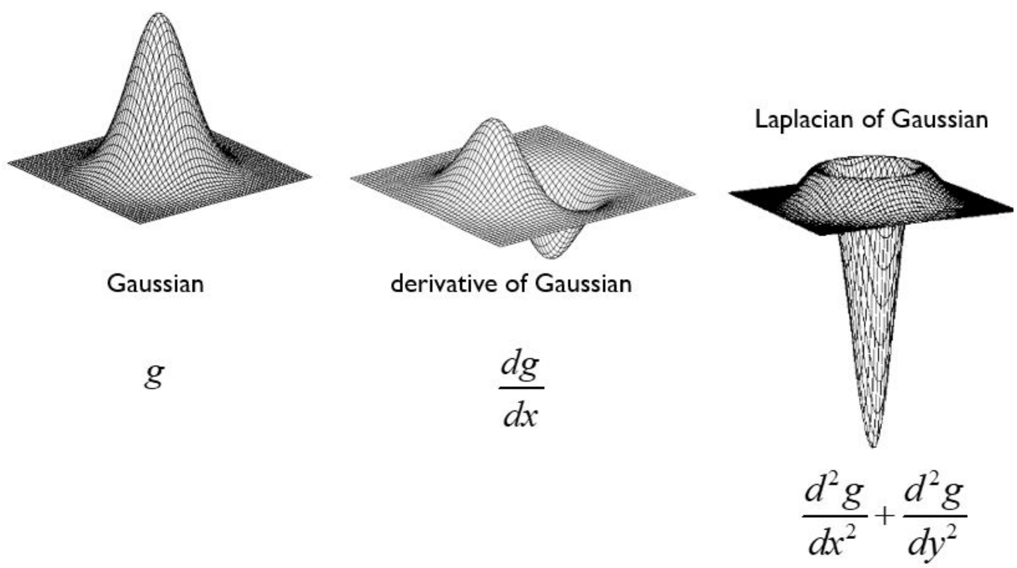

- Smoothed derivative removes noise, but blurs edge.
  - Also finds edges at different “scales”.

## Laplacian of Gaussian (LoG)



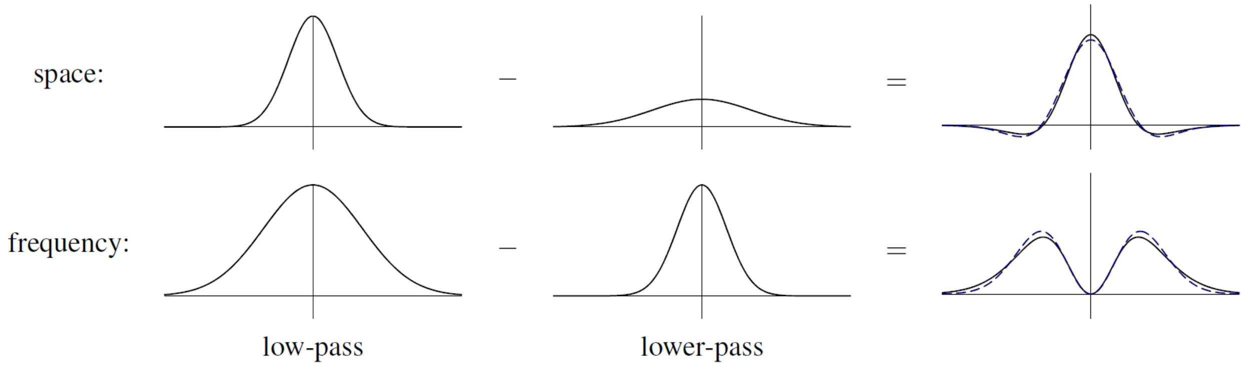

- Where is the edge?
  - Zero-crossings of bottom graph

## 2D Edge Detection Filters

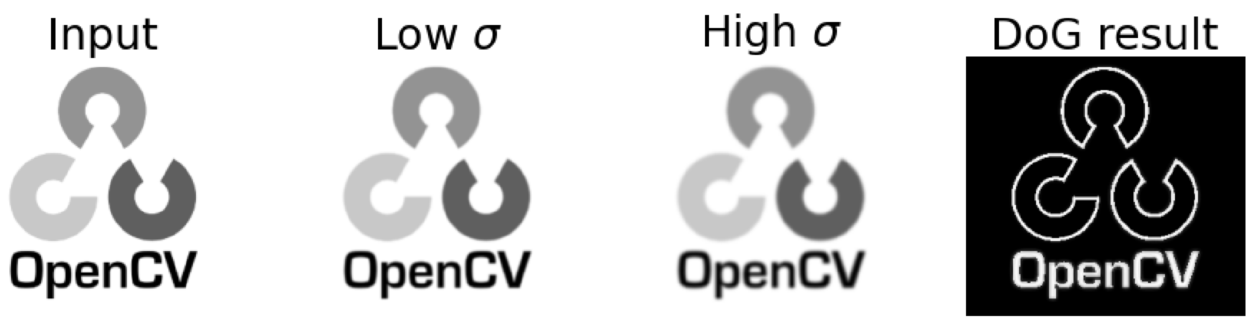



## DoG: Difference of Gaussians

- DoG can approximate LoG fairly good in space/frequency
  - Dashed blue is LoG, and black is DoG.

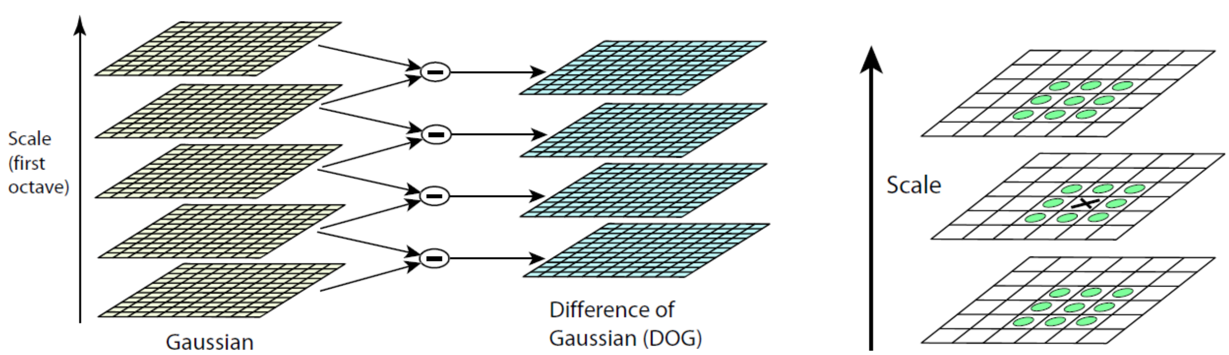



In [4]:
```
# DoG example on opencv logo
img = cv2.imread('assets/opencv_logo_gray.png')

# Apply 3x3 and 7x7 Gaussian blur
low_sigma = cv2.GaussianBlur(img,(3,3),0)
high_sigma = cv2.GaussianBlur(img,(7,7),0)

# Calculate the DoG by subtracting
dog = low_sigma - high_sigma

# show the result
plot_images([img,low_sigma,high_sigma,dog], ['Input','Low $\sigma$','High $\sigma$','DoG result'],
            subplot_shape=(1,4), figsize=(16,4))
```




### Gaussian Pyramids and DoG

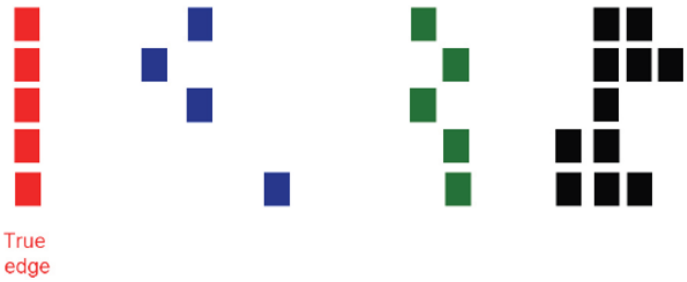
- DoG is usually used with Gaussian pyramids for scale-invariant feature detection




(a) (b)

### What is a Good Edge Detector?

- Good detection:
  - Minimize false positives (wrong detections)
  - Minimize false negatives (missing real edges)
  - Maximize true detections
- Good localization:
  - Detected edges should be as close as possible to the true edges
- Single response:
  - Return a single detection for each true edge point
- Connect detections to lines



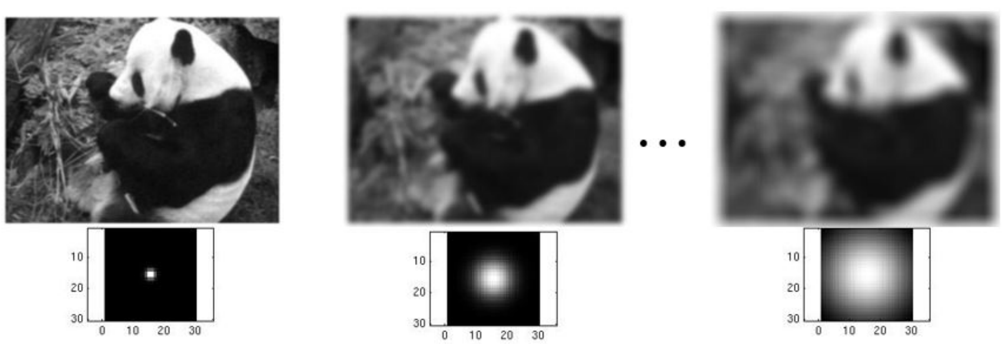

- Which of these detections is the best?

## What Are the Parameters?

- Scale
- Threshold

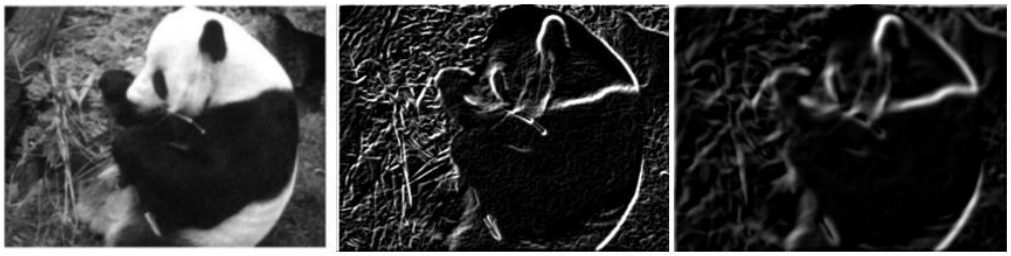
## Scale Selection

- Recall: We first smooth the image with a Gaussian kernel to reduce noise.
- The scale of the Gaussian determines how much smoothing we apply



## Effect of $\sigma$ On Derivatives

- The apparent structures differ depending on Gaussian's scale parameter.
- Large scale: larger scale edges detected
- Small scale: finer features detected



σ = 1 pixel σ = 3 pixels

### How Do We Choose the Scale?

- It depends what we're looking for:

- Too fine of a scale...
  - Can't see the forest for the trees.
- Too coarse of a scale...
  - Can't tell the maple grain from the cherry.

### What Are the Parameters?

- Scale
- Threshold

### Thresholding

- Choose a threshold value
- Set any pixels less than thresh to zero (off)
- Set any pixels greater than or equal to thresh to one (on)

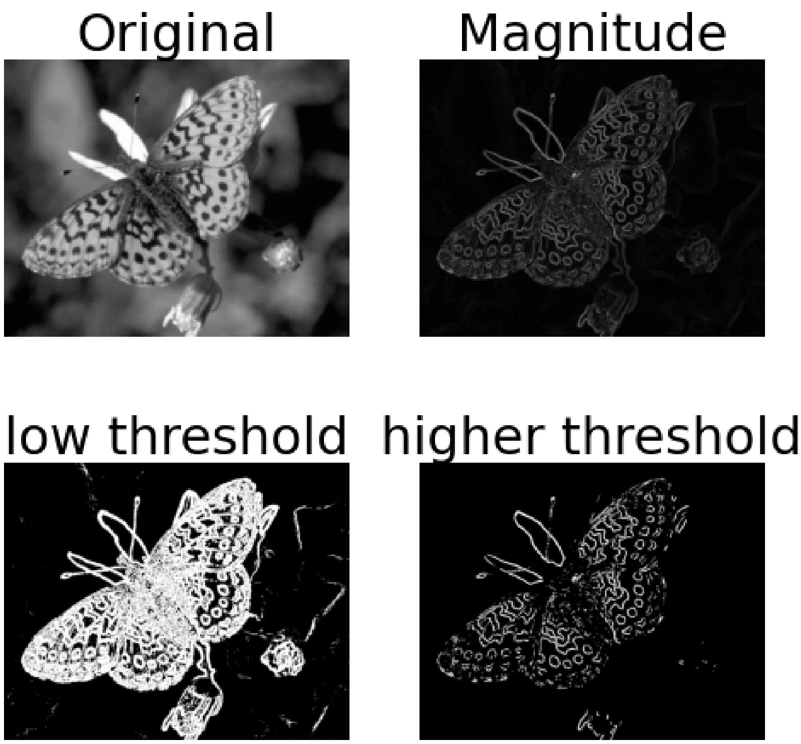
In [5]:

```
im_o = cv2.imread('./assets/buttefly.png')
im = cv2.cvtColor(im_o, cv2.COLOR_BGR2GRAY)
ksize = 5

# blur image
im = cv2.GaussianBlur(im, (ksize, ksize), 0)

# edge extraction:
k_x = np.array([[0, 0, 0], [-1, 0, 1], [0, 0, 0]])
k_y = np.array([[0, -1, 0], [0, 0, 0], [0, 1, 0]])
im_x = cv2.filter2D(im, cv2.CV_64F, k_x)
im_y = cv2.filter2D(im, cv2.CV_64F, k_y)
```

```python
# gradient magnitude:
im_grad_mag = np.sqrt(np.square(im_x) + np.square(im_y))

low_thresh = im_grad_mag > 7 # low threshold
high_thresh = im_grad_mag > 30 # High threshold

# plot_images([im, im_x, im_y], ['Original', 'Deriv. X', 'Deriv. Y'], subplot_shape=(1,3), figsize=(18,6),
```

In [6]:

```python
# figures:
plot_images([im, im_grad_mag, low_thresh, high_thresh], ['Original', 'Magnitude', 'low threshold', 'highe
            subplot_shape=(2,2), figsize=(8,8))
```




## The Canny Edge Detector

- Probably the most widely used edge detector in Computer Vision
- Key idea: Detect step-edges that are corrupted by additive Gaussian noise
- Theorem: Canny has shown that the first derivative of the Gaussian closely approximates the operator that optimizes the product of signal-to-noise ratio and localization
- J. Canny, A Computational Approach To Edge Detection, IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679---714, 1986.
    - 38458 citations until today!

## The Canny Edge Detector - Building Blocks

- Filter image with derivative of Gaussian
- Find magnitude and orientation of gradient
- Non-maximum suppression: (Localization)
    - Thin multi-pixel wide “ridges” down to single pixel width

- Linking and thresholding (hysteresis): (Linking)
    - Define two thresholds: low and high
    - Use the high threshold to start edge curves and the low threshold to continue them
- In OpenCV: `cv2.Canny()`

## Canny Example - Input

In [7]:

```
# Load Image
img = cv2.imread('./assets/tut_panda.jpg')

# convert to RGB for matplotlib
img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

# convert to gray and crop for canny
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
in_x_min = 100
in_x_max = 400
in_y_min = 300
in_y_max = 700
gray_cut = gray[in_y_min:in_y_max, in_x_min:in_x_max]
```

In [8]:

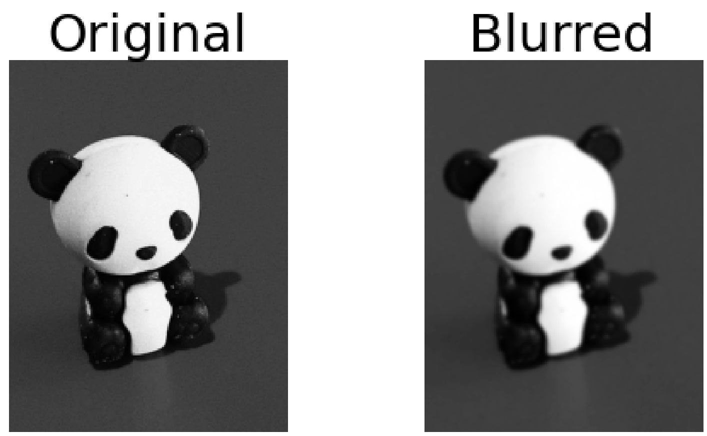
```
plot_images([img_rgb, gray, gray_cut], ['Original', 'Gray', 'Gray Cut'], cmap=[None, 'gray', 'gray'],
            subplot_shape=(1, 3), figsize=(12, 4))
```


- Photo by Pedro Gonzalez from Unsplash

## Canny Example - Step 1 - Blur

In [9]:

```
# Gaussian Blurring
blur = cv2.GaussianBlur(gray_cut, (9,9), 0)
plot_images([gray_cut, blur], ['Original','Blurred'], cmap=['gray', 'gray'], subplot_shape=(1,2), figsize
```



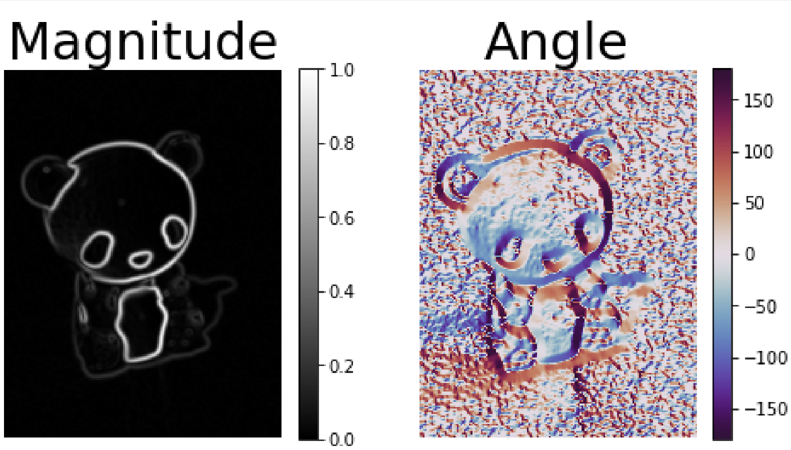

## Canny Example - Step 2 - Find Magnitude and Orientation of Gradient

In [10]:

```
# Apply Sobel:
sobelx_64 = cv2.Sobel(blur, cv2.CV_64F, 1, 0, ksize=3)
sobely_64 = cv2.Sobel(blur, cv2.CV_64F, 0, 1, ksize=3)

# From gradients calculate the magnitude and changing
mag = np.hypot(sobelx_64, sobely_64)
mag = mag / mag.max()

# Find the direction and change it to degree
theta = np.arctan2(sobely_64, sobelx_64)
angle = np.rad2deg(theta)
```

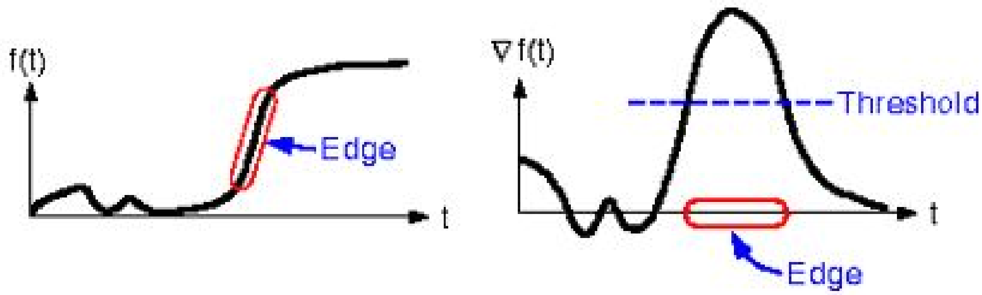
In [11]:

```
plot_images([mag, angle], ['Magnitude', 'Angle'], subplot_shape=(1,2), figsize=(8,4), cmap=['gray', 'twil
            cbar=True)
```

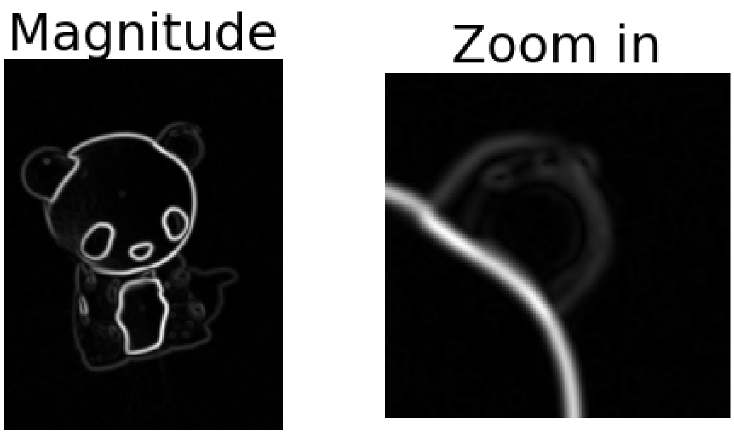



## Canny Example - Step 3 - Localization

- How to turn these thick regions of the gradient into curves?

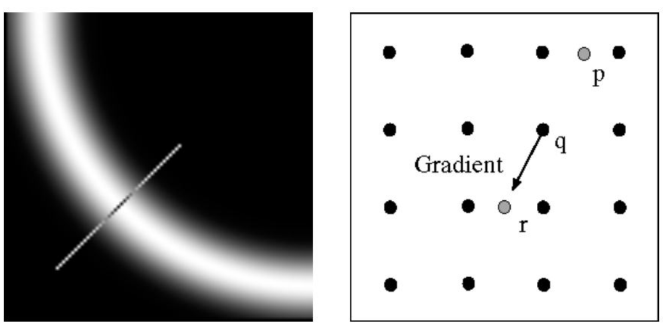



In [12]:
```
# Zoom in at the problem (ridge instead of edge)
in_x_min, in_x_max, in_y_min, in_y_max = (150, 250, 50, 150)
mag_cut = mag[in_y_min:in_y_max, in_x_min:in_x_max]
# ang_cut = mag[in_y_min:in_y_max, in_x_min:in_x_max]
plot_images([mag, mag_cut], ['Magnitude','Zoom in'], subplot_shape=(1,2), figsize=(8,4))
```



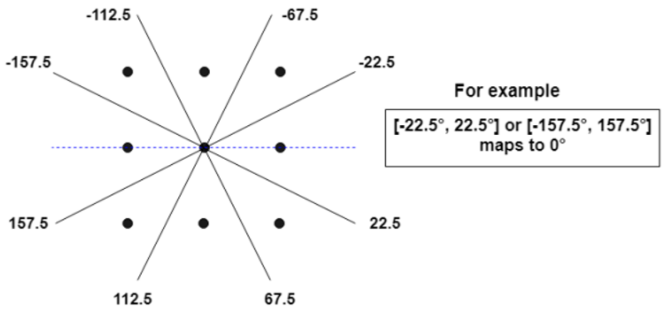

### Non-Maximum Suppression (NMS)

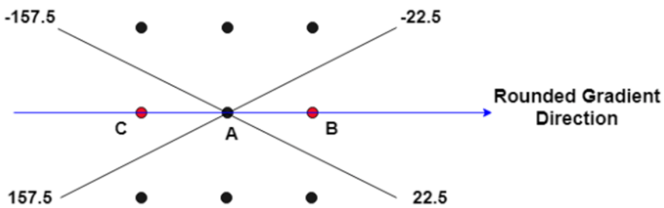
- Check if pixel is local maximum along gradient direction, select single max across width of the edge
- Requires checking interpolated pixels $p$ and $r$




### Non-Maximum Suppression (NMS)

- Simpler solution using rounded gradient direction



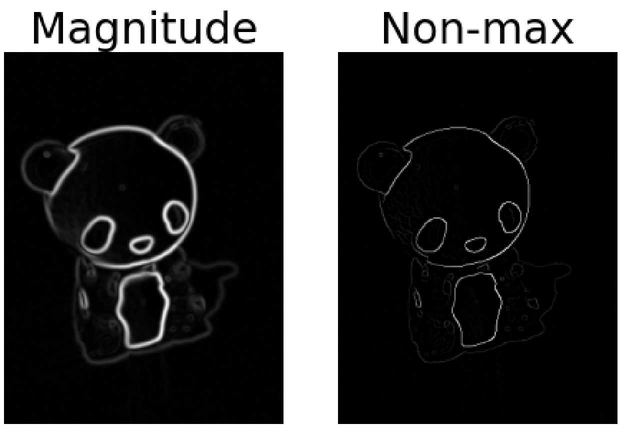



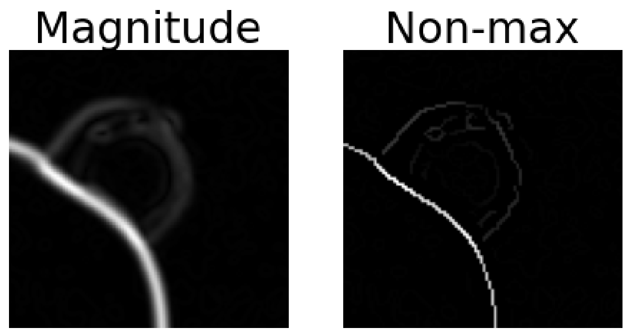

In [13]:

```
# Find the neighbouring pixels (b,c) in the rounded gradient direction
# and then apply non-max suppression
M, N = mag.shape
Non_max = np.zeros((M,N), dtype= np.float64)

for i in range(1,M-1):
    for j in range(1,N-1):
       # Horizontal 0
        if (0 <= angle[i,j] < 22.5) or (157.5 <= angle[i,j] <= 180) or (-22.5 <= angle[i,j] < 0)\
        or (-180 <= angle[i,j] < -157.5):
            b = mag[i, j+1]
            c = mag[i, j-1]
        # Diagonal 45
        elif (22.5 <= angle[i,j] < 67.5) or (-157.5 <= angle[i,j] < -112.5):
            b = mag[i+1, j+1]
            c = mag[i-1, j-1]
        # Vertical 90
        elif (67.5 <= angle[i,j] < 112.5) or (-112.5 <= angle[i,j] < -67.5):
            b = mag[i+1, j]
            c = mag[i-1, j]
        # Diagonal 135
        elif (112.5 <= angle[i,j] < 157.5) or (-67.5 <= angle[i,j] < -22.5):
            b = mag[i+1, j-1]
            c = mag[i-1, j+1]

        # Non-max Suppression
        if (mag[i,j] >= b) and (mag[i,j] >= c):
            Non_max[i,j] = mag[i,j]
        else:
            Non_max[i,j] = 0
```

In [14]:

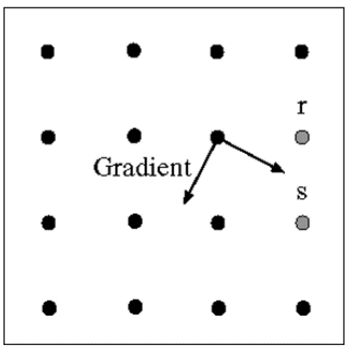
```
mag_cut = mag[in_y_min:in_y_max, in_x_min:in_x_max]
Non_max_cut = Non_max[in_y_min:in_y_max, in_x_min:in_x_max]
plot_images([mag, Non_max, mag_cut, Non_max_cut], ['Magnitude', 'Non-max', 'Magnitude', 'Non-max'],
            subplot_shape=(1,4), figsize=(16,8))
```



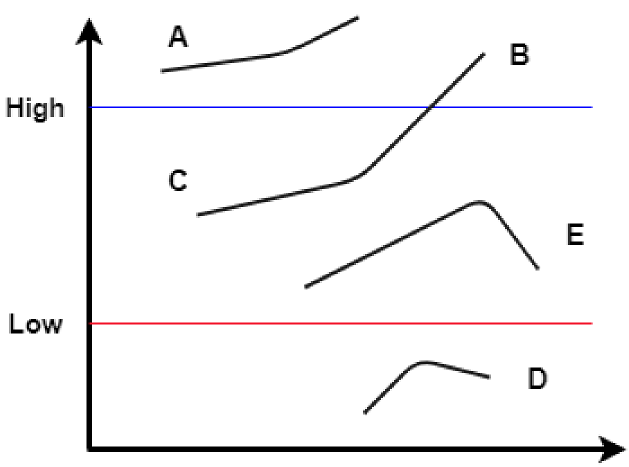

### Canny Example - Step 4 - Edge Linking

- Assume the marked point is an edge point.
- Then we construct the tangent to the edge curve (which is normal to the gradient at that point) and use this to predict the next points (here either $r$ or $s$).




### Hysteresis Thresholding

- Check that maximum value of gradient value is sufficiently large
  - Drop-outs? Use hysteresis
    - Use a high threshold to start edge curves and a low threshold to continue them.

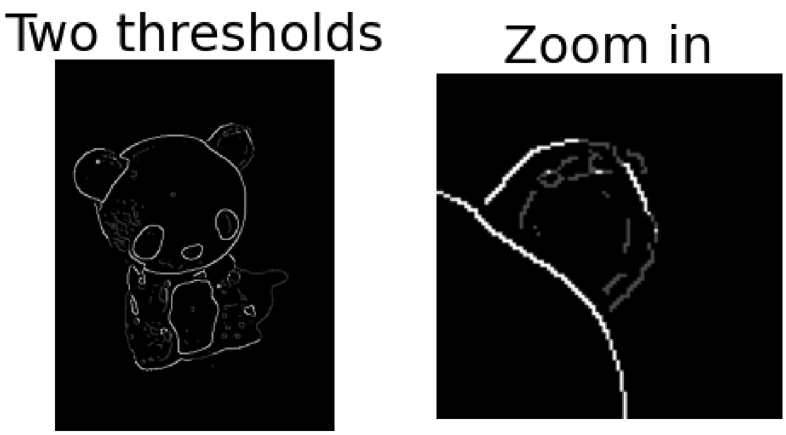



In [15]:

```
# Hysteresis - step 1 - two tresholds
# Set high and low threshold
highThreshold = 40 / 255
lowThreshold = 10 / 255

M, N = Non_max.shape
out = np.zeros((M,N), dtype= np.float64)

# If edge intensity is greater than 'High' it is a sure-edge
# below 'low' threshold, it is a sure non-edge
strong_i, strong_j = np.where(Non_max >= highThreshold)
zeros_i, zeros_j = np.where(Non_max < lowThreshold)

# weak edges
weak_i, weak_j = np.where((Non_max <= highThreshold) & (Non_max >= lowThreshold))

# Set same intensity value for all edge pixels
out[strong_i, strong_j] = 255
out[zeros_i, zeros_j ] = 0
out[weak_i, weak_j] = 75
```

In [16]:

```
plot_images([out, out[in_y_min:in_y_max, in_x_min:in_x_max]], ['Two thresholds', 'Zoom in'],
            subplot_shape=(1,2), figsize=(8,4))
```




### Linking edges - simplified implementation

In [17]:

```
# Hysteresis - step 2
out1 = np.copy(out)
new_points = []
M, N = out1.shape
for i in range(1, M-1):
    for j in range(1, N-1):
        if (out1[i,j] == 75):
            # 8 neighbors search:
            if 255 in [out1[i+1, j-1], out1[i+1, j], out1[i+1, j+1], out1[i, j-1], out1[i, j+1],
                       out1[i-1, j-1], out1[i-1, j], out1[i-1, j+1]]:
                out1[i, j] = 255
                new_points.append(np.array([i,j]))
            else:
                out1[i, j] = 0
new_points = np.stack(new_points,-1)
```

In [18]:

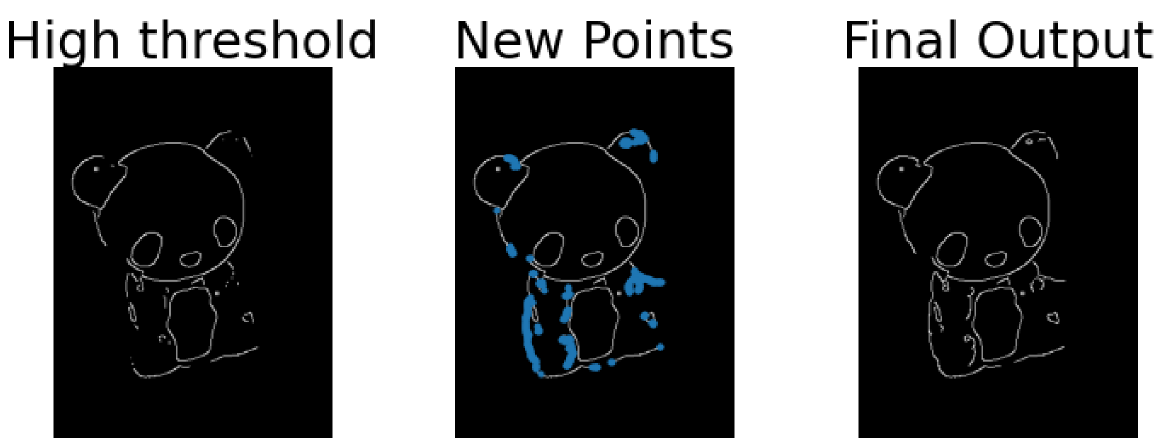
```
# Hysteresis output
plot_images([Non_max, out, out > 75], ['Non-max', 'Two thresholds', 'High threshold'], subplot_shape=(1,3
```


In [19]:

```
plt.figure(figsize=(12,4))
plt.subplot(1,3,1)
plt.imshow(out > 75,cmap='gray')
plt.title('High threshold',fontsize=30)
plt.axis('off')
plt.subplot(1,3,2)
plt.imshow(out1,cmap='gray')
plt.title('New Points',fontsize=30)
plt.plot(new_points[1],new_points[0],'.')
plt.axis('off')
plt.subplot(1,3,3)
plt.imshow(out1,cmap='gray')
plt.title('Final Output',fontsize=30)
plt.axis('off')
```

Out[19]:

```
(-0.5, 299.5, 399.5, -0.5)
```




### Linking edges - Improved implementation

In [20]:

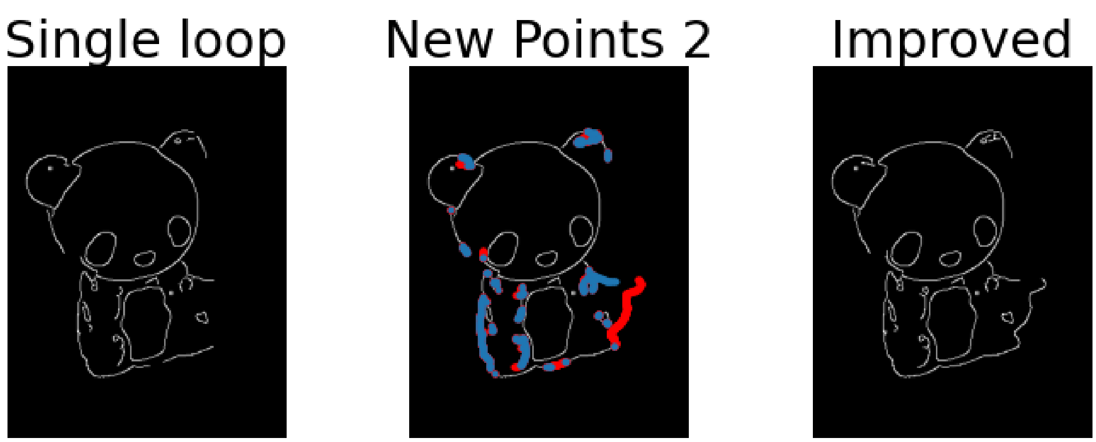
```
new_points2 = []

b2t = np.copy(out)
for i in range(M - 1, 0, -1):
    for j in range(N - 1, 0, -1):
        if (b2t[i, j] == 75):
            if 255 in [b2t[i+1, j-1], b2t[i+1, j], b2t[i+1, j+1], b2t[i, j-1], b2t[i, j+1],
                       b2t[i-1, j-1], b2t[i-1, j], b2t[i-1, j+1]]:
                b2t[i, j] = 255
                new_points2.append(np.array([i,j]))
            else:
                b2t[i, j] = 0

r2l = np.copy(out)
for i in range(1,M):
    for j in range(N-1,0,-1):
```

```python
        if (r2l[i, j] == 75):
            if 255 in [r2l[i+1, j-1], r2l[i+1, j], r2l[i+1, j+1], r2l[i, j-1], r2l[i, j+1],
                       r2l[i-1, j-1], r2l[i-1, j], r2l[i-1, j+1]]:
                r2l[i, j] = 255
                new_points2.append(np.array([i,j]))
            else:
                r2l[i, j] = 0

l2r = np.copy(out)
for i in range(M - 1, 0, -1):
    for j in range(1, N):
        if (l2r[i, j] == 75):
            if 255 in [l2r[i+1, j-1], l2r[i+1, j], l2r[i+1, j+1], l2r[i, j-1], l2r[i, j+1],
                       l2r[i-1, j-1], l2r[i-1, j], l2r[i-1, j+1]]:
                l2r[i, j] = 255
                new_points2.append(np.array([i,j]))
            else:
                l2r[i, j] = 0

new_points2 = np.stack(new_points2,-1)
```

In [21]:

```python
# final output is the sum
out2 = out1 + b2t + r2l + l2r
out2[out2 > 255] = 255

# plot result
plt.figure(figsize=(12,4))
plt.subplot(1,3,1)
plt.imshow(out1,cmap='gray')
plt.title('Single loop',fontsize=30)
plt.axis('off')
plt.subplot(1,3,2)
plt.imshow(l2r + r2l + b2t + out1 >= 255,cmap='gray')
plt.title('New Points 2',fontsize=30)
plt.plot(new_points2[1],new_points2[0],'.r')
plt.plot(new_points[1],new_points[0],'.')
plt.axis('off')
plt.subplot(1,3,3)
plt.imshow(out2,cmap='gray')
plt.title('Improved',fontsize=30)
plt.axis('off')
```

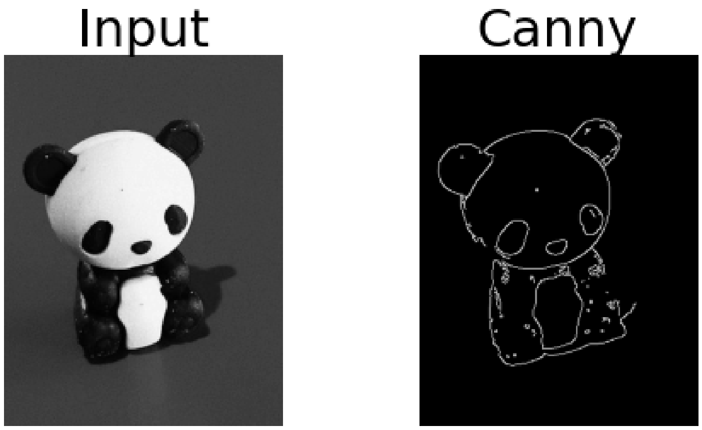
Out[21]: (-0.5, 299.5, 399.5, -0.5)




### Canny in one line (OpenCV)

In [22]:

```python
# Canny
im_canny = cv2.Canny(gray_cut, 70, 250)  # 70, 250
plot_images([gray_cut, im_canny], ['Input', 'Canny'], subplot_shape=(1,2), figsize=(8,4))
```




## Line Fitting

- Hough Transform
- RANSAC
- SCNN

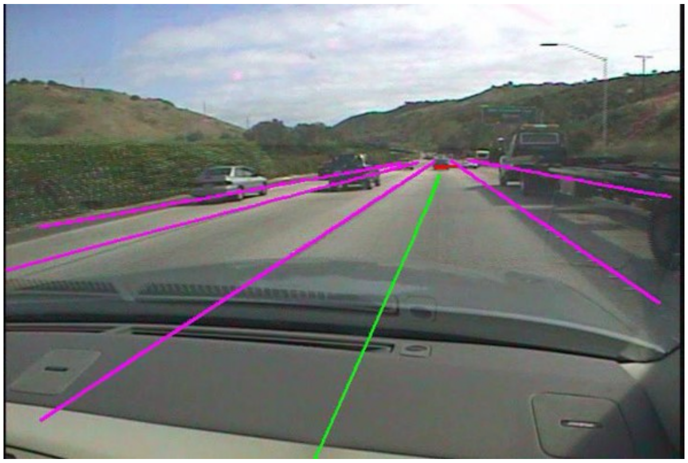
### Fitting a Parametric Model to Data

- Design questions:
  - What is a good model to represent our data?
  - Do we plan to fit multiple instances?
- Challenges:
  - Which features belong to the model? To which instance?
  - How many instances are there?
  - Computational complexity (typically we cannot examine all possible models).

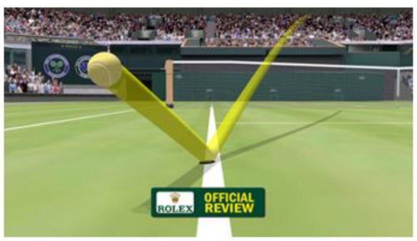
### Line Fitting Applications

- Detection of power lines in helicopter navigation systems

- Image credit: Horev et al. SIAM’15
- Lane detection from car cameras in crash preventing systems



- Sports

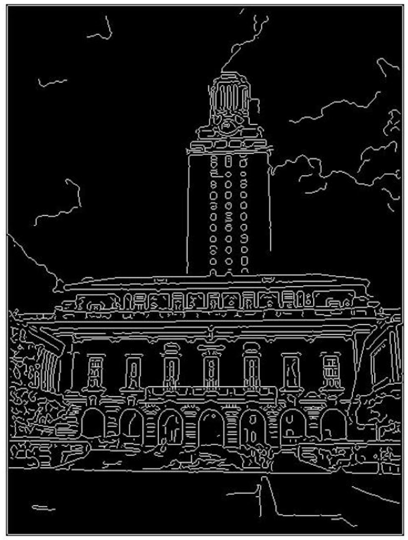




- “Interactive 3D Architectural Modeling from Unordered Photo Collections” Sinha et al. 2008*

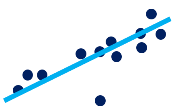
## Challenges of Line Fitting

- Not all the lines in the image are continuous

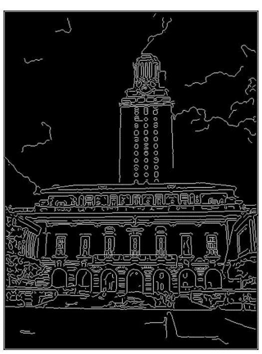


## Challenges of Line Fitting

- Which points on which line?
- Noisy edge detection:
  - Clutter
  - Missed parts
  - Points are only approximately along the line

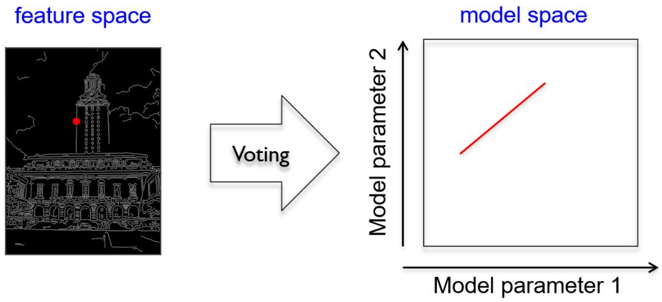


- Large search space
- How many lines are there?



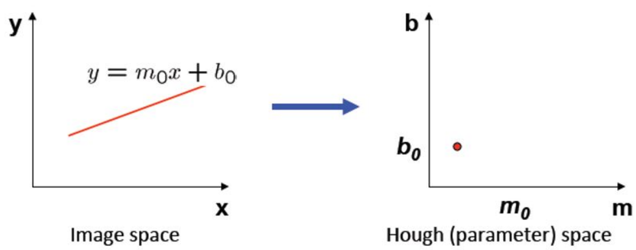
## Voting

- Problem:
  - We cannot try all possible models
- Solution by voting:
  - Features (points) vote for models they are compatible with
  - Search for models with lots of votes

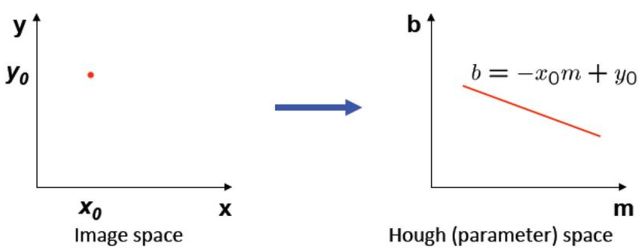



## The Hough Transform

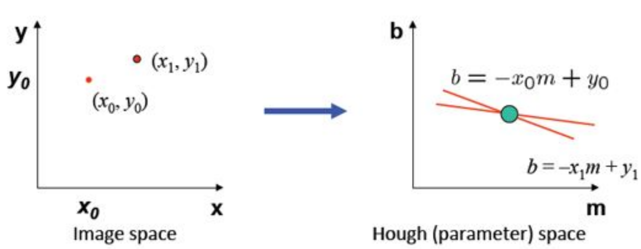
- Transformation from image space $(x, y)$ to Hough space $(m, b)$
- A line in the image corresponds to a point in Hough space
  - Image $\rightarrow$ Hough: Given a set of points $(x, y)$ find all $(m, b)$ such that $y = mx + b$




- Hough $\rightarrow$ Image: A point $(x_0, y_0)$ in the image is the solution of $b = -x_0 m + y_0$



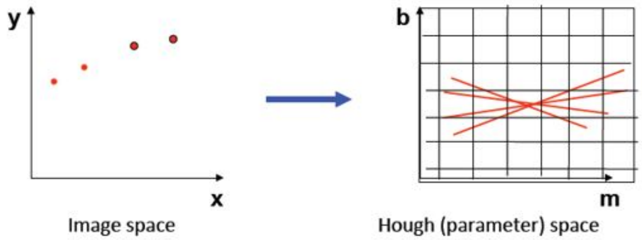

- The line that contains both points $(x_0, y_0)$ and $(x_1, y_1)$ is the intersection of the lines $b = -x_0 m + y_0$ and $b = -x_1 m + y_1$




## Finding Lines with the Hough Transform

- Each edge point votes for a set of possible parameters in Hough space

- Count votes in a discrete set of bins
- Parameters with lots of votes indicate lines in image space

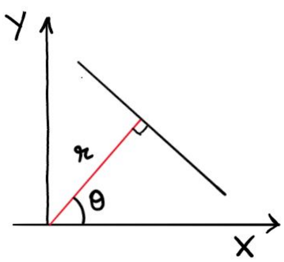



## Polar Representation for Lines

- Problem: The familiar line equation $y = mx + b$ is problematic:
  - Can take infinite values $(m, b)$
  - Undefined for vertical lines
- Solution: Use polar representaton

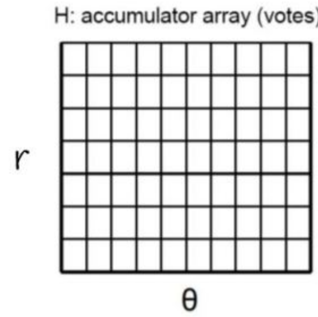
$$r = x\cos\theta + y\sin\theta$$

$$r \in R, \theta \in [0, \pi)$$




## The Hough-Transform Algorithm

- Use polar representaton $x\cos\theta + y\sin\theta = r, \;\; r \in R, \theta \in [0, \pi)$
- Quantize Hough space
- Initialize the accumulator (H) to all zeros
- for each edge pixel $(x_i, y_i)$ in the image:
  - for $\theta \in [0, \pi)$:
    - Calculate $r(\theta) = x_i\cos\theta + y_i\sin\theta$
    - $H(r(\theta), \theta) = H(r(\theta), \theta) + 1$
  - end for
- end for

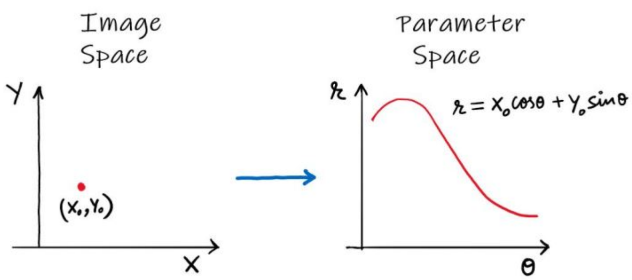


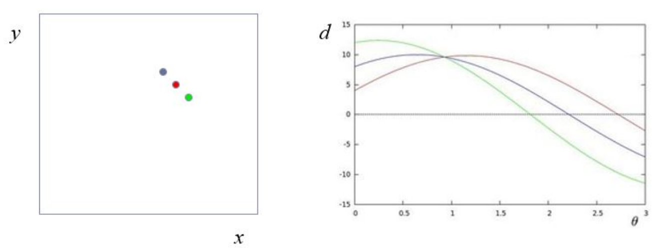

- Find the $(r, \theta)$ bin(s), where $H(r, \theta)$ is above a suitable threshold value.

## Hough-Transform Example

- For a given point $(x_0, y_0)$

$$r(\theta) = x_0 \cos\theta + y_0 \sin\theta$$



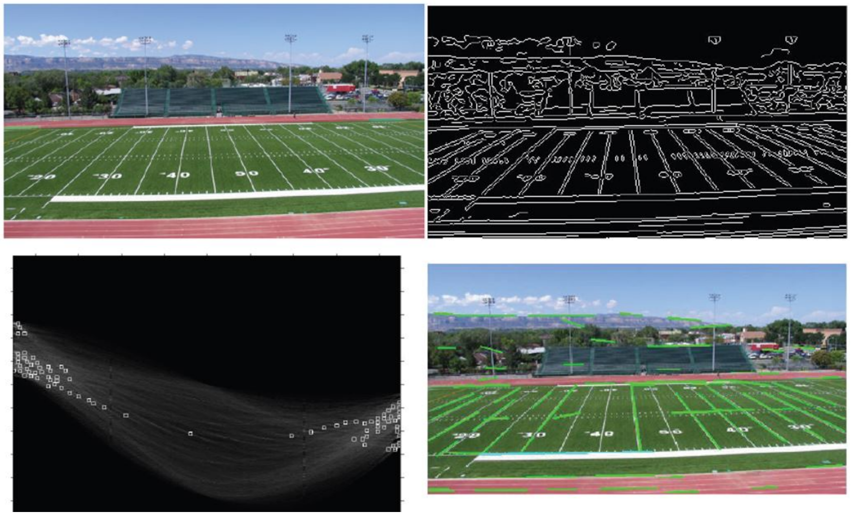




- For three points along a line ($d \equiv r$)

## Hough-Transform Properties

- Noise and clutter votes are inconsistent, so will not accumulate.
- Can handle occlusions if not all points are present as long as model gets enough votes.
- Efficient.

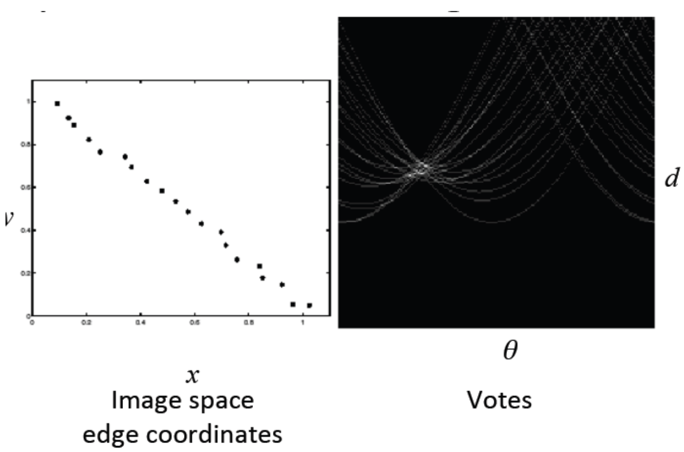
## Hough-Transform Example on Real Images



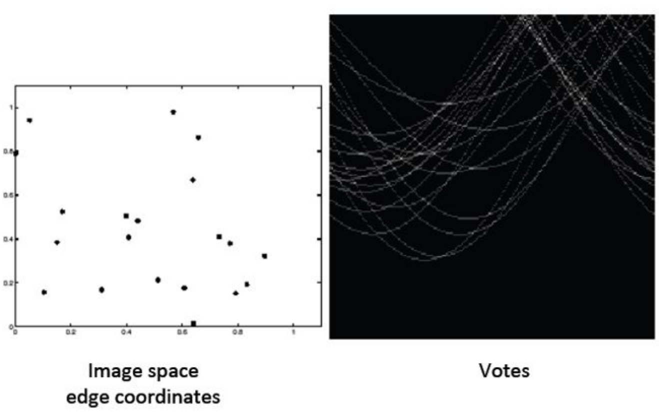
- Showing the longest segments found
- Line detection video
    - Video source

## Impact of Noise on Hough Transform

- What difficulties does noise introduce? ($d \equiv r$)




- Here everything is “noise” but we still see peaks in the vote space



## Voting: Practical Tips

- Use only trustworthy points
  - E.g., edges points with significant gradient magnitude (alternatively weight votes)
- Choose a good quantization grid
  - Not too coarse – too many lines fall in the same bucket
  - Not too fine – collinear points vote for different lines
- Smooth the voting (vote also for neighbors)
- Non-maxima suppression
- Refit line using accumulated votes
- Reduce number of parameters, if possible

## Hough Transform Summary

- **Pros**
  - Can handle occlusions
  - Some robustness to noise
  - Can detect multiple lines in a single pass over the image
- **Cons**
  - Complexity increases exponentially with the number of parameters
  - Clutter can produce spurious peaks in parameter space
  - Hard to select the right quantization

## Hough Lines in OpenCV

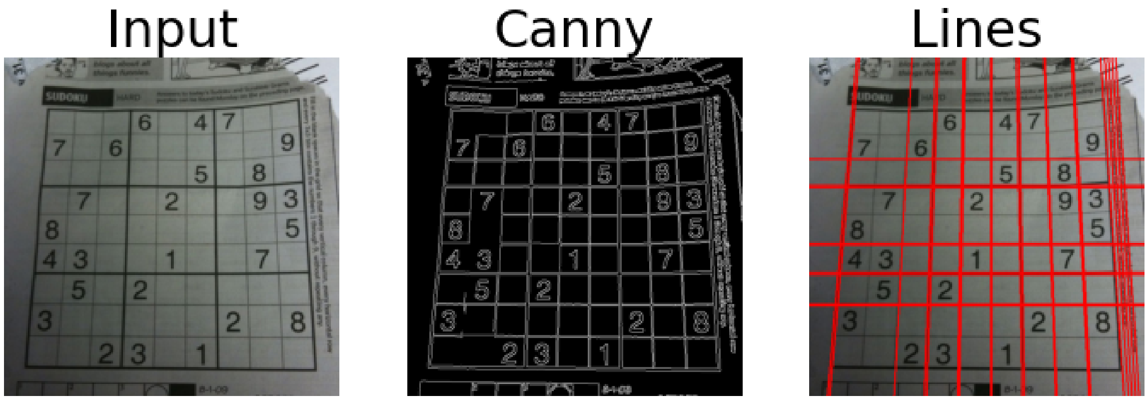
In [23]:

```
# Read the image
img_orig = cv2.imread('assets/sudoku.png')
img = img_orig.copy()

# Convert to grayscale
gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)

# Find the edges using Canny detector
edges = cv2.Canny(gray,50,150,apertureSize = 3)

# Apply the hough transform
lines = cv2.HoughLines(edges,1,np.pi/180,200)

# Draw the lines
for line in lines:
    rho,theta = line[0]
    a = np.cos(theta)
    b = np.sin(theta)
    x0 = a*rho
    y0 = b*rho
    x1 = int(x0 + 1000*(-b))
    y1 = int(y0 + 1000*(a))
    x2 = int(x0 - 1000*(-b))
    y2 = int(y0 - 1000*(a))
    cv2.line(img,(x1,y1),(x2,y2),(0,0,255),2)
```

In [24]:

```
# show the result
img_orig = cv2.cvtColor(img_orig, cv2.COLOR_BGR2RGB)
```

```
img_lines = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
plot_images([img_orig, edges, img_lines], ['Input', 'Canny', 'Lines'], subplot_shape=(1,3), figsize=(12,4
```




### Generalized Hough Transform

- Can be extended to other parametric models such as: **circles, ellipses, rectangles** etc. (See Recommended Videos)
- Complexity increases exponentially with the number of parameters
  - Circles - 3D accumulator $(x_c, y_c, r)$,

$$(x - x_c)^2 + (y - y_c)^2 = r^2$$

  - Ellipses - 4D accumulator $(x_c, y_c, a, b)$,

$$\left(\frac{x - x_c}{a}\right)^2 + \left(\frac{y - y_c}{b}\right)^2 = 1$$

  - etc..
- OpenCV uses more trickier method, **Hough Gradient Method** which uses the gradient information of edges.
- Implementation in OpenCV: `cv2.HoughCircles()`

## RANSAC

### RANdom SAmple Consensus [Fischler & Bolles 1981]

- Key ideas:
  - Look for “inliers” and use only them
  - If we fit a model to “outliers” we will not get a good fitting

### RANSAC Algorithm

*Loop*:

1. Randomly select a group of points
2. Fit a model to the selected group
3. Find the inliers of the computed model
4. If number of inliers is large enough re-compute model using only inliers

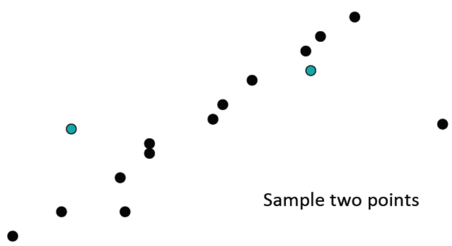
5. Compute number of inliers of updated model

**The winner**: model with the largest number of inliers

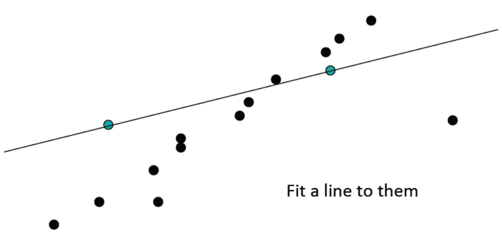
## Line Fitting with RANSAC

- Input: A set of edge points

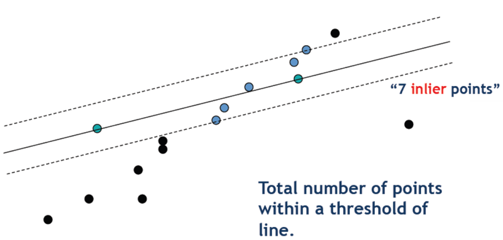
- **Step 1**: Select two points




- **Step 2**: Fit a line to the selected points

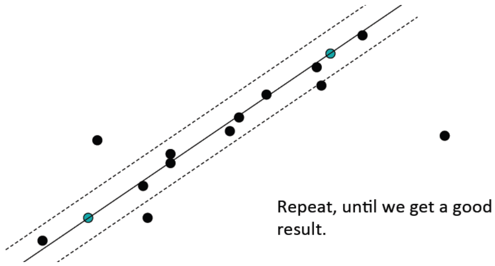



- **Step 3**: Identify inliers

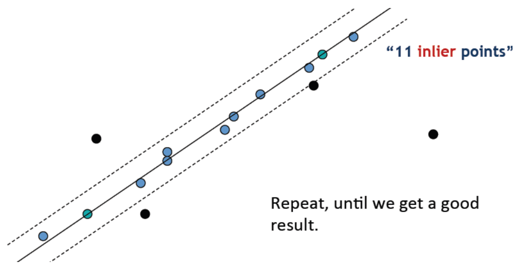



- **Step 4**: Repeat Steps 1-3 until convergence

- **Iteration 2**: Steps 1-2:
  - Sample new pts and fit a line




- **Iteration 2**: Step 3:
  - Count number of new inliers




## RANSAC – Stopping Criteria

- **Option 1**: when the model is good enough:
  - By the number of inliers
  - By its fitting error
- **Option 2**: according to probability
  - Let $K$ be the number of iterations
  - Let $n$ be the number of points needed to compute the model
  - Let $f$ be the fraction of inliers of a model
  - Then the probability that a single sample is correct: $f^n$
  - The probability that all $K$ samples fail is $(1 - f^n)^K$
  - Choose $K$ high enough to keep the failure rate low enough

## RANSAC – For Multiple Models?

- How can we use RANSAC to compute multiple models?
  - Apply RANSAC multiple times, each time we remove the detected inliers.

## RANSAC - Summary

- **Pros**
  - General method that works well for lots of model fitting problems
  - Easy to implement
- **Cons**
  - When the percentage of outliers is high too many iterations are needed and failure rate increases
- **Implementation**

- OpenCV usage with Homographies (Tutorial 7): `cv2.findHomography(src_pts, dst_pts, cv2.RANSAC)`
- Scikit-image: `skimage.measure.ransac()`
- Scikit-learn: `sklearn.linear_model.RANSACRegressor()`
- and many more..

### Example in Scikit-learn

---

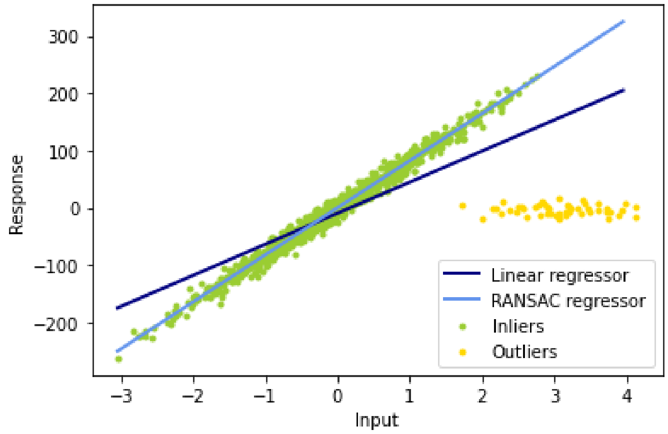
In [25]:

```
from sklearn import linear_model, datasets

# create inlier and outlier dataset
n_samples, n_outliers = 1000, 50
X, y, coef = datasets.make_regression(n_samples=n_samples, n_features=1,
                                      n_informative=1, noise=10,
                                      coef=True, random_state=0)
np.random.seed(0)
X[:n_outliers] = 3 + 0.5 * np.random.normal(size=(n_outliers, 1))
y[:n_outliers] = -3 + 10 * np.random.normal(size=n_outliers)

# Fit line using all data
lr = linear_model.LinearRegression()
lr.fit(X, y)

# Robustly fit line with RANSAC algorithm
ransac = linear_model.RANSACRegressor()
ransac.fit(X, y)
inlier_mask = ransac.inlier_mask_
outlier_mask = np.logical_not(inlier_mask)

# Predict data of estimated models
line_X = np.arange(X.min(), X.max())[:, np.newaxis]
line_y = lr.predict(line_X)
line_y_ransac = ransac.predict(line_X)
```

In [26]:

```
# Compare estimated coefficients
print('True Slope: {:.2f}'.format(coef))
print('Est. LS: {:.2f}'.format(lr.coef_[0]))
print('Est. RANSAC: {:.2f}'.format(ransac.estimator_.coef_[0]))

# plot the fit
plt.scatter(X[inlier_mask], y[inlier_mask], color='yellowgreen', marker='.',
            label='Inliers')
plt.scatter(X[outlier_mask], y[outlier_mask], color='gold', marker='.',
            label='Outliers')
plt.plot(line_X, line_y, color='navy', linewidth=2, label='Linear regressor')
plt.plot(line_X, line_y_ransac, color='cornflowerblue', linewidth=2,
         label='RANSAC regressor')
plt.legend(loc='lower right')
plt.xlabel("Input")
plt.ylabel("Response")
plt.show()
```

```
True Slope: 82.19
Est. LS: 54.17
Est. RANSAC: 82.09
```




## CNNs for Line Detection

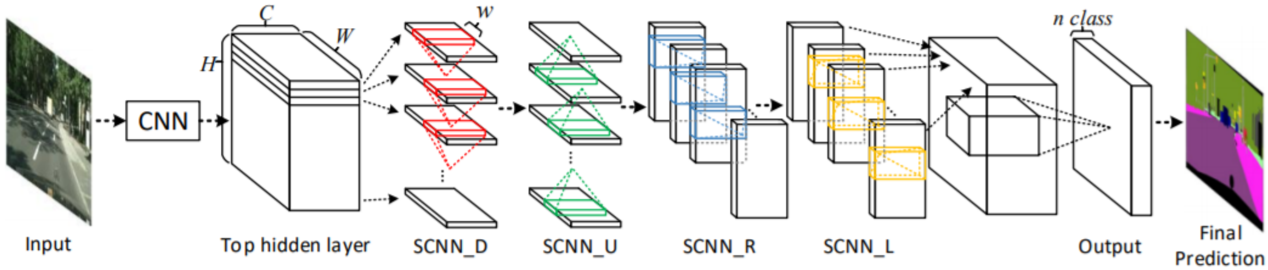

- Image Source

## Spatial CNN (SCNN)

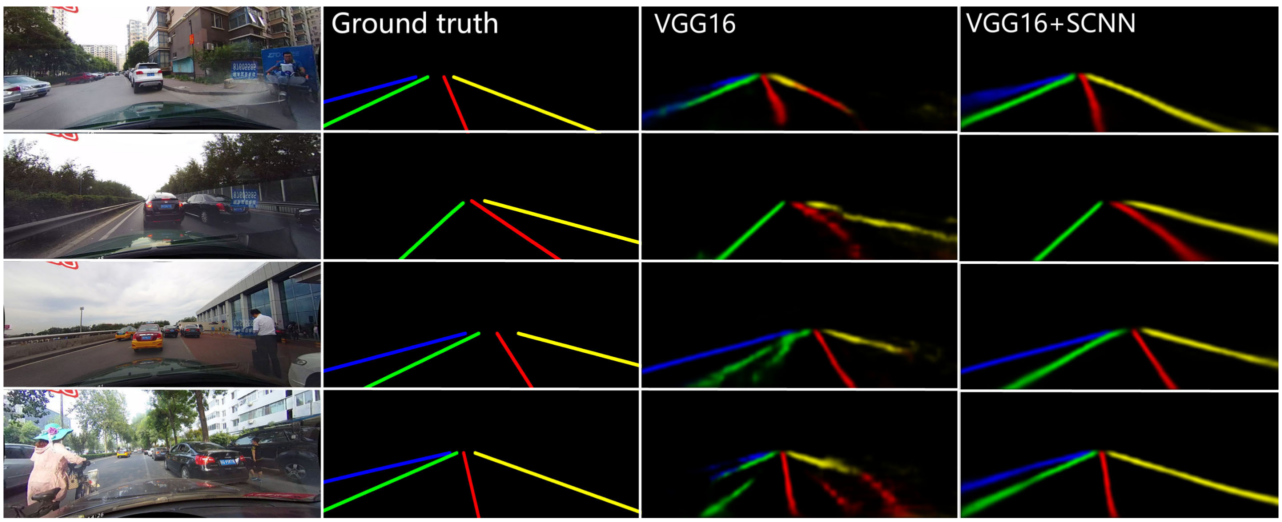
- Traditional CNN has no spatial awareness
  - Does not capture the spatial relationships (e.g. rotational and translational relationships)
- Spatial relationships are important
  - Traffic poles - usually exhibit similar spatial relationships such as to stand vertically and are placed alongside the left and right of roads
  - Lanes

## Spatial CNN - Architecture

- Based on layer-by-layer convolutions: each convolution layer receives input from its preceding layer, applies convolutions and nonlinear activation, and sends the output to the succeeding layer
- Refer to rows and columns as the “layers”

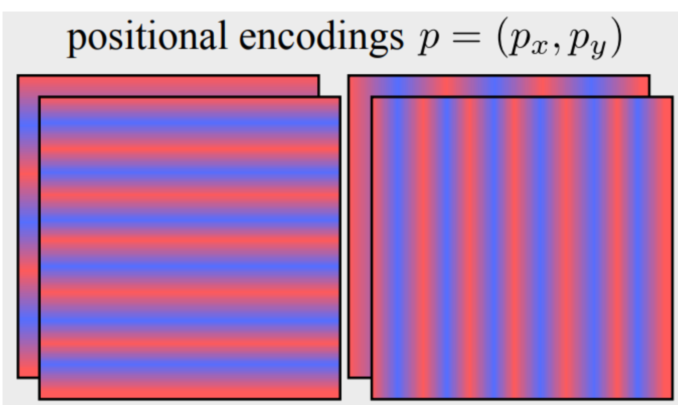



### Spatial CNN - Results



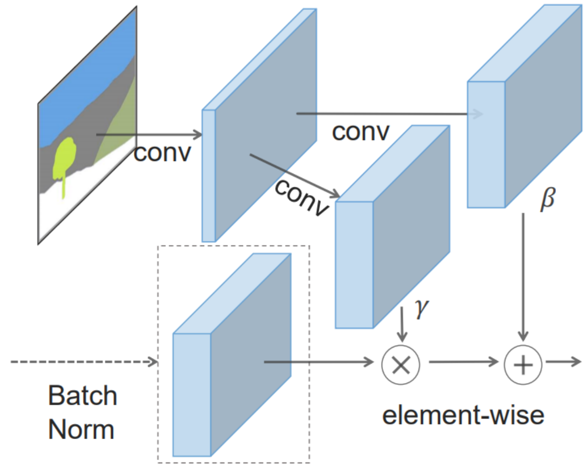

- Line detection video - SCNN
  - Video source

### Nowadays, can be achieved with "Positional encoding"




- Image source
- Discussion is still ongoing whether we actually want CNNs to be spatially-equivariant
  - (e.g. paper 1, paper 2,..)

### Alternatively, using "Spatially-adaptive" Normalization




- See the SPADE paper for further details.

## Recommended Videos

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### Warning!

- These videos do not replace the lectures and tutorials.
- Please use these to get a better understanding of the material, and not as an alternative to the written material.

### Video By Subject

- Edge Detection (Sobel + Canny) - CSCI 512 - Lecture 09-1 Edge Detection | CSCI 512 - Lecture 09-2 Edge Detection
    - Edge Detection (Sobel) - Finding the Edges (Sobel Operator) - Computerphile
    - Edge Detection (Canny) - Canny Edge Detector - Computerphile -
- Hough Transform - Computer Vision Basics: Hough Transform | By Dr. Ry @Stemplicity
    - Circle Hough Transform - How Circle Hough Transform works
- RANSAC - RANSAC - Random Sample Consensus (Cyrill Stachniss, 2020)

# Credits

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- EE 046746 Spring 2020 - Dahlia Urbach
- Slides - Lihi Zelnik-Manor
- Computer Vision: Algorithms and Applications - Richard Szeliski - Sections 4.2 and 4.3.
- Canny Edge Detector - Code - theailearner
- Canny Edge Detector - Code v2 - adeveloperdiary
- Tutorial: Build a lane detector - Chuan-en Lin
- Hough Transform for Line Detection - Fun with Python Programming
- Robust linear model estimation using RANSAC - Scikit-learn
- SCNN - Pan et al. - code
- Photo by Pedro Gonzalez from Unsplash
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