EE 046746 - Technion - Computer Vision

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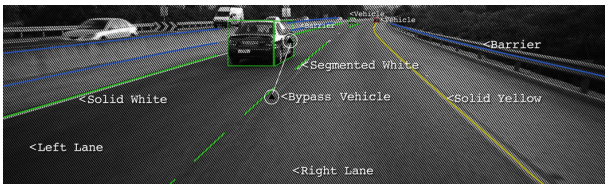
Tutorial 04 - Edge and Line Detection



- Image source (https://towardsdatascience.com/tutorial-build-a-lane-detector-679fd8953132)

Agenda

In [2]:
```
# 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 [3]:
```
# plot images function
def plot_images(image_list, title_list, subplot_shape=(1,1), axis='off', fontsize=30, figsize=(4,4), cmap=
['gray']):
    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)
```

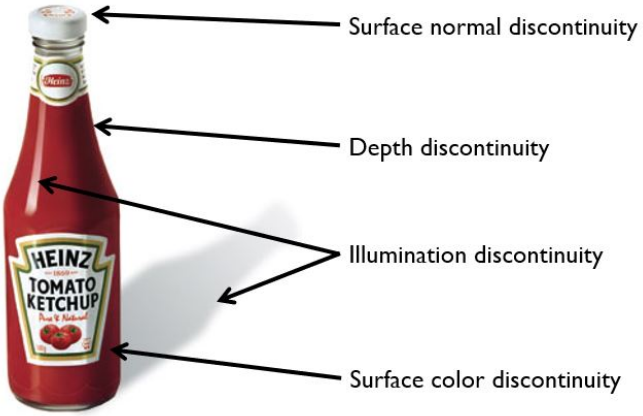
Corners For Features, Edges For What?

- 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.

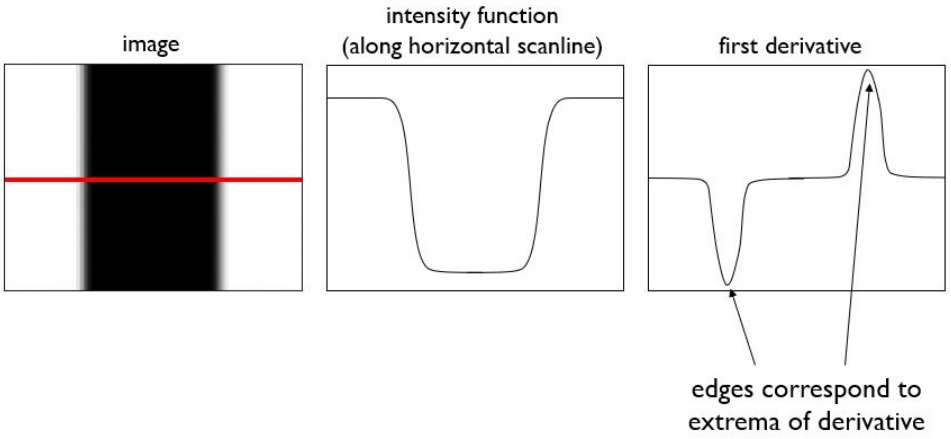
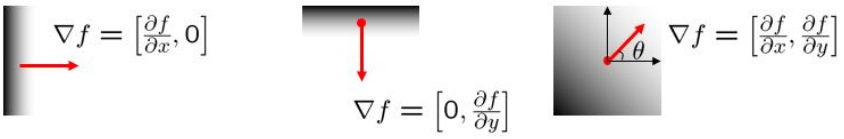


Image Gradient

- 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: $M_x =$

-1	0	1
-1	0	1
-1	0	1

; $M_y =$

1	1	1
0	0	0
-1	-1	-1

Sobel: $M_x =$

-1	0	1
-2	0	2
-1	0	1

; $M_y =$

1	2	1
0	0	0
-1	-2	-1

Roberts: $M_x =$

0	1
-1	0

; $M_y =$

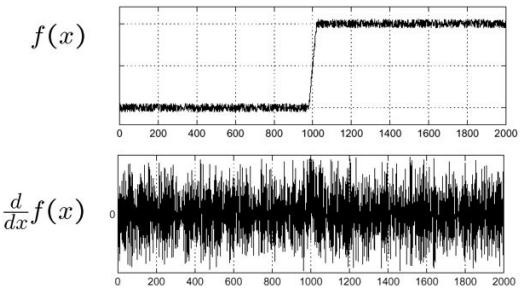
1	0
0	-1

In [4]:
```
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:

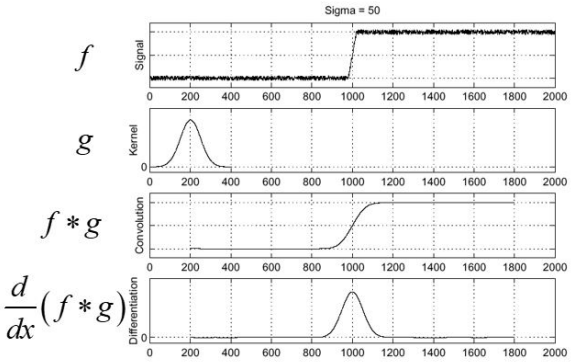


- Where is the edge?

- 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

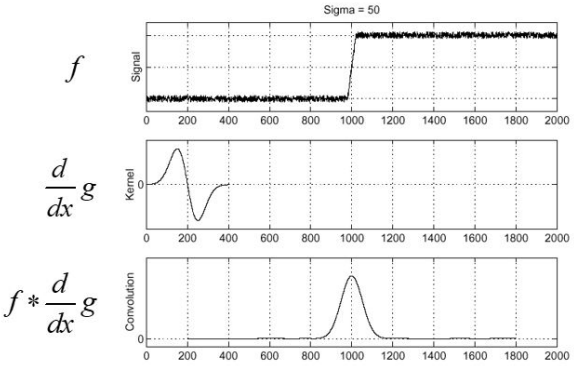
Solution: Smooth First



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

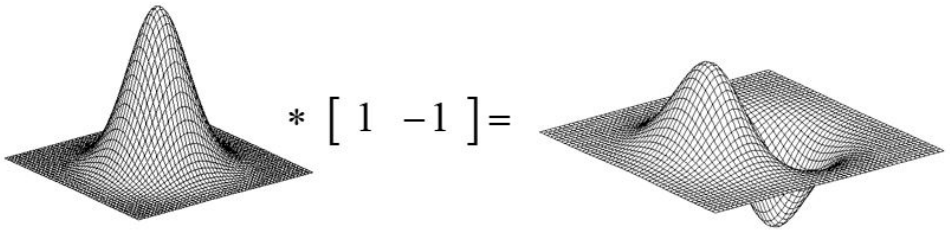
Derivative Theorem of Convolution

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



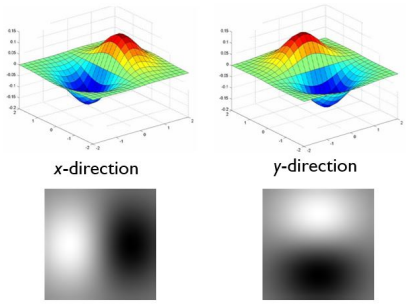
Derivative of Gaussian Filter

- Is this a separable filter?



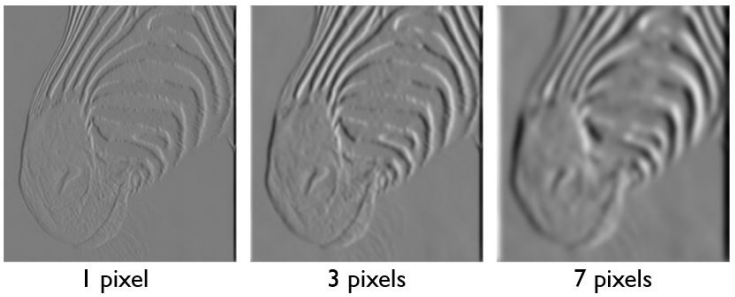
- Yes, we can split it into two filters in which their order does not matter
- Median is a non-separable filter

Derivative of Gaussian Filter



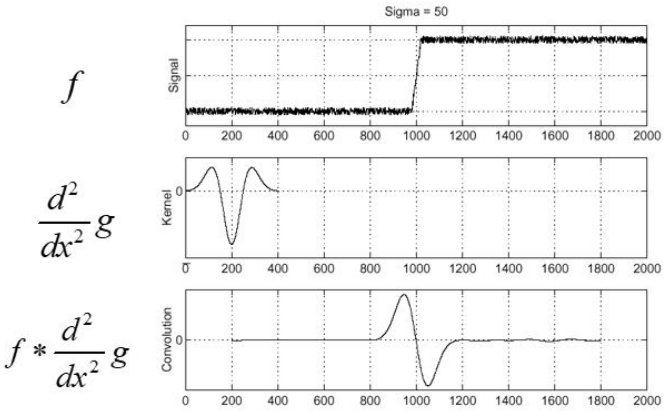
- Which one finds horizontal/vertical edges?

Smoothing Tradeoffs



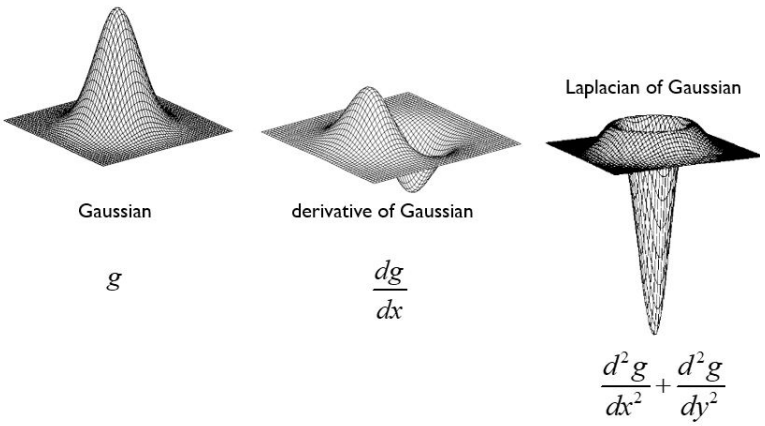
- Smoothed derivative removes noise, but blurs edge.
  - Also finds edges at different “scales”.

Laplacian of Gaussian (LoG)



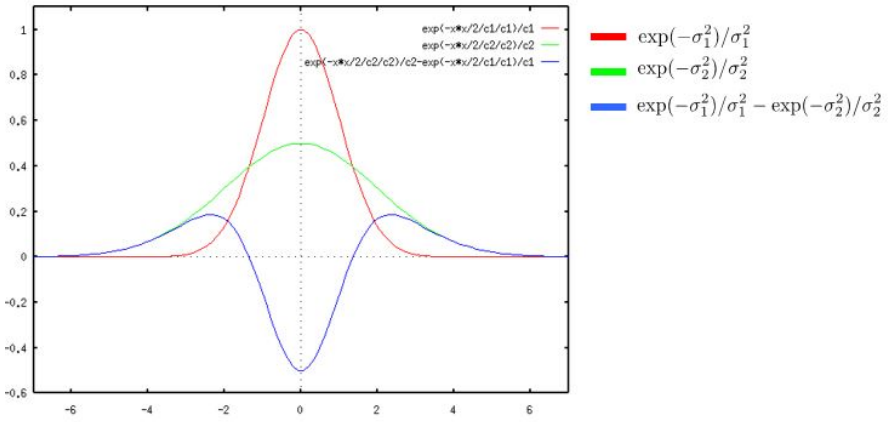
- Where is the edge?
  - Zero-crossings of bottom graph

2D Edge Detection Filters



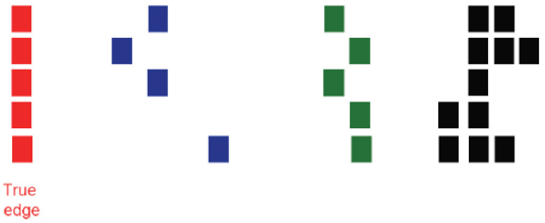
DoG: Difference of Gaussians

- Can approximate Laplacian filter



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



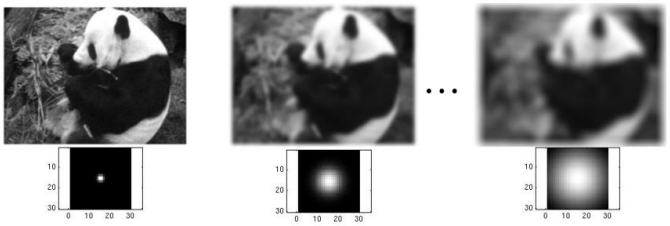
- Which of these detections is the best?

What Are the Parameters?

- Scale
- Threshold

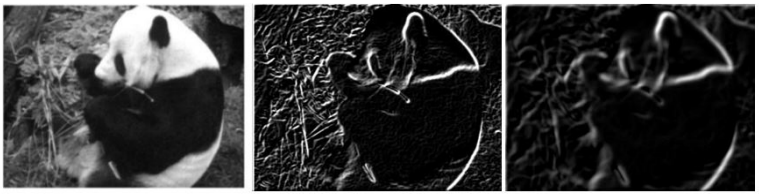
Scale Selection

- 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 σ On Derivatives

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



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?

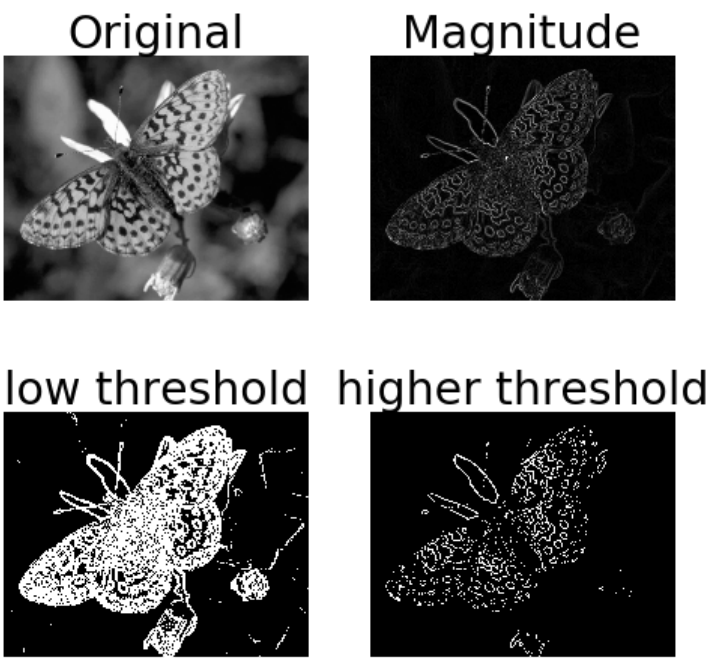
- Scale
- Threshold

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

# 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
```

In [6]:
```
# figures:
plot_images([im, im_grad_mag, low_thresh, high_thresh], ['Original', 'Magnitude', 'low threshold', 'higher threshold'],
            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. (https://scholar.google.com/scholar?cluster=6445737130860653197&hl=en&as_sdt=0,5&sciodt=0,5)
  - 34189 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

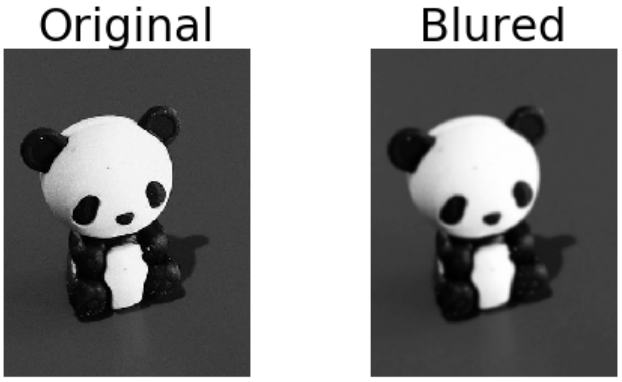
In [7]:
```
# Load Image
img = cv2.imread('./assets/tut_panda.jpg')
img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
in_x_min = 100
in_x_max = 400
in_y_min = 300
in_y_max = 700
gray_cut = gray[in_y_min:in_y_max, in_x_min:in_x_max]
```

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 (https://unsplash.com/@pgonzalez_95?utm_medium=referral&utm_campaign=photographer-credit&utm_content=creditBadge/) from Unsplash (https://unsplash.com/)

Canny Example - Step 1 - Blur

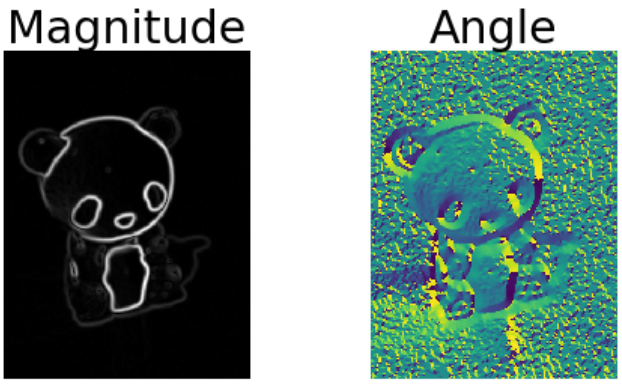
In [9]:
```
# Gaussian Blurring
blur = cv2.GaussianBlur(gray_cut, (9,9), 0)
plot_images([gray_cut, blur], ['Original','Blured'], cmap=['gray', 'gray'], subplot_shape=(1,2), figsize=(
8,4))
```



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

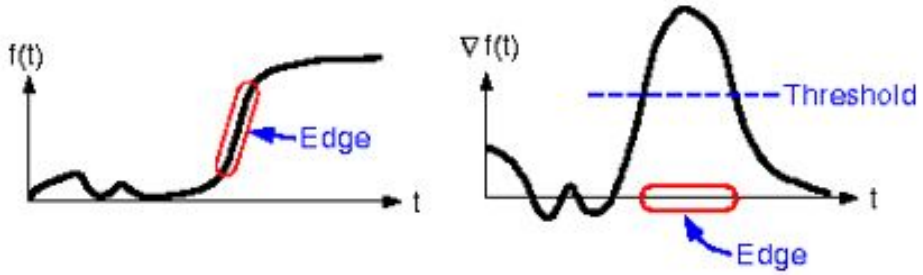
In [10]:
```
# Apply Sobel:
sobelx_64 = cv2.Sobel(blur, cv2.CV_64F, 1, 0, ksize=3)
sobely_64 = cv2.Sobel(blur, cv2.CV_64F, 0, 1, ksize=3)

# 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', None])
```

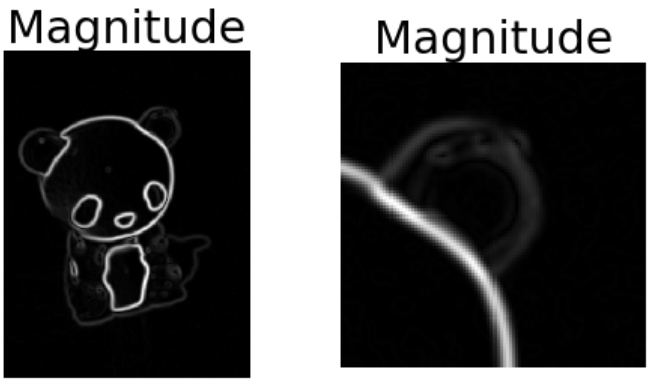


Canny Example - Step 3 - Localization

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

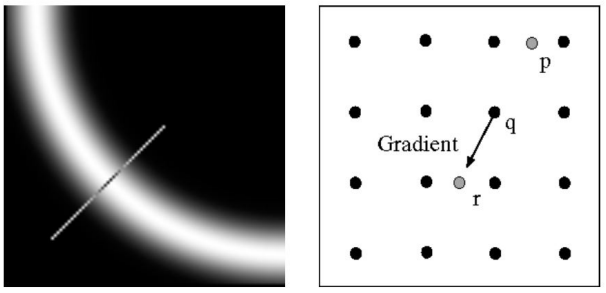


In [12]:
```
in_x_min, in_x_max, in_y_min, in_y_max = (150, 250, 50, 150)
mag_cut = mag[in_y_min:in_y_max, in_x_min:in_x_max]
plot_images([mag, mag_cut], ['Magnitude','Magnitude'], subplot_shape=(1,2), figsize=(8,4))
```



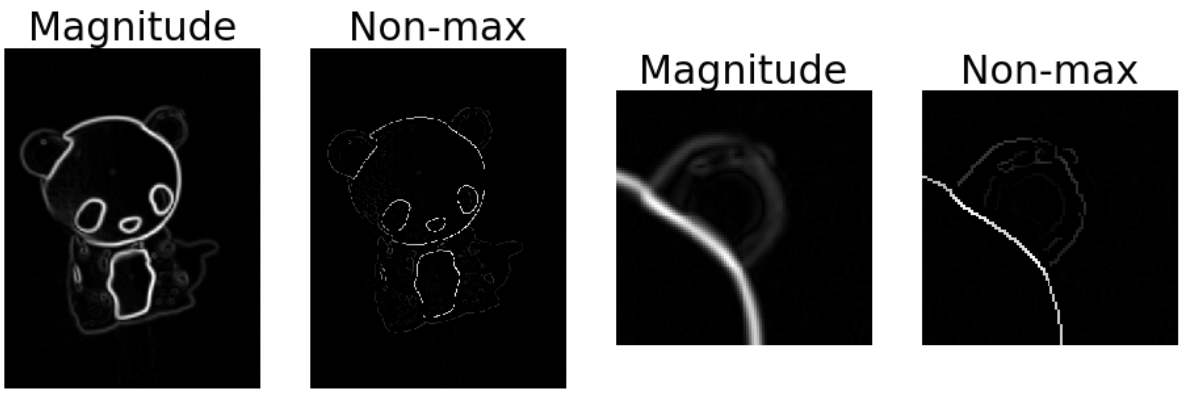
Non-Maximum Suppression (NMS)

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



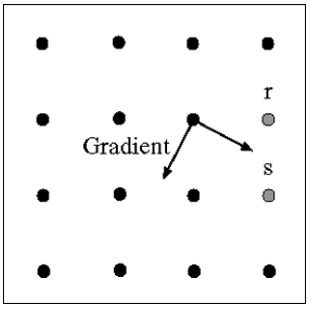
In [13]:
```
# Find the neighbouring pixels (b,c) in the rounded gradient direction
# and then apply non-max suppression
M, N = mag.shape
Non_max = np.zeros((M,N), dtype= np.float64)

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))
```



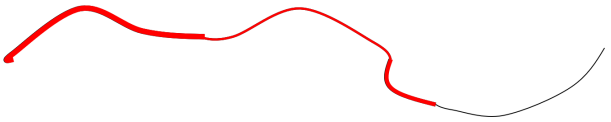
Canny Example - Step 4 - Edge Linking

- 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).



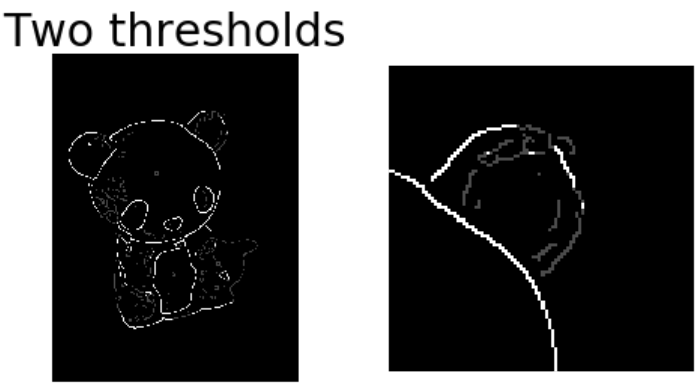
Hysteresis Thresholding

- 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]:
```
# Hysterasis - 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
```

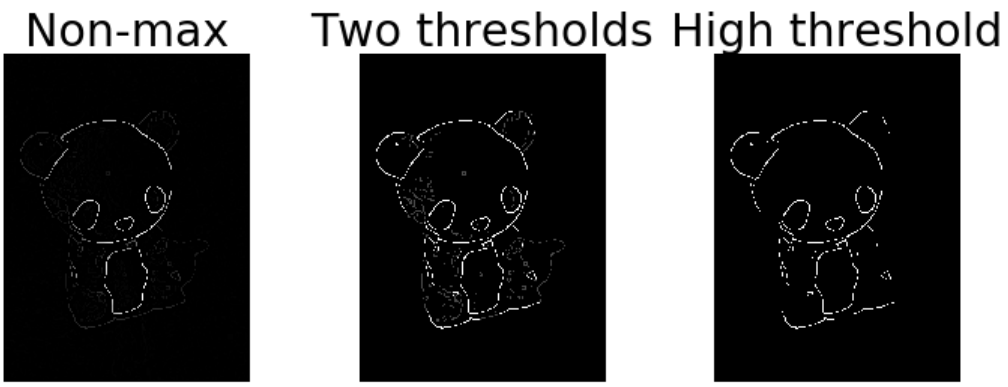
In [16]:
```
plot_images([out, out[in_y_min:in_y_max, in_x_min:in_x_max]], ['Two thresholds', ''],
            subplot_shape=(1,2), figsize=(8,4))
```



Linking edges

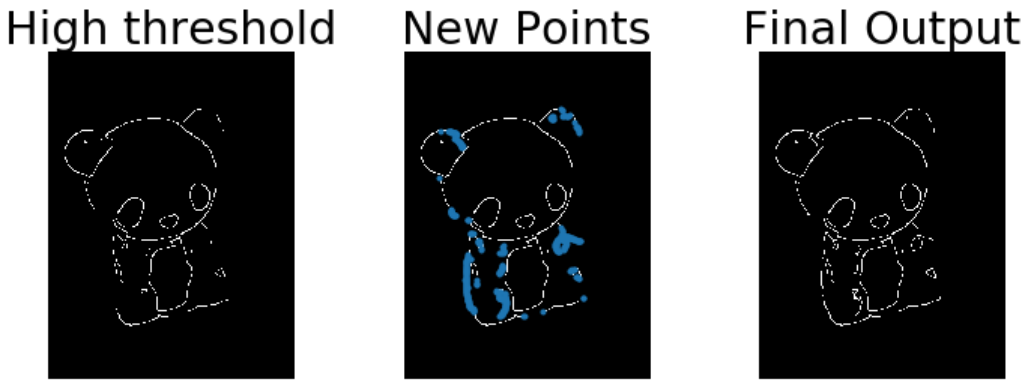
In [17]:
```
# Hysterasis - step 2
out1 = np.copy(out)
new_points = []
M, N = out1.shape
for i in range(1, M-1):
    for j in range(1, N-1):
        if (out1[i,j] == 75):
            # 8 nieghbors search:
            if 255 in [out1[i+1, j-1], out1[i+1, j], out1[i+1, j+1], out1[i, j-1], out1[i, j+1],
                       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 [29]:
```
# Hysterasis output
plot_images([Non_max, out, out > 75], ['Non-max', 'Two thresholds', 'High threshold'], subplot_shape=(1,3
), figsize=(12,4))
```



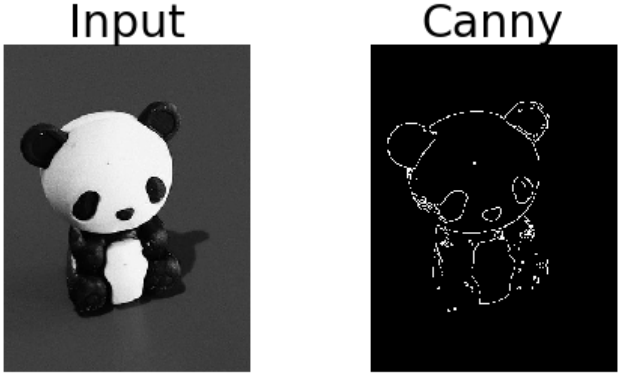
In [20]:
```
plt.figure(figsize=(12,4))
plt.subplot(1,3,1)
plt.imshow(out > 75,cmap='gray')
plt.title('High threshold',fontsize=30)
plt.axis('off')
plt.subplot(1,3,2)
plt.imshow(out1,cmap='gray')
plt.title('New Points',fontsize=30)
plt.plot(new_points[1],new_points[0],'.')
plt.axis('off')
plt.subplot(1,3,3)
plt.imshow(out1,cmap='gray')
plt.title('Final Output',fontsize=30)
plt.axis('off')
```

Out[20]: (-0.5, 299.5, 399.5, -0.5)



Canny in one line (OpenCV)

In [27]:
```
# Canny
im_canny = cv2.Canny(gray_cut, 50, 260)
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

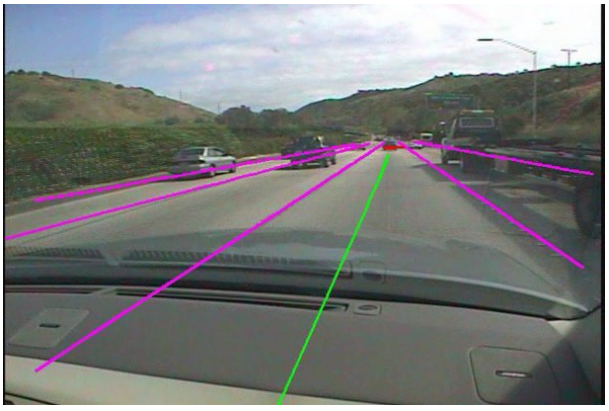
- Design questions:
  - What is a good model to represent our data?
  - Do we plan to fit multiple instances?
- Challenges:
  - Which features belong to the model? To which instance?
  - How many instances are there?
  - Computational complexity (typically we cannot examine all possible models).

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

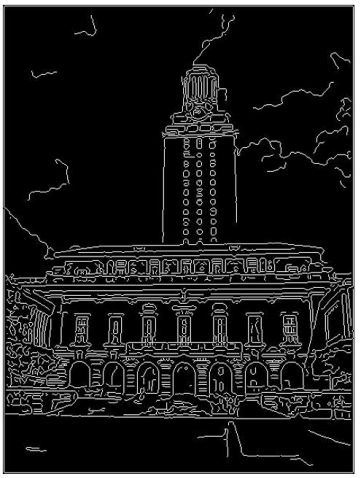


- Sports

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

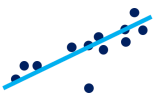
Challenges of Line Fitting

- Not all the lines in the image are continuous

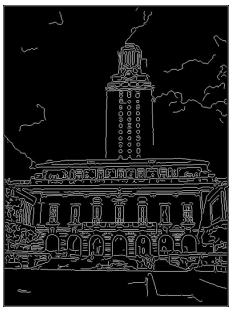



Challenges of Line Fitting

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

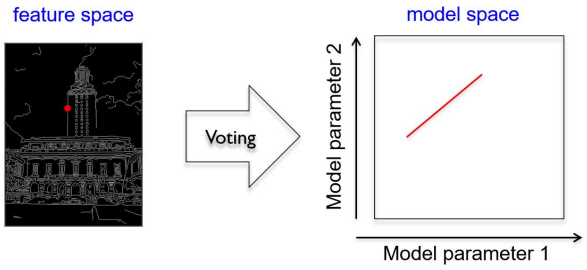


- Large search space
- How many lines are there?



Voting

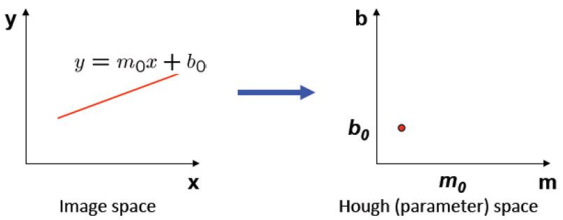
- Problem:
  - We cannot try all possible models
- Solution by voting:
  - Features (points) vote for models they are compatible with
  - Search for models with lots of votes



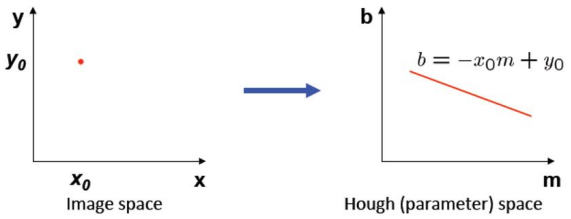
The Hough Transform

- Transformation from image space (x, y) to Hough space (m, b)

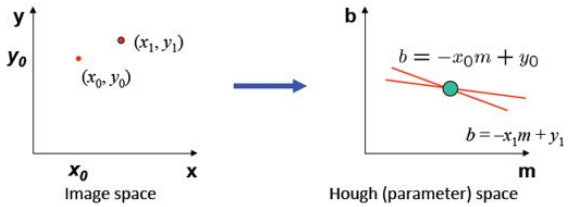
- A line in the image corresponds to a point in Hough space
  - Image $\rightarrow$ Hough: Given a set of points (x, y) find all (m, b) such that $y = mx + b$



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

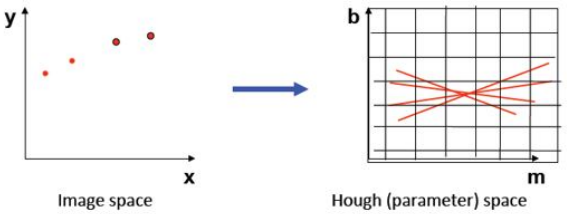


- The line that contains both points (x_0, y_0) and (x_1, y_1) is the intersection of the lines $b = -x_0 m + y_0$ and $b = -x_1 m + y_1$



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

$$x \cos\theta + y \cos\theta = d$$
$$\theta \in [0, \pi), d \in R$$

The Hough-Transform Algorithm

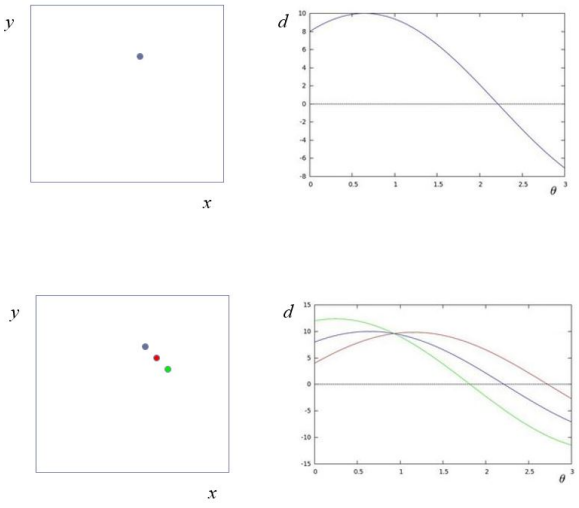
- Use polar representaton $x\cos\theta + y\cos\theta = d,\ \ \theta \in [0,\pi), d \in R$
- Quantize Hough space
- Loop:

  1. Initialize $H[d,\theta] = 0$
  2. For each edge point (x,y) in the image $H[d,\theta] += 1$
  3. Find bins $H[d,\theta] = 0$ with maximum value

Hough-Transform Example

- For a given point (x_0, y_0)

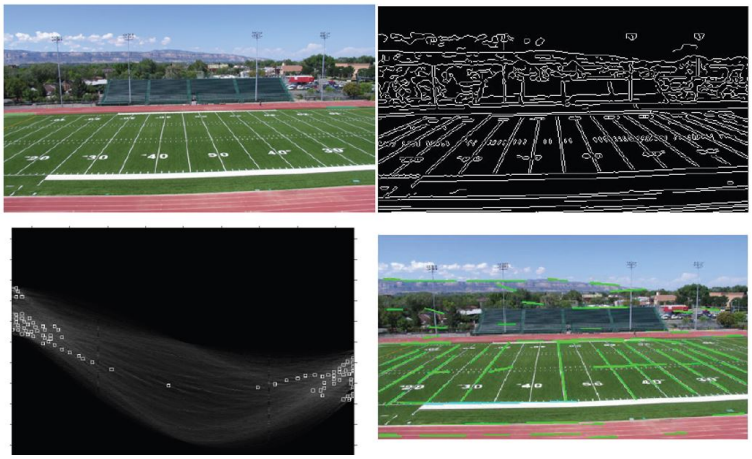
$$d(\theta) = x_0\cos\theta + y_0\sin\theta$$



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.

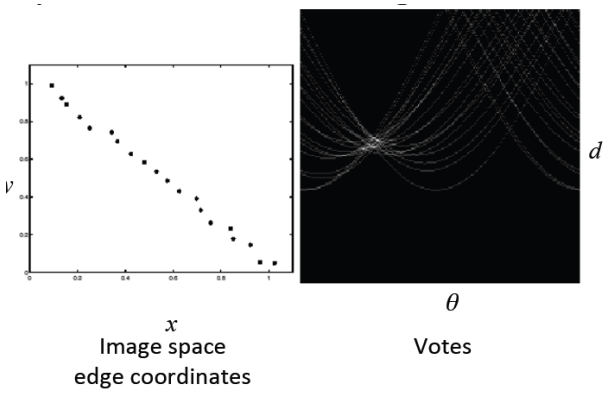
Hough-Transform Example on Real Images



- Showing the longest segments found
- Line detection video (https://youtu.be/u1pZE5VpDAQ)
  - Video source (https://towardsdatascience.com/tutorial-build-a-lane-detector-679fd8953132)

Impact of Noise on Hough Transform

- What difficulties does noise introduce?



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

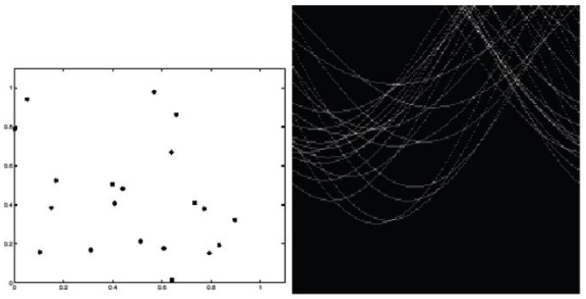


Image space
edge coordinates

Votes

Voting: Practical Tips

- Use only trustworthy points
  - E.g., edges points with significant gradient magnitude (alternatively weight votes)
  - Szeliski suggests using edges instead of points
- 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

Generalized Hough Transform

- Can be extended to other parametric models such as: **circles, ellipses, rectangles** etc.
- Complexity increases exponentially with the number of parameters.
- Can be used to detect complex non-parametric models as described in *Leibe et al. “Combined object categorization and segmentation with an implicit shape model”.*

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:

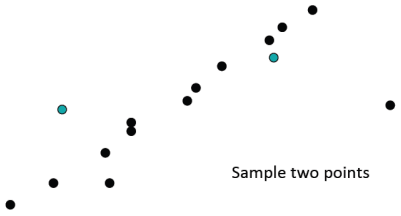
1. Randomly select a group of points
2. Fit a model to the selected group
3. Find the inliers of the computed model
4. If number of inliers is large enough re-compute model using only inliers
5. Compute number of inliers of updated model

The winner: model with the largest number of inliers

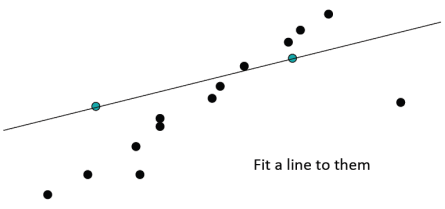
Line Fitting with RANSAC

- Input: A set of edge points

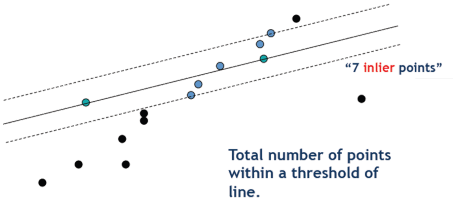
- **Step 1**: Select two points



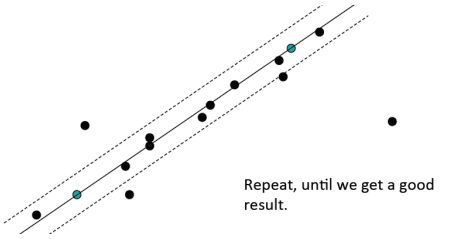
- **Step 2**: Fit a line to the selected points



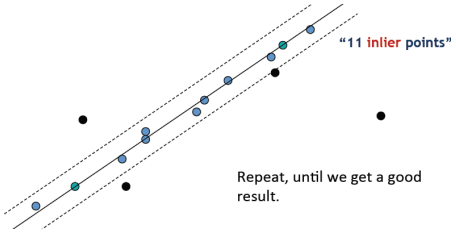
- **Step 3**: Identify inliers



- **Step 4**: Fit line to inliers



- **Step 5**: 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 $\left(1 - f^n\right)^K$
  - 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

CNNs for Line Detection

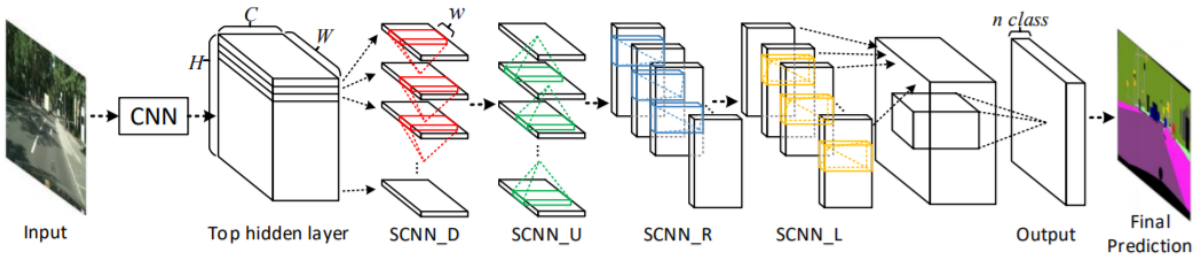
- Image Source (https://towardsdatascience.com/tutorial-build-a-lane-detector-679fd8953132)

Spatial CNN (SCNN)

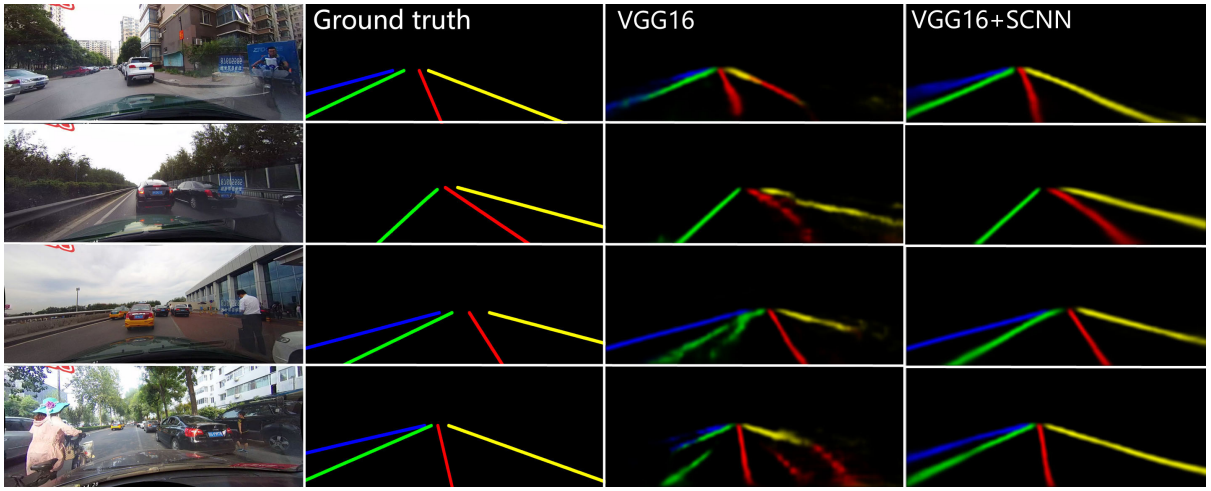
- Traditional CNN has no spatial awareness
  - Does not capture the spatial relationships (e.g. rotational and translational relationships)
- Spatial relationships are important
  - Traffic poles - usually exhibit similar spatial relationships such as to stand vertically and are placed alongside the 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 (https://youtu.be/ey5XPs1012k?t=9)
  - Video source (https://github.com/XingangPan/SCNN)

Recommended Videos

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 (https://www.youtube.com/watch?v=07qwMn2c5iY) I CSCI 512 - Lecture 09-2 Edge Detection (https://www.youtube.com/watch?v=PUcbhaGhgtE)
  - Edge Detection (Sobel) - Finding the Edges (Sobel Operator) - Computerphile (https://www.youtube.com/watch?v=uihBwtPIBxM)
  - Edge Detection (Canny) - Canny Edge Detector - Computerphile (https://www.youtube.com/watch?v=sRFM5IEqR2w)-
- Hough Transform - Computer Vision Basics: Hough Transform | By Dr. Ry @Stemplicity (https://www.youtube.com/watch?v=6yVMpaloxIU)
  - Circle Hough Transform - How Circle Hough Transform works (https://www.youtube.com/watch?v=Ltqt24SQQoI)
- RANSAC - Robotics - 4.3.3 - RANSAC - Random Sample Consensus (https://www.youtube.com/watch?v=BpOKB3OzQBQ)
  - RANSAC - RANSAC - Random Sample Consensus (Cyrill Stachniss, 2020) (https://www.youtube.com/watch?v=Cu1f6vpEilg)

Credits

- Slides - Lihi Zelnik-Manor
- Computer Vision: Algorithms and Applications - Richard Szeliski - Sections 4.2 and 4.3.
- Canny Edge Detector - Code - theailearner (https://theailearner.com/2019/05/22/canny-edge-detector)
- Tutorial: Build a lane detector - Chuan-en Lin (https://towardsdatascience.com/tutorial-build-a-lane-detector-679fd8953132)
- SCNN - Pan et al. (https://arxiv.org/pdf/1712.06080.pdf) - code (https://github.com/XingangPan/SCNN)
- Photo by Pedro Gonzalez (https://unsplash.com/@pgonzalez_95?utm_medium=referral&utm_campaign=photographer-credit&utm_content=creditBadge/) from Unsplash (https://unsplash.com/)
- Icons from Icon8.com (https://icons8.com/) - https://icons8.com (https://icons8.com)