

$$\begin{aligned}
H(\vec{X}_d||\vec{X}_c) &= \sum \int p(\vec{x}_d||\vec{x}_c) \log(p(\vec{x}_d||\vec{x}_c)) d\vec{x}_c \\
&= \sum p(\vec{X}_d = \vec{x}_d) \int p(\vec{x}_c|\vec{X}_d = \vec{x}_d) \log(p(\vec{X}_d = \vec{x}_d)p(\vec{x}_c|\vec{X}_d = \vec{x}_d)) d\vec{x}_c
\end{aligned}$$

$$p(\vec{x}_c|\vec{X}_d = \vec{x}_d) = \frac{1}{n_{\vec{x}_d} \sqrt{2^m \pi^m |\rho|}} \sum_{i=1}^{n_{\vec{x}_d}} e^{-\frac{1}{2}(\vec{x} - \vec{x}_i)^T \rho^{-1} (\vec{x} - \vec{x}_i)}$$

where  $\rho = \rho(n_{\vec{x}_d}, m)\sigma$  where  $c(n_{\vec{x}_d}, m) \in (0, 1]$  and  $\sigma$  is the covariance matrix of  $\vec{X}_c|(\vec{X}_d = \vec{x}_d)$  and  $m$  is the dimensionality of  $\vec{x}_c$

$$H(\vec{X}_d||\vec{X}_c) = \sum \frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^m \pi^m |\rho|}} \sum_{i=1}^{n_{\vec{x}_d}} \int e^{-\frac{1}{2}(\vec{x} - \vec{x}_i)^T \rho^{-1} (\vec{x} - \vec{x}_i)} \log\left(\frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^m \pi^m |\rho|}} \sum_{j=1}^n e^{-\frac{1}{2}(\vec{x} - \vec{x}_j)^T \rho^{-1} (\vec{x} - \vec{x}_j)}\right) d\vec{x}_c$$

$$\text{Let } \vec{u}_i = \vec{x}_c - \vec{x}_i \implies d\vec{u}_i = d\vec{x}_i$$

$$H(\vec{X}_d||\vec{X}_c) = \sum \frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^k \pi^k |\rho|}} \sum_{i=1}^n \int e^{-\frac{1}{2}\vec{u}_i^T \rho^{-1} \vec{u}_i} \log\left(\frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^k \pi^k |\rho|}} \sum_{j=1}^n e^{-\frac{1}{2}(\vec{u}_i + \vec{x}_i - \vec{x}_j)^T \rho^{-1} (\vec{u}_i + \vec{x}_i - \vec{x}_j)}\right) d\vec{u}_i$$

Let  $\theta$  be the orthogonal svd of  $\rho$

$$\text{Let } \vec{\mu}_i = \frac{1}{\sqrt{2}}\theta^{-1}\vec{u}_i \implies \vec{u}_i = \sqrt{2}\theta\vec{\mu}_i \implies \vec{u}_i^T = \sqrt{2}\vec{\mu}_i^T \theta^T \implies d\vec{u}_i = \sqrt{2}|\theta|d\vec{\mu}_i$$

$$\implies e^{-\frac{1}{2}\vec{u}_i^T \rho^{-1} \vec{u}_i} = e^{-\frac{1}{2}\sqrt{2}\vec{\mu}_i^T \theta^T \rho^{-1} \sqrt{2}\theta\vec{\mu}_i} = e^{-\vec{\mu}_i^T \theta^T \rho^{-1} \theta\vec{\mu}_i} = e^{-\vec{\mu}_i^T D \lambda \vec{\mu}_i} = e^{-\sum_{k=1}^m \lambda_k \mu_{i,k}^2} = \prod_{k=1}^m e^{-\lambda_k \mu_{i,k}^2}$$

$$\begin{aligned}
\implies H(\vec{X}_d||\vec{X}_c) &= \sum_{\vec{x}_d \in \vec{X}_d} \frac{\sqrt{2}|\theta_{\vec{x}_d}|p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^k \pi^k |\rho_{\vec{x}_d}|}} \sum_{i=1}^{n_{\vec{x}_d}} \int_{R^m} \prod_{k=1}^m e^{-\lambda_k \mu_{i,k}^2} \log\left(\frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^k \pi^k |\rho_{\vec{x}_d}|}} \sum_{j=1}^n e^{-\frac{1}{2}(\sqrt{2}\theta\vec{\mu}_i + \vec{x}_i - \vec{x}_j)^T \rho^{-1} (\sqrt{2}\theta\vec{\mu}_i + \vec{x}_i - \vec{x}_j)}\right) d\vec{\mu}_i \\
&= \sum_{\vec{x}_d \in \vec{X}_d} \frac{\sqrt{2}|\theta_{\vec{x}_d}|p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^k \pi^k |\rho_{\vec{x}_d}|}} \sum_{i=1}^{n_{\vec{x}_d}} \int_{-\infty}^{\infty} e^{-\lambda_1 \mu_{i,1}^2} \int_{-\infty}^{\infty} e^{-\lambda_2 \mu_{i,2}^2} \dots \int_{-\infty}^{\infty} e^{-\lambda_m \mu_{i,m}^2} \log\left(\frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^k \pi^k |\rho_{\vec{x}_d}|}} \sum_{j=1}^n e^{-\frac{1}{2}(\sqrt{2}\theta\vec{\mu}_i + \vec{x}_i - \vec{x}_j)^T \rho^{-1} (\sqrt{2}\theta\vec{\mu}_i + \vec{x}_i - \vec{x}_j)}\right) d\mu_{i,m} \dots d\mu_{i,2} d\mu_{i,1}
\end{aligned}$$

$$\text{Let } \tau_{i,k} = \sqrt{\lambda_k} \mu_{i,k} \implies \vec{\tau}_i = \vec{\mu}_i \odot \vec{\sqrt{\lambda}} \implies \vec{\mu}_i = \left(\frac{\vec{1}}{\sqrt{\lambda}}\right) \odot \vec{\tau}_i \implies d\vec{\mu}_i = \prod_{k=1}^m \frac{1}{\sqrt{\lambda_k}} d\vec{\tau}_i = \frac{1}{\sqrt{|\rho_{\vec{x}_d}|}} d\vec{\tau}_i = \sqrt{|\rho_{\vec{x}_d}|^{-1}} d\vec{\tau}_i$$

$$\implies H(\vec{X}_d||\vec{X}_c) = \sum_{\vec{x}_d \in \vec{X}_d} \frac{\sqrt{2}|\theta_{\vec{x}_d}|p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^m \pi^m}} \sum_{i=1}^{n_{\vec{x}_d}} \int_{-\infty}^{\infty} e^{-\tau_{i,1}^2} \int_{-\infty}^{\infty} e^{-\tau_{i,2}^2} \dots \int_{-\infty}^{\infty} e^{-\tau_{i,m}^2} \log\left(\frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^m \pi^m |\rho_{\vec{x}_d}|}} \sum_{j=1}^{n_{\vec{x}_d}} e^{-\frac{1}{2}(\sqrt{2}\theta((\frac{\vec{1}}{\sqrt{\lambda}}) \odot \vec{\tau}_i) + \vec{x}_i - \vec{x}_j)^T \rho^{-1} (\sqrt{2}\theta((\frac{\vec{1}}{\sqrt{\lambda}}) \odot \vec{\tau}_i) + \vec{x}_i - \vec{x}_j)}\right) d\tau_{i,m} \dots d\tau_{i,2} d\tau_{i,1}$$

Using Gaussian – Hermite Quadrature where  $H_l$  is the set of Hermitian abscissas with  $l$  evaluation points

$$H(\vec{X}_d||\vec{X}_c) \approx \sum_{\vec{x}_d \in \vec{X}_d} \frac{\sqrt{2}|\theta_{\vec{x}_d}|p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^m \pi^m}} \sum_{i=1}^{n_{\vec{x}_d}} \sum_{\vec{\tau}_i \in H_l^m} \omega_{\tau_i} \log\left(\frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d} \sqrt{2^m \pi^m |\rho_{\vec{x}_d}|}} \sum_{j=1}^{n_{\vec{x}_d}} e^{-\frac{1}{2}(\sqrt{2}\theta((\frac{\vec{1}}{\sqrt{\lambda}}) \odot \vec{\tau}_i) + \vec{x}_i - \vec{x}_j)^T \rho^{-1} (\sqrt{2}\theta((\frac{\vec{1}}{\sqrt{\lambda}}) \odot \vec{\tau}_i) + \vec{x}_i - \vec{x}_j)}\right)$$

$$= \sum_{\vec{x}_d \in \vec{X}_d} \frac{\sqrt{2}|\theta_{\vec{x}_d}|p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d}\sqrt{2^m\pi^m}} \sum_{\vec{\tau}_i \in H_l^m} \omega_{\tau_i} \sum_{i=1}^{n_{\vec{x}_d}} \log\left(\frac{p(\vec{X}_d = \vec{x}_d)}{n_{\vec{x}_d}\sqrt{2^m\pi^m}|\rho_{\vec{x}_d}|}\right) \sum_{j=1}^{n_{\vec{x}_d}} e^{-\frac{1}{2}(\sqrt{2}\theta((\frac{\vec{1}}{\sqrt{\lambda}})\odot\vec{\tau}_i)+\vec{x}_i-\vec{x}_j)^T \rho^{-1}(\sqrt{2}\theta((\frac{\vec{1}}{\sqrt{\lambda}})\odot\vec{\tau}_i)+\vec{x}_i-\vec{x}_j)}$$

$$H(\vec{A}_d||\vec{A}_c, \vec{B}_d||\vec{B}_c) = \sum \int p(\vec{a}_d||\vec{a}_c) \log(p(\vec{b}_d||\vec{b}_c)) d\vec{x}_c \text{ --- cross entropy}$$

$$= \sum p(\vec{A}_d = \vec{x}_d) \int p(\vec{x}_c|\vec{A}_d = \vec{x}_d) \log(p(\vec{B}_d = \vec{x}_d)p(\vec{x}_c|\vec{B}_d = \vec{x}_d)) d\vec{x}_c$$

$$p_A(\vec{x}_c|\vec{A}_d = \vec{x}_d) = \frac{1}{n_{\vec{A}_d=\vec{x}_d}\sqrt{2^m\pi^m}|\rho_A|} \sum_{i=1}^{n_{\vec{A}_d=\vec{x}_d}} e^{-\frac{1}{2}(\vec{x}-\vec{x}_i)^T \rho_A^{-1}(\vec{x}-\vec{x}_i)}$$

The maximum Entropy for a continuous sample distribution is when the sample distribution is Gaussian.

Using the Kernel Density Estimation

$$p(\vec{x}_c|\vec{X}_d = \vec{x}_d) = \frac{1}{n_{\vec{x}_d}\sqrt{2^m\pi^m}|\rho|} \sum_{i=1}^{n_{\vec{x}_d}} e^{-\frac{1}{2}(\vec{x}-\vec{x}_i)^T \rho^{-1}(\vec{x}-\vec{x}_i)}$$

the covariance