

Assignment 2

Statistical Methods in Applied Computer Science

DD2447

Jim Holmström 890503-7571
jimho@kth.se

November 21, 2012

Exercise A1 Compute $p(D|T \in \text{Polytree})$ with Bernoulli CPD's
Show how to compute $p(D|T)$ where T is a DGM which is a polytree and $D = \{x_1, \dots, x_N\}$ (and x_i is an assignment of values to all variables of T). Assume that all variables are binary and all CPD's Bernoulli.

Solution.

Exercise A2 Marginalize over non-observed variables
Assume instead that each x_i is an assignment to a subset of the variables say O . Show how to marginalize over $V \setminus O$ (i.e., the non-observed variables).

Solution.

Exercise 11.3 EM for the mixtures of Bernoullis

- Show that the M step for ML estimation of a mixture of Bernoullis is given by

$$\mu_{kj} = \frac{\sum_i r_{ik} x_{ij}}{\sum_i r_{ik}} \quad (1)$$

- Show that the M step for MAP estimation of a mixture of Bernoullis with a $\beta(\alpha, \beta)$ prior is given by

$$\mu_{kj} = \frac{(\sum_i r_{ik} x_{ij}) + \alpha - 1}{(\sum_i r_{ik}) + \alpha + \beta - 1} \quad (2)$$

Solution. The M step is to optimize the auxiliary function Q with respect to π, θ' . Q is the expected log-likelihood with respect to the former parameter θ and the observed data D .¹ The expression for this is

$$Q(\theta', \theta) = \mathbb{E} [\ell(\theta') | D, \theta] \quad (3)$$

and to derive the expression we will use when optimizing with ML/MAP we start with introducing the latent variable z_i which corresponds to the hidden or missing variables which basically is the *r.v.* for how x_i is in the class k ².

$$Q(\theta', \theta) = \mathbb{E} \left[\sum_i \log p(x_i, z_i | \theta') \right] \quad (4)$$

since \mathbb{E} is linear and we can factor on the different classes and the factors becomes given only the parameters (π_k, θ'_k) of class k :

$$= \sum_i \mathbb{E} \left[\log \left[\prod_k (\pi_k p(x_i | \theta'_k))^{\mathbb{I}(z_i=k)} \right] \right] \quad (5)$$

then log the inner parts and let \mathbb{E} operate on the expression like this:

$$= \sum_i \sum_k \mathbb{E} [\mathbb{I}(z_i = k)] \log [p(x_i | \theta'_k)] \quad (6)$$

then we put the expected $\mathbb{E} [\mathbb{I}(z_i = k)]$ to be $p(z_i = k | x_i, \theta) = r_{ik}$ that is the expected class belonging of x_i given the previous parameters θ . Now put in the denotation r_{ik} and use the log on product rule to finally get

$$= \sum_i \sum_k r_{ik} \log \pi_k + \sum_i \sum_k r_{ik} \log p(x_i | \theta'_k) \quad (7)$$

Now since we have that $\sum_{i,k} r_{ik} \log \pi_k \perp \sum_{i,k} r_{ik} \log p(x_i | \theta'_k)$ we can optimize the parameters π_k and θ'_k separately and only the θ'_k -term is asked for in the exercise which will be denoted by $\ell(\theta'_k)$.

The model parameters in this case is denoted by μ_k which is a vector and in index-notation μ_{kj} ³.

We start with the ML

$$\hat{\mu}'_k = \underset{\mu'_k}{argmax} \left\{ \sum_i r_{ik} \log p(x_i | \mu'_k) \right\} \quad (8)$$

¹It can be shown that Q is so that the new parameters is always better or as good as the last one, but exclude this proof.

²Responsibility $r_{ik} \triangleq p(z_i = k | x_i, \theta)$

³Not using Einstein notation for Tensor product.

which we find by $\frac{\partial \ell(\mu'_k)}{\partial \mu'_k} = 0$, where $\prod_j p(x_{ij} | \mu'_{kj})$ is the multivariate Bernoulli for class k

$$\frac{\partial(\ell(\mu'_k))}{\partial \mu'_{kj}} = \frac{\partial \sum_i r_{ik} \log \prod_{j'} p(x_{ij'} | \mu'_{kj'})}{\partial \mu'_{kj}} = \frac{\partial \sum_{i,j'} r_{ik} \log p(x_{ij'} | \mu'_{kj'})}{\partial \mu'_{kj}} = \left\{ \frac{\partial \sum_{j \neq j'} (\cdot)}{\partial \mu'_{kj}} = 0 \right\} = \quad (9)$$

$$= \frac{\partial \sum_i r_{ik} \log \left(\mu'_{kj} x_{ij} (1 - \mu'_{kj})^{(1-x_{ij})} \right)}{\partial \mu'_{kj}} = \frac{\partial \sum_i r_{ik} x_{ij} \log \mu'_{kj} + r_{ik} (1 - x_{ij}) \log(1 - \mu'_{kj})}{\partial \mu'_{kj}} = \quad (10)$$

$$= \sum_i r_{ik} \frac{x_{ij}}{\mu'_{kj}} - r_{ik} \frac{1 - x_{ij}}{1 - \mu'_{kj}} = \sum_i r_{ik} \frac{\mu'_{kj} - x_{ij}}{\mu'_{kj}(\mu'_{kj} - 1)} \quad (11)$$

now find the zero of this expression

$$\sum_i r_{ik} \frac{\mu'_{kj} - x_{ij}}{\mu'_{kj}(\mu'_{kj} - 1)} = 0 \quad (12)$$

$$\sum_i r_{ik} \mu'_{kj} - r_{ik} x_{ij} = 0 \quad (13)$$

$$\mu'_{kj} \sum_i r_{ik} = \sum_i r_{ik} x_{ij} \quad (14)$$

$$\mu'_{kj} = \frac{\sum_i r_{ik} x_{ij}}{\sum_i r_{ik}} \quad (15)$$

which is the same as the equation (1).