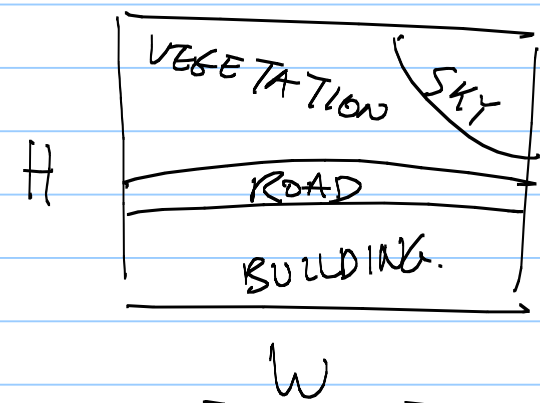
Lecture 1
Day 2.

Image Labelling

Note Title 4/15/2007

Images



Dataset of images. The images are segmented by hand into different regions labelled by $m \in M$ M - set of labels

E.g. $M = \{$ sky, vegetation, road, building, other $\}$.

Images. $\quad I(i,j) \quad i = 1$ to W
$j = 1$ to H

$I(i,j) \in \{0, 1, 2, \dots, 255\}$.

Colour images: $R(i,j), B(i,j), G(i,j)$
red, blue, green.

(2)

Apply filters to the images.

Filter $\phi_\mu(i,j)$, linear filter. $\mu \in \Lambda$

Discrete $\phi_\mu * I(i,j) = \sum_{k,l} \phi_\mu(i-k, j-l)\, I(k,l)$

Continuous. $\phi_\mu * I(x,y) = \int \phi_\mu(x-u, y-v)\, I(u,v)\, du\, dv.$

Strategy: used the labelled images to learn conditional distribution.

$P(\phi_\mu(i,j) \mid (i,j) \in \text{Region Class } m)$

Problem: (i) how to represent the distribution and learn it.
(ii) how to generalize the distribution to next images?

Representation of the distribution:
(i) parametric distributions (e.g. Gaussian)
(ii) non-parametric (e.g. histogram).

(3)

Trade-offs.

Probability models involve only a small number of parameters (e.g. mean and variance of Gaussian).

This makes it easier to learn them and requires less training data. Typically you need $k \times m$ examples to learn a probability model with m degrees of freedom, and $k \sim 5, 10$.

Learning: Generalization versus Memorization

Basic Assumptions of Learning:

Training examples. $D = \{X_i : i = 1 \text{ to } N\}$ assumed to come from an unknown distribution $P(X)$.

How can we learn the distribution from D, so that the model applies to data from $P(x)$ than we haven't seen yet.

(4)

<u>Memorization</u>: the model learnt from data D is un-representative of $P(x)$.

<u>Generalization</u>: the model learnt from D is similar to $P(x)$.

Learning requires generalization — otherwise it is only memorization.

A sufficient amount of data is required for memorization — $k \times M$ (M no. of parameters)

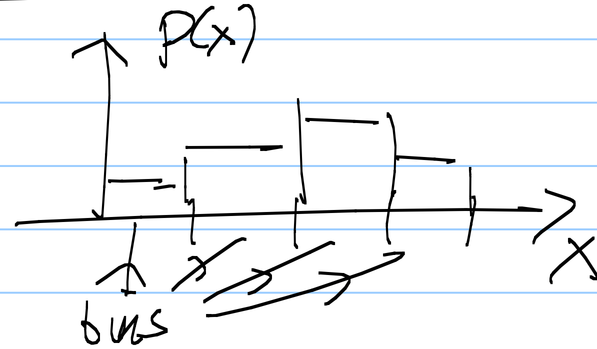
<u>Curse of Dimensionality</u>

the number of parameters increases with the dimensionality of the data. E.G. Gaussian model requires $O(N^2)$ parameters, where N is the dimension of the space.

Amount of data required for generalization grows by $O(N^2)$ as the dimensionality of the data increases.

(5)

Histogram Representation.



$$P(x) = \frac{n_i}{n}, \quad \text{if} \quad x \in [x_{i-1}, x_i]$$

$\{x_i : i = 0, \ldots, m\}$ bin boundaries

$$\sum_{i=1}^{m} n_i = n. \qquad \{n_i \geq 0,\ i = 1, \ldots, m\}.$$

Note: the bin boundaries can be evenly spaced, or adaptively spaced (better, but more complicated).

The histogram makes few assumptions about the distribution.

Bad in many dimensions — the number of bins grows like $\{m\}^N$ (exponentially)

(6)

Back to Images and Segmentation.

Apply filters to images

Filters: Typical image filters.

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

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}.$$

Gaussian

2x2 matrix. $\underline{\underline{N}} = \int G(x:) \, \underline{\nabla I} \, \underline{\nabla I}^T dx$

$$\underline{\nabla I} = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right) \text{ vector.}$$

On image lattice, approximate the derivatives by finite differences. E.G. $\frac{\partial I}{\partial x} \to (I_{i+1,j} - I_{i,j})$

or higher order discretizations

We can smooth images by a Gaussian, and then apply these operators. Gives a scale space representation.

Choose a representation for the distribution.

Learn $P(\phi_\mu(i,j) \mid (i,j) \in \text{Region } m)$

Classify $m^*(i,j) = \underset{m}{\text{ARG MAX}}\ P(\phi_\mu(i,j) \mid m)$

To obtain errors, calculate the confusion table $P(m^* \mid m)$. If $m^* = m$, then correct classification — otherwise an error.

Results → see Konishi & Yuille paper

This approach is effective at classifying pixels for classes {ROAD, SKY, VEGETATION}

Combine cues by joint distribution
$P(\phi_\mu(i,j), \phi_\nu(i,j) \mid (i,j) \in \text{Region } m)$

Moral: simple statistics can work.