

**GRAPHICAL MARKOV MODELS (WS2016)**  
**3. SEMINAR**

**Assignment 1\*** Suppose that a regular language  $\mathcal{L}$  of strings over the finite alphabet  $\Sigma$  is described by a non-deterministic finite-state machine. Given a string  $y \notin \mathcal{L}$ , the task is to find the string  $x \in \mathcal{L}$  with smallest Hamming distance to  $y$ , i.e.

$$x^* = \arg \min_{x \in \mathcal{L}} d_h(x, y),$$

where  $d_h$  denotes the Hamming distance. Construct an efficient algorithm for solving this task.

**Assignment 2.** Let  $\mathbf{x}$  be a grey value image of size  $n \times m$ , where  $x_{ij}$  denotes the grey value of the pixel with coordinates  $(i, j)$ . The task is to segment such images into an upper and lower part by a boundary represented as a sequence of height values  $s_j \in \{1, 2, \dots, n\}$  for all  $j = 1, 2, \dots, m$ .

The prior probability for boundaries is assumed to be a homogeneous Markov chain such that  $p(s_j | s_{j-1}) = 0$  if  $|s_j - s_{j-1}| > 1$ . The appearance model for columns  $\mathbf{x}_j$  given the boundary value  $s_j$ , is assumed to be conditional independent

$$p(\mathbf{x}_j | s_j) = \prod_{i \leq s_j} p_1(x_{ij}) \cdot \prod_{i > s_j} p_2(x_{ij}),$$

where  $p_1()$  and  $p_2()$  are two distributions for grey values.

**a)** Deduce an efficient algorithm for determining the most probable boundary.

**b\*)** Suppose that the loss function  $\ell(s, s')$  for incorrectly recognised boundaries is defined by

$$\ell(s, s') = \sum_{j=1}^m (s_j - s'_j)^2.$$

Formulate the segmentation task for this case. Deduce an efficient inference algorithm.

**Assignment 3.** Consider an HMM for pairs of sequences  $(\mathbf{x}, \mathbf{s})$ ,  $\mathbf{x} \in F^n$ ,  $\mathbf{s} \in K^n$  with unknown transition probabilities and emission probabilities. It is however known that the model is homogeneous. An i.i.d. sample of training data  $\mathcal{T} = \{(\mathbf{x}^j, \mathbf{s}^j) | j = 1, \dots, m\}$  is given for learning. Modify the formulae for the maximum likelihood estimate (see Sec. 7 in lecture notes) for this situation. Prove correctness.

**Assignment 4.** Consider the following variation of the previous assignment. The observable features are no longer discrete – instead, they are real numbers, i.e.,  $F = \mathbb{R}$ . It is known, that the emission probabilities are Gaussian distributions. For each hidden state  $k \in K$  there is a Gaussian p.d.

$$p(x | k) = \frac{1}{\sqrt{2\pi}\sigma_k} e^{-\frac{(x-\mu_k)^2}{2\sigma_k^2}}$$

with unknown mean and variance. Derive formulae for learning these model parameters.