CS6640 week 12 Image Segmentation

segmentation : partition image into semantically meaningful sets of pixels

Approaches :
- Edge / boundary
- Region-based

Thresholding : seen this before

Split and merge

```
regions = image          (i.e., M x N array)
while new regions        % split
  for every region in regions
    if region is not homogeneous
      split region into 4 subregions
      and add those to regions
    end
  end
end
% merge
merge neighboring regions with similar properties
```

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Watershed

Segment overlapping similar objects

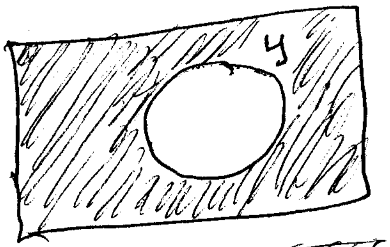
Look at Figure 10.9
+ Example 10.5
Not too useful for us.

Markov random fields $\xrightarrow{\text{reduce to}}$ Bayes Law

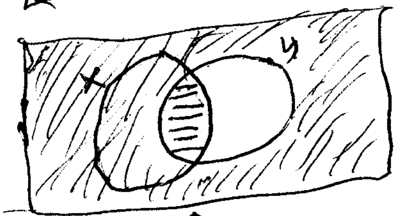
Bayes

$$p(x|y) = \frac{p(y|x)\,p(x)}{p(y)}$$

Consider we know (or assume) y is true



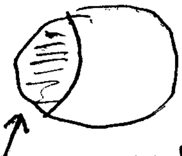
suppose y is true



What's the prob of x in this case

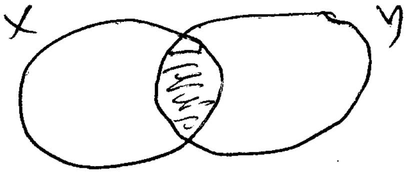
The intersection of x + y is Prob(x & y)

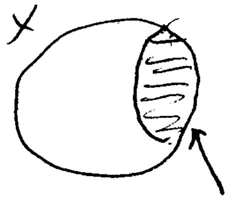
Consider the y circle:



$$\text{Prob}(x|y) = \frac{\text{Prob}(x \,\&\, y)}{\text{Prob}(y)}$$

It works the same for Prob(y|x)





Prob(y&x)

$$\text{Prob}(y|x) = \frac{\text{Prob}(y \& x)}{\text{Prob}(x)}$$

Given:

$$\text{Prob}(y|x) = \frac{\text{Prob}(y \& x)}{\text{Prob}(x)}$$

$$\text{Prob}(x|y) = \frac{\text{Prob}(x \& y)}{\text{Prob}(y)}$$

rewrite:

$$\text{Prob}(x|y)\,\text{Prob}(y) = \text{Prob}(x \& y)$$
$$\text{Prob}(y|x)\,\text{Prob}(x) = \text{Prob}(x \& y)$$

$$\Rightarrow \quad \text{Prob}(x|y)\,\text{Prob}(y) = \text{Prob}(y|x)\,\text{Prob}(x)$$

$$\boxed{\Rightarrow \quad \text{Prob}(x|y) = \frac{\text{Prob}(y|x)\,\text{Prob}(x)}{\text{Prob}(y)}}$$

The <u>normal</u> (or Gaussian distribution)

<u>1D</u> $$\mathcal{N}(\mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

<u>in Matlab</u>

```
samps = sigma * randn(n,1) + mu;
```

<u>n-D</u>

$$\mathcal{N}(\bar{\mu}, \Sigma) = \frac{e^{-\frac{1}{2}(\bar{x}-\bar{\mu})^T \Sigma^{-1} (\bar{x}-\bar{\mu})}}{\sqrt{(2\pi)^n |\Sigma|}}$$

$\bar{\mu}$ is an n-D vector

Σ is an $n \times n$ covariance matrix

$|\Sigma|$ is determinant of Σ

$\bar{x}$ is n-D vector

Consider 1D method for maps

e.g., map1

Determine Prob(class | gray level)

$$\text{Prob}(\text{class} \mid \text{gray level}) = \frac{\text{Prob}(\text{gray level} \mid \text{class})\ \text{Prob}(\text{class})}{\text{Prob}(\text{gray level})}$$

$$\text{Prob}(\text{gray level} \mid \text{class}) = \frac{\#\text{ pixels of class with gray level}}{\#\text{ pixels in class}}$$

$$\text{Prob}(\text{class}) = \frac{\#\text{ pixels of class}}{\#\text{ pixels in image}}$$

$$\text{Prob}(\text{gray level}) = \frac{\#\text{ pixels with gray level}}{\#\text{ pixels in image}}$$

<u>Build table</u>

gray-level, class

Consider n-D method

Given an image feature vector set

im: M × N × P

~~and~~ image class indicator (proportioned according to probability ~~of~~ class)

im c: M × N × 1

* Get class probabilities

$$\text{Prob (class)} = \frac{\text{\# pixels in class}}{\text{\# pixels in all classes}}$$

* Build models
  + Get all vectors from im that are associated with class
  + Get mean vector mu
  + Get covariance Sigma

* Classify all image pixels
  + set y ← pixel vector
  + plug into formula to get $p(y|x)$
  + plug into formula to get $p(x|y) = p(y|x)\,p(x)$

    [prob of model given vector equals Prob of vector given class times Prob of class

→ No need to divide by prob (y): it's same for all classes