Weekly Exercise 10

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June 21, 2016 (submission deadline: June 28, 2016)

Mean Field Approximation (4 Points)

Exercise 1 (**Naive Mean Field**, 4 Points)**.** Assume a graphical model $G = (\mathcal{V}, \mathcal{E})$ and consider a factorized distribution in the following form:

$$q(y) = \prod_{i \in \mathcal{V}} q_i(y_i). \tag{1}$$

a) Show that the marginal distribution of a factor F is given by:

$$\mu_{F,y_F}(q) = q_{N(F)}(y_F) = \prod_{i \in N(F)} q_i(y_i) \ .$$

b) Show that the entropy decomposes as:

$$H(q) = \sum_{i \in \mathcal{V}} H_i(q_i) \ ,$$

where

$$H_i(q) = -\sum_{y_i \in \mathcal{Y}_i} q_i(y_i) \log q_i(y_i) \ .$$

Programming (10 Points)

Exercise 2 (**Multi-class image segmentation with fully connected CRF**, 10 points)**.** Let us consider the multi-class labeling problem for image segmentation. Assuming the label set $\mathcal{L}$, we define the following energy function for $\mathbf{y} \in \mathcal{L}^{\mathcal{V}}$:

$$E(\mathbf{y}) = \sum_{i \in \mathcal{V}} E_i(y_i) + \sum_{(i,j) \in \mathcal{E}} E_{ij}(y_i, y_j) \ , \tag{2}$$

on a fully connected CRF model, i.e. $\mathcal{E} = \{(i,j) \in \mathcal{V} \times \mathcal{V} \mid i < j\}$.

The goal of the exercise is to implement the `naive mean field approximation` algorithm in order to obtain multi-class segmentation results for test images shown in Figure 1. As you have seen in the previous exercises, these images come from a subset of the MSRC image understanding dataset, which contains 21 classes, i.e. $\mathcal{L} = \{1, 2, \ldots, 21\}$.

To define the unary energy functions E_i for $i \in \mathcal{V}$, use the provided `*.c_unary` files. Each test image has its own unary file, specified by the same filename. In each unary file, you can read out a $K \times H \times W$ array of float numbers. The H and W are the image height and width, and $K = 21$ is the number of possible classes. This array contains the 21-class probability distribution for each pixel. We provide the `multilabel_demo.cpp` to demonstrate how to load the unary file and read out the corresponding probability values. The unary energy functions E_i for all $i \in \mathcal{V}$ are then defined as

$$E_i(y_i = l) = -\log(p_l) \ .$$

To define the pairwise energy E_{ij} for $(i,j) \in \mathcal{E}$, use the contrast sensitive Potts model:

$$E_{ij}(y_i, y_j) = [\![y_i \neq y_j]\!] \left(w_1 \exp\left(-\frac{|p_i - p_j|^2}{2\theta_\alpha^2} - \frac{|I_i - I_j|^2}{2\theta_\beta^2} \right) + w_2 \exp\left(-\frac{|p_i - p_j|^2}{2\theta_\gamma^2} \right) \right),$$

where the parameter are chosen as

$$w_1 = 10,\ w_2 = 3,\ \theta_\alpha = 80,\ \theta_\beta = 13,\ \theta_\gamma = 3\ .$$

Figure 1: Test images for multi-class image segmentation.