CS-E4820 Machine Learning: Advanced Probabilistic Methods

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Problem 1. "EM for missing observations."

Suppose random variables X_i follow a bivariate normal distribution $X_i \sim \mathcal{N}_2(0, \Sigma)$, where

 $\Sigma = \left[\begin{array}{cc} 1 & \rho \\ \rho & 1 \end{array} \right].$

Suppose further that we have observations on $X_1 = (X_{11}, X_{12})^T$, $X_2 = (X_{21}, X_{22})^T$ and $X_3 = (X_{31}, X_{32})^T$, such that X_1 and X_3 are fully observed, and from X_2 we have observed only the second coordinate. Thus, our data matrix can be written as

$$\left[\begin{array}{cc} x_{11} & x_{12} \\ ? & x_{22} \\ x_{31} & x_{32} \end{array}\right],$$

where the rows correspond to the transposed observations $\mathbf{x}_1^T, \mathbf{x}_2^T, \mathbf{x}_3^T$. Suppose we want to learn the unknown parameter ρ using the EM-algorithm. Denote the missing observation by Z and derive the E-step of the algorithm, i.e., (1) write the complete data log-likelihood $\ell(\rho)$, (2) compute the posterior distribution of the missing observation, given the observed variables and current estimate for ρ , and (3) evaluate the expectation of $\ell(\rho)$ with respect to the posterior distribution of the missing observations.

Hints:

1. In general, for $X \sim \mathcal{N}_2(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where $X = (X_1, X_2)^T$, $\boldsymbol{\mu} = (\mu_1, \mu_2)^T$ and $\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{pmatrix}$, we have

$$X_1|X_2 = x_2 \sim \mathcal{N}\left(\mu_1 + \frac{\sigma_1}{\sigma_2}\rho(x_2 - \mu_2), (1 - \rho^2)\sigma_1^2\right),$$

with ρ being the correlation coefficient.

- 2. For evaluating the expectation of $\ell(\rho)$, you can make use of the following two rules:
 - $\mathbf{x}_2^T \mathbf{\Sigma}^{-1} \mathbf{x}_2 = \operatorname{trace}(\mathbf{\Sigma}^{-1} \mathbf{x}_2 \mathbf{x}_2^T)$.
 - if $X \sim \mathcal{N}(\mu, \sigma^2)$ then $\langle X^2 \rangle = \mu^2 + \sigma^2$.

Problem 2. "Extension of the "simple example" from the lecture."

Suppose that we have N independent observations $\mathbf{x} = (x_1, \dots, x_N)$ from a two-component mixture of univariate Gaussian distributions with unknown mixing coefficients and unknown mean of the second component:

$$p(x_n|\theta,\tau) = (1-\tau)\mathcal{N}(x_n|0,1) + \tau\mathcal{N}(x_n|\theta,1).$$

- (a) Write down the complete data log-likelihood and derive the EM-algorithm for learning the maximum likelihood estimates for θ and τ .
- (b) Implement the EM-algorithm. Simulate some data from the model (N=100 samples) with the true values of parameters $\theta=3$ and $\tau=0.5$. Run your EM algorithm to see whether the learned parameters converge close to the true values (by e.g. just listing the estimates from a few iterations or plotting them). Instructions: Use ex5.2 template.py as a starting point. As a further aid, you can

Instructions: Use ex5_2_template.py as a starting point. As a further aid, you can use ex5_2_simple_em.py, which is a Python implementation of simple_example.pdf from the lecture material. Include your implementation of the E and M steps in your solutions.

Problem 3. "Probabilistic programming with Edward."

Read the first four pages of the article: Dustin Tran, Alp Kucukelbir, Adji B. Dieng, Maja Rudolph, Dawen Liang, and David M. Blei (2016). *Edward: A library for probabilistic modeling, inference, and criticism*, https://arxiv.org/abs/1610.09787. Get familiar with Edward using the notebook getting_started.ipynb, and answer the following questions (you can also refer to Edward's documentation in http://edwardlib.org/or any other source you can find):

- 1. What is a probabilistic programming language?
- 2. Why is probabilistic programming needed?
- 3. What is Edward?
- 4. What are the three steps in the iterative process for probabilistic modeling that Edward is built around?
- 5. Identify parts of the example probabilistic program (on p. 3–4) that correspond to the three steps mentioned in the previous question.