

ANALYZING THE EFFECT OF INTRODUCING A KURTOSIS PARAMETER IN GAUSSIAN BAYESIAN NETWORKS



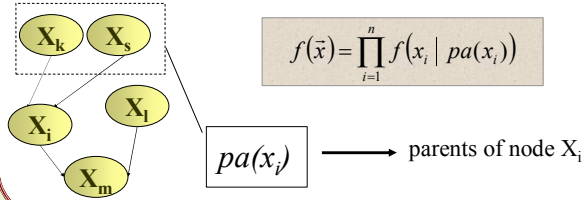
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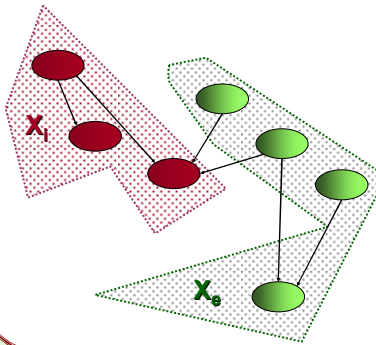
GAUSSIAN BAYESIAN NETWORKS

$\mathbf{X} = (X_1, \dots, X_n)$ Multivariate Normal $N_n(\boldsymbol{\mu}, \boldsymbol{\Sigma})$



$$f(\vec{x}) = \prod_{i=1}^n f(x_i | pa(x_i))$$

NETWORK'S OUTPUT



$\mathbf{X} = \begin{cases} X_i & \rightarrow \text{"interest"} \\ X_e & \rightarrow \text{"evidence"} \end{cases}$

Conditional Distribution

$$f(X_i | X_e)$$

EXPONENTIAL POWER DISTRIBUTION

$\mathbf{X} = (X_1, \dots, X_n)$ random vector $EP_n(\boldsymbol{\mu}, \boldsymbol{\Sigma}, \beta)$

$$f_\beta(\vec{x}) = \frac{n \Gamma\left(\frac{n}{2}\right)}{\pi^{\frac{n}{2}} \Gamma\left(1 + \frac{n}{2\beta}\right) 2^{\frac{1+n}{2\beta}}} |\boldsymbol{\Sigma}|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}[(\vec{x} - \vec{\mu})^T \boldsymbol{\Sigma}^{-1}(\vec{x} - \vec{\mu})]^\beta\right\}$$

$\beta \in (0, \infty)$

$\beta = 1$ Multivariate Normal

$\beta = 0.5$ Multivariate Double Exponential

$\beta \rightarrow \infty$ Uniform

KULLBACK-LEIBLER DIVERGENCE

A quantity which measures the difference between two probability distributions

$$D_{KL}(p, q) = \int p(x) \log\left(\frac{p(x)}{q(x)}\right) dx$$

SENSITIVITY ANALYSIS

$\mathbf{X} = \begin{cases} (X_i)^{(p)} \\ (X_e)^{(n-p)} \end{cases} \begin{cases} \rightarrow EP_n(\boldsymbol{\mu}, \boldsymbol{\Sigma}, \beta) \rightarrow f_\beta(X_i | X_e) \sim E_p(\boldsymbol{\mu}_{i,e}, \boldsymbol{\Sigma}_{i,e}, \mathbf{g}_{i,e}) \text{ (elliptical distribution)} \\ \rightarrow N_n(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \rightarrow f(X_i | X_e) \sim N_p(\boldsymbol{\mu}_{i,e}, \boldsymbol{\Sigma}_{i,e}) \end{cases}$

$$\begin{aligned} \boldsymbol{\mu}_{i,e} &= \boldsymbol{\mu}_i + \boldsymbol{\Sigma}_{ie}(\boldsymbol{\Sigma}_{ee})^{-1}(\mathbf{x}_e - \boldsymbol{\mu}_e); \boldsymbol{\Sigma}_{i,e} = \boldsymbol{\Sigma}_{ii} - \boldsymbol{\Sigma}_{ie}(\boldsymbol{\Sigma}_{ee})^{-1}\boldsymbol{\Sigma}_{ei} \\ \mathbf{g}_{i,e}(\mathbf{t}) &= \exp\{-\frac{1}{2}(\mathbf{t} + \mathbf{q}_e)^\beta\} \\ \mathbf{q}_e &= (\mathbf{x}_e - \boldsymbol{\mu}_e)^T (\boldsymbol{\Sigma}_{ee})^{-1} (\mathbf{x}_e - \boldsymbol{\mu}_e) \end{aligned}$$

$$D_{KL}(f(X_i | X_e), f_\beta(X_i | X_e))$$

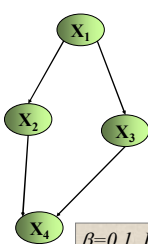
$$f_\beta(x_i | x_e) = \frac{\Gamma\left(\frac{p}{2}\right)}{\pi^{\frac{p}{2}} \int_0^\infty t^{\frac{p}{2}-1} \exp\left\{-\frac{1}{2}(t + q_e)^\beta\right\} dt} |\boldsymbol{\Sigma}_{i,e}|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2} \left[(x_i - \boldsymbol{\mu}_{i,e})^T (\boldsymbol{\Sigma}_{i,e})^{-1} (x_i - \boldsymbol{\mu}_{i,e}) + q_e \right]^\beta\right\}; f(x_i | x_e) = \frac{1}{(2\pi)^{\frac{p}{2}}} |\boldsymbol{\Sigma}_{i,e}|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2} (x_i - \boldsymbol{\mu}_{i,e})^T (\boldsymbol{\Sigma}_{i,e})^{-1} (x_i - \boldsymbol{\mu}_{i,e})\right\}$$

$$D_{KL}(f(x_i | x_e), f_\beta(x_i | x_e)) = \int \left[\log \frac{f(x_i | x_e)}{f_\beta(x_i | x_e)} \right] f(x_i | x_e) dx_i =$$

$$= \log \frac{\int_0^\infty t^{\frac{p}{2}-1} \exp\left\{-\frac{1}{2}(t + q_e)^\beta\right\} dt}{2^{\frac{p}{2}} \Gamma\left(\frac{p}{2}\right)} - \frac{1}{2} \int \left\{ (x_i - \boldsymbol{\mu}_{i,e})^T (\boldsymbol{\Sigma}_{i,e})^{-1} (x_i - \boldsymbol{\mu}_{i,e}) - \left[(x_i - \boldsymbol{\mu}_{i,e})^T (\boldsymbol{\Sigma}_{i,e})^{-1} (x_i - \boldsymbol{\mu}_{i,e}) + q_e \right]^\beta \right\} f(x_i | x_e) dx_i =$$

$$= \log \frac{\int_0^\infty t^{\frac{p}{2}-1} \exp\left\{-\frac{1}{2}(t + q_e)^\beta\right\} dt}{2^{\frac{p}{2}} \Gamma\left(\frac{p}{2}\right)} - \frac{p}{2} + \frac{(q_e)^{\beta + \frac{p}{2}}}{2^{\frac{p}{2}}} \underbrace{U\left(a = \frac{p}{2}, b = \beta + \frac{p}{2} + 1, z = \frac{q_e}{2}\right)}_{\text{KUMMER FUNCTION}}$$

EXAMPLE 1



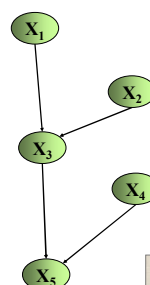
$$\boldsymbol{\mu} = \begin{pmatrix} 3 \\ 4 \\ 9 \\ 14 \end{pmatrix}, \boldsymbol{\Sigma} = \begin{pmatrix} 4 & 4 & 8 & 12 \\ 4 & 5 & 8 & 13 \\ 8 & 8 & 20 & 28 \\ 12 & 13 & 28 & 42 \end{pmatrix}$$

"evidence" $\{X_1=7, X_2=8, X_3=17\} \rightarrow q_e = 4$

"interest" $\{X_4\}$

$$\begin{aligned} \beta=0.1, D_{KL}=52.732; \beta=0.6, D_{KL}=1.808; \beta=0.6, D_{KL}=0.418 \\ \beta=0.9, D_{KL}=0.1043; \beta=1, D_{KL}=0; \beta=1.1, D_{KL}=0.1093 \\ \beta=1.4, D_{KL}=2.046; \beta=2, D_{KL}=21.684; \beta=3, D_{KL}=326.2 \end{aligned}$$

EXAMPLE 2



$$\boldsymbol{\mu} = \begin{pmatrix} 2 \\ 3 \\ 3 \\ 4 \\ 5 \end{pmatrix}, \boldsymbol{\Sigma} = \begin{pmatrix} 3 & 0 & 6 & 0 & 6 \\ 0 & 2 & 2 & 0 & 2 \\ 6 & 2 & 15 & 0 & 15 \\ 0 & 0 & 0 & 2 & 4 \\ 6 & 2 & 15 & 4 & 26 \end{pmatrix}$$

"evidence" $\{X_1=7, X_2=8\} \rightarrow q_e = 20.83$

"interest" $\{X_3, X_4, X_5\}$

$$\begin{aligned} \beta=0.1, D_{KL}=70.59; \beta=0.6, D_{KL}=2.986; \beta=0.8, D_{KL}=0.795 \\ \beta=0.9, D_{KL}=0.213; \beta=1, D_{KL}=0; \beta=1.1, D_{KL}=0.259 \\ \beta=1.4, D_{KL}=6.114; \beta=2, D_{KL}=109.82; \beta=3, D_{KL}=4484.8 \end{aligned}$$