

- $d \in \mathbb{N}^*$ (latent space dimension)
- $\mu \in \mathbb{R}^d$
- $\forall i \in [1, d], \sigma_i \in \mathbb{R}^+$
- $\Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_d^2)$
- $P \sim \mathcal{U}(\mu, \Sigma)$ (latent space distribution)
- $Q \sim \mathcal{U}(0_d, I_d)$ (target distribution)
- We denote by p (resp. q) the density associated with P (resp. Q)

$$\begin{aligned}
 \textcircled{1} \quad (P \parallel Q) &= \int_{-\infty}^{\infty} p(x) \log \left(\frac{p(x)}{q(x)} \right) dx = \mathbb{E}_P \left\{ \log \left(\frac{p(x)}{q(x)} \right) \right\} \\
 &= \mathbb{E}_P \left\{ \log \left(\frac{\frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left[-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) \right]}{\frac{1}{(2\pi)^{d/2} |I_d|^{1/2}} \exp \left[-\frac{1}{2} (x-0_d)^T I_d^{-1} (x-0_d) \right]} \right) \right\} \\
 &= \mathbb{E}_P \left\{ \log \left(\frac{|\Sigma|^{-1/2} \exp \left[-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) \right]}{\exp \left[-\frac{1}{2} x^T x \right]} \right) \right\} \\
 &= \mathbb{E}_P \left\{ \log \left(|\Sigma|^{-1/2} \exp \left[-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) + \frac{1}{2} x^T x \right] \right) \right\} \\
 &= \mathbb{E}_P \left\{ -\frac{1}{2} \log(|\Sigma|) - \frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) + \frac{1}{2} x^T x \right\} \\
 &= \frac{1}{2} (-\alpha - \beta + \gamma)
 \end{aligned}$$

where $\alpha = \mathbb{E}_P \{ \log(|\Sigma|) \}$, $\beta = \mathbb{E}_P \{ (x-\mu)^T \Sigma^{-1} (x-\mu) \}$

and $\gamma = \mathbb{E}_P \{ x^T x \}$.

$$\cdot \alpha = E_p \{ \log(1/\Sigma) \} = \log(1/\Sigma) \text{ because } \log(1/\Sigma) \text{ is a constant.}$$

$$\alpha = \log(1/\Sigma) = \log\left(\prod_{i=1}^d \sigma_i^{-2}\right) \text{ because } \Sigma \text{ is diagonal.}$$

$$= \sum_{i=1}^d \log(\sigma_i^{-2}).$$

$$\cdot \beta = E_p \left\{ \underbrace{(x-\mu)^T \Sigma^{-1} (x-\mu)}_{\in \mathbb{R}} \right\} = E_p \{ \text{tr}[(x-\mu)^T \Sigma^{-1} (x-\mu)] \}$$

$$= E_p \left\{ \text{tr} \left[\underbrace{(x-\mu)(x-\mu)^T}_{=M} \Sigma^{-1} \right] \right\} \text{ because } \text{tr}(ABC) = \text{tr}(CAB)$$

$$= E_p \left\{ \sum_{i=1}^d (M)_{i,i} \right\} = \sum_{i=1}^d \left(E_p \{ (M)_{i,i} \} \right)$$

$$= \text{tr} \begin{pmatrix} E_p \{ (M)_{1,1} \} & E_p \{ (M)_{1,2} \} & \dots \\ E_p \{ (M)_{2,1} \} & E_p \{ (M)_{2,2} \} & \dots \\ \vdots & \vdots & \ddots \\ & & E_p \{ (M)_{d,d} \} \end{pmatrix}$$

$$= \text{tr} [E_p \{ M \}] = \text{tr} [E_p \{ (x-\mu)(x-\mu)^T \Sigma^{-1} \}]$$

$$= \text{tr} [E_p \{ (x-\mu)(x-\mu)^T \} \Sigma^{-1}] \text{ because } \Sigma^{-1} \text{ is a constant.}$$

$$= \text{tr} [\text{Var}(P) \Sigma^{-1}] = \text{tr} [\Sigma \Sigma^{-1}] = \text{tr} [\mathbf{I}_d] = d.$$

$$\cdot \gamma = E_p \left\{ \overbrace{x^T x}^{\in \mathbb{R}} \right\} = E_p \left\{ \text{tr} [x^T x] \right\} = E_p \left\{ \text{tr} [\overbrace{xx^T}^{\in \mathbb{N}}] \right\}$$

$$= E_p \left\{ \sum_{i=1}^d (N)_{i,i} \right\} = \sum_{i=1}^d \left(E_p \{ (N)_{i,i} \} \right) = \text{tr} [E_p \{ N \}]$$

$$\begin{aligned}
&= \text{tr} \left[\mathbb{E}_p \{ x x^t \} \right] = \text{tr} \left[\mathbb{E}_p \{ x x^t + (\mu \mu^t - x \mu^t - \mu x^t) - (\mu \mu^t - x \mu^t - \mu x^t) \} \right] \\
&= \text{tr} \left[\mathbb{E}_p \{ (x - \mu)(x - \mu)^t - (\mu \mu^t - x \mu^t - \mu x^t) \} \right] \\
&= \text{tr} \left[\mathbb{E}_p \{ (x - \mu)(x - \mu)^t \} - \mathbb{E}_p \{ \mu \mu^t \} + \mathbb{E}_p \{ x \mu^t \} + \mathbb{E}_p \{ \mu x^t \} \right] \\
&= \text{tr} \left[\text{Var}(P) - \mu \mu^t + \mathbb{E}_p \{ x \} \mu^t + \mu (\mathbb{E}_p \{ x \})^t \right] \text{ because } \mu \text{ is a constant} \\
&= \text{tr} \left[\Sigma - \mu \mu^t + \mu \mu^t + \mu \mu^t \right] = \text{tr} \left[\Sigma + \mu \mu^t \right] = \text{tr} [\Sigma] + \text{tr} [\mu \mu^t] \\
&= \sum_{i=1}^d \sigma_i^2 + \sum_{i=1}^d \mu_i^2 = \sum_{i=1}^d (\mu_i^2 + \sigma_i^2)
\end{aligned}$$

$$\begin{aligned}
\mathcal{D}_{KL}(P \parallel Q) &= \frac{1}{2}(-\alpha - \beta + \gamma) = \frac{1}{2} \left[-\sum_{i=1}^d (\log(\sigma_i^2)) - d - \sum_{i=1}^d (\mu_i^2 + \sigma_i^2) \right] \\
&= \frac{1}{2} \sum_{i=1}^d [\mu_i^2 + \sigma_i^2 - 1 - \log(\sigma_i^2)]
\end{aligned}$$