

Question:

Considering The graphical model $z \rightarrow x$ where z and x are two random variables. And the joint distribution of x, z can be given as follows:

$$P(x, z) = P(z)P(x|z)$$

Where z is a latent variable. If we assume $p(z) = N(z|\mathbf{0}, \mathbf{I})$ and $x = \mathbf{W}z + \boldsymbol{\mu} + \epsilon$. The dimension of each sample is D , $\boldsymbol{\mu}$ is the mean vector of random variable x and $\epsilon \sim N(\mathbf{0}, \sigma^2 \mathbf{I})$. Denote \mathbf{X} as data matrix. Try to derive the maximum likelihood form of variable x .

solution:

If $P(x, z) = P(z)P(x|z)$, then we have $p(x) = \int p(x|z)p(z)dz$. And we can get:

$$\begin{aligned} E[x] &= \int_{-\infty}^{+\infty} x f_X(x) dx = \int_{-\infty}^{+\infty} x \left[\int_{-\infty}^{+\infty} f_Z(z) f_{X|Z}(x|z) dz \right] dx \\ &= \int_{-\infty}^{+\infty} \left\{ \int_{-\infty}^{+\infty} x f_{X|Z}(x|z) dx \right\} f_Z(z) dz \\ &= E_z[E_x[x|z]] = E_z[\mathbf{W}z + \boldsymbol{\mu}] \end{aligned}$$

$$\begin{aligned} Var[x] &= E_z\{E_x(x^2|z) - E_x^2(x|z)\} \\ &= E[x^2] - E_z[E_x^2(x|z)] + E_z[E_x^2(x|z)] - E_z^2(E_x[x|z]) \\ &= E_z[Var_x[x|z]] + Var_z[E_x[x|z]] \\ &= E_z[\sigma^2 \mathbf{I}] + Var_z[\mathbf{W}z + \boldsymbol{\mu}] = \sigma^2 \mathbf{I} + \mathbf{W}\mathbf{W}^T \end{aligned}$$

Thus, $p(x) = N(x|\boldsymbol{\mu}, \mathbf{W}\mathbf{W}^T + \sigma^2 \mathbf{I})$, which lead to $P(\mathbf{X}|\boldsymbol{\mu}, \mathbf{W}, \sigma^2) = \prod_{n=1}^N p(x_n|\boldsymbol{\mu}, \mathbf{W}, \sigma^2)$. The log likelihood function can be written as:

$$\begin{aligned} \log p(\mathbf{X}|\boldsymbol{\mu}, \mathbf{W}, \sigma^2) &= \sum_{n=1}^N \log p(x_n|\boldsymbol{\mu}, \mathbf{W}, \sigma^2) \\ &= -\frac{ND}{2} \log(2\pi) - \frac{N}{2} \log |\mathbf{W}\mathbf{W}^T + \sigma^2 \mathbf{I}| \\ &\quad - \frac{1}{2} \sum_{n=1}^N (x_n - \boldsymbol{\mu})^T (\mathbf{W}\mathbf{W}^T + \sigma^2 \mathbf{I}) (x_n - \boldsymbol{\mu}) \\ &= -\frac{N}{2} \{D \log(2\pi) + \log |\mathbf{C}| + Tr(\mathbf{C}^{-1} \mathbf{S})\} \end{aligned}$$

where $\mathbf{C} = \mathbf{W}\mathbf{W}^T + \sigma^2\mathbf{I}$, $\mathbf{S} = \frac{1}{N} \sum_{n=1}^N (x_n - \mu)(x_n - \mu)^T$