1 A binary child given a binary parent

Let X and Y be two binary variables. The conditional probability of the child-node X given the parent-node Y is expressed as follows:

$$p(X|Y) = p_{x|y}^{I(Y=0)I(X=0)} p_{\bar{x}|y}^{I(Y=0)I(X=1)} p_{x|\bar{y}}^{I(Y=1)I(X=0)} p_{\bar{x}|\bar{y}}^{I(Y=1)I(X=1)}$$

This conditional probability can be expressed in different exponential forms as follows:

• First form:

$$\ln p(X|Y) = \theta^T s(X,Y) - A(\theta)$$

$$= \begin{pmatrix} \ln p_{x|y} \\ \ln p_{\bar{x}|y} \\ \ln p_{x|\bar{y}} \\ \ln p_{\bar{x}|\bar{y}} \end{pmatrix}^T \begin{pmatrix} I(X=0)I(Y=0) \\ I(X=1)I(Y=0) \\ I(X=0)I(Y=1) \\ I(X=1)I(Y=1) \end{pmatrix} - 0$$

• Second form:

$$\ln p(X|Y) = \theta(Y)^T s(X) - A(Y)
= \begin{pmatrix} I(Y=0) \ln p_{x|y} + I(Y=1) \ln p_{x|\bar{y}} \\ I(Y=0) \ln p_{\bar{x}|y} + I(Y=1) \ln p_{\bar{x}|\bar{y}} \end{pmatrix}^T \begin{pmatrix} I(X=0) \\ I(X=1) \end{pmatrix} - 0
= \begin{pmatrix} m_0^Y \cdot \theta_0 + m_1^Y \cdot \theta_2 \\ m_0^Y \cdot \theta_1 + m_1^Y \cdot \theta_3 \end{pmatrix}^T \begin{pmatrix} I(X=0) \\ I(X=1) \end{pmatrix} - 0$$

• Third form:

$$\begin{split} \ln p(X|Y) &= \theta(X)^T s(Y) - A(X) \\ &= \left(\begin{matrix} I(X=0) \ln p_{x|y} + I(X=1) \ln p_{\bar{x}|y} \\ I(X=0) \ln p_{x|\bar{y}} + I(X=1) \ln p_{\bar{x}|\bar{y}} \end{matrix} \right)^T \left(\begin{matrix} I(Y=0) \\ I(Y=1) \end{matrix} \right) - 0 \\ &= \left(\begin{matrix} m_0^X \theta_0 + m_1^X \theta_1 \\ m_0^X \theta_2 + m_1^X \theta_3 \end{matrix} \right)^T \left(\begin{matrix} I(Y=0) \\ I(Y=1) \end{matrix} \right) - 0 \end{split}$$

2 A multinomial child given a set of multinomial parents

Let X be a multinomial variable whose state space is $\{x^1,...,x^k\}$, and let $\mathbf{Y}=Y_1,...,Y_n$ denote the set of parents of X, such that all of them are multinomial. Each parent Y_i has r_i states $\{y_1^{r_1},y_2^{r_2},...,y_n^{r_n}\}$ with $r_i\geq 2$. The log-conditional probability of the child-node X given the parent-nodes \mathbf{Y} can be expressed as follows:

$$\ln p(X|Y_1,\ldots,Y_n) =$$

Similarly the above conditional probability can be expressed in the following exponential forms:

• First form:

$$\ln p(X|Y_1,\ldots,Y_n) = \theta^T s(X,Y_1,\ldots,Y_n) - A(\theta)$$

• Second form:

$$\ln p(X|Y_1,...,Y_n) = \theta(Y_1,...,Y_n)^T s(X) - A(Y_1,...,Y_n)$$

• Third form:

$$\ln p(X|Y_1, \dots, Y_n) = \theta(X, Y_1, \dots, Y_{l-1}, Y_l, \dots, Y_n)^T s(Y_l) - A(X, Y_1, \dots, Y_{l-1}, Y_l, \dots, Y_n)$$

3 A normal child given a set of normal parents

Let X be a normal variable and $\mathbf{Y} = \{Y_1, \dots, Y_n\}$ denote the set of parents of X, such that all of them are normal. The log-conditional probability of X given \mathbf{Y} can be expressed as follows:

$$\ln p(X|Y_1,\ldots,Y_n) = \ln \left(\frac{1}{\sigma \sqrt{2(\beta_0 + \sum_{i=1}^n \beta_i Y_i)}} e^{-\frac{(y - (\beta_0 + \sum_{i=1}^n \beta_i Y_i))^2}{2\sigma^2}} \right)$$

Similarly the above conditional probability can be expressed in the following exponential forms:

• First form:

$$\begin{array}{lll} \ln p(X|Y) & = & \theta^T s(X,Y) - A(\theta) + h(Y) \\ & \begin{pmatrix} \frac{-1}{2\sigma^2} & = & \theta_{-1} \\ -\frac{\beta^2}{2\sigma^2} & = & \theta_{1^2} \\ \vdots & \ddots & & & \\ -\frac{\beta^2}{2\sigma^2} & = & \theta_0 \\ \frac{\beta_1}{\sigma^2} & = & \theta_0 \\ \frac{\beta_1}{\sigma^2} & = & \theta_1 \\ \vdots & \ddots & & & \\ -\frac{\beta_0\beta_1}{\sigma^2} & = & \theta_0 \\ -\frac{\beta_0\beta_1}{\sigma^2} & = & \theta_{01} \\ \vdots & \ddots & & & \\ -\frac{\beta_0\beta_n}{\sigma^2} & = & \theta_{0n} \\ -\frac{\beta_1\beta_2}{\sigma^2} & = & \theta_{12} \\ \vdots & \ddots & & & \\ -\frac{\beta_1\beta_n}{\sigma^2} & = & \theta_{1n} \\ \vdots & \ddots & & & \\ -\frac{\beta_1\beta_n}{\sigma^2} & = & \theta_{1n} \\ \vdots & \ddots & & & \\ -\frac{\beta_n-1\beta_n}{\sigma^2} & = & \theta_{n-1n} \end{pmatrix} - \begin{pmatrix} \frac{\beta^2}{2\sigma^2} + \ln \sigma \end{pmatrix} + \frac{1}{\ln \sqrt{2\mu_{X|Y}}} \\ \begin{pmatrix} XY_n \\ XY_1 \\ \vdots \\ Y_n \\ Y_1Y_2 \\ \vdots \\ Y_n \\ Y_1Y_n \\ \vdots \\ Y_{n-1}Y_n \end{pmatrix}$$

• Second form:

$$\begin{split} \ln p(X|Y) &= \theta(Y)^T s(X) - A(\theta(Y)) + h(Y) \\ &= \left(\frac{\frac{\mu_{X|Y}}{\sigma_1^2}}{\frac{\sigma_1^2}{2\sigma^2}}\right)^T \left(\frac{X}{X^2}\right) - \left(\frac{\mu_{X|Y}^2}{2\sigma^2} + \ln \sigma\right) + \ln \frac{1}{\sqrt{2\mu_{X|Y}}} \\ &= \left(\frac{\theta_0 + \theta_i m_0^{Y_i}}{\theta_{-1}}\right)^T \left(\frac{X}{X^2}\right) - \left(\frac{\mu_{X|Y}^2}{2\sigma^2} + \ln \sigma\right) + \ln \frac{1}{\sqrt{2\mu_{X|Y}}} \end{split}$$

where $\mu_{X|Y} = \beta_0 + \sum_{i=1}^{n} \beta_i Y_i$

• Third form:

$$\begin{array}{lll} \ln p(X|Y) & = & \theta(X)^T s(Y) - A(\theta(X)) + h(Y) \\ & = & \begin{pmatrix} -\frac{\beta_1^2}{2\sigma^2} \\ \vdots \\ -\frac{\beta_n^2}{2\sigma^2} \\ \frac{\beta_1(X-\beta_0)}{\sigma^2} \\ \vdots \\ -\frac{\beta_1\beta_2}{\sigma^2} \\ \vdots \\ -\frac{\beta_1\beta_n}{\sigma^2} \\ \vdots \\ -\frac{\beta_{n-1}\beta_n}{\sigma^2} \end{pmatrix}^T \begin{pmatrix} Y_1^2 \\ \vdots \\ Y_n \\ Y_1Y_2 \\ \vdots \\ Y_1Y_2 \\ \vdots \\ \vdots \\ Y_{n-1}Y_n \end{pmatrix} \\ & = & \begin{pmatrix} \theta_{1^2} \\ \vdots \\ \theta_{n^2} \\ \theta_1 m_0^X + \theta_{01} \\ \vdots \\ \theta_n m_0^X + \theta_{0n} \\ \theta_{12} \\ \vdots \\ \theta_n m_0^X + \theta_{0n} \\ \theta_{12} \\ \vdots \\ \theta_{n-1n} \end{pmatrix}^T \begin{pmatrix} Y_1^2 \\ \vdots \\ Y_n \\ Y_1Y_2 \\ \vdots \\ Y_n \\ \vdots \\ Y_n \\ Y_1Y_2 \\ \vdots \\ \vdots \\ Y_1Y_1 \\ \vdots \\ Y_n \\ Y_1Y_2 \\ \vdots \\ \vdots \\ Y_1Y_n \\ \vdots \\ Y_1Y_1 \\ \vdots$$

Notations

The list below presents a summary of the used notations:

Child variable
Range of possible values of a multinomial variable \boldsymbol{X}
Parent variable
Set of parent variables
Number of parent variables
Range of possible values of a multinomial variable Y_i
Parent variable index
Probability distribution