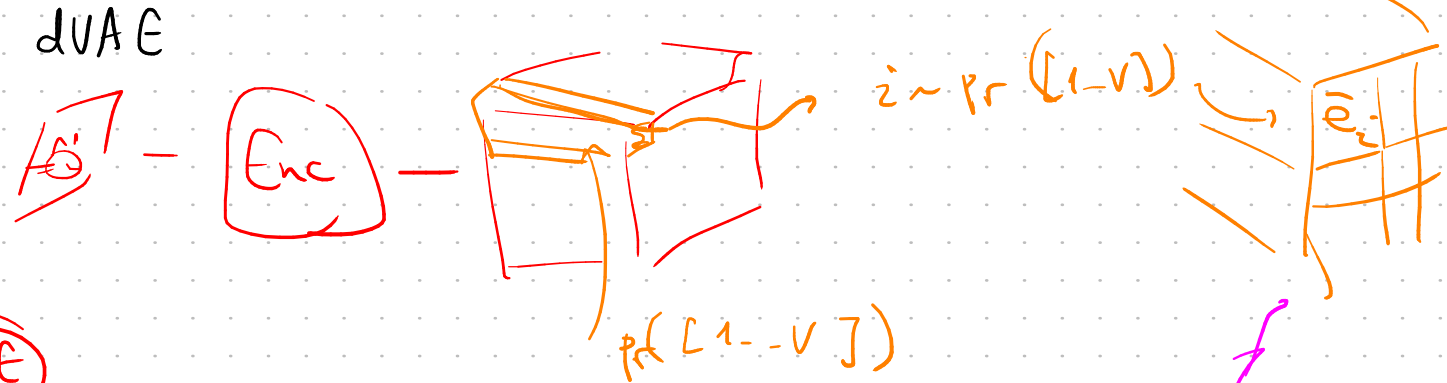
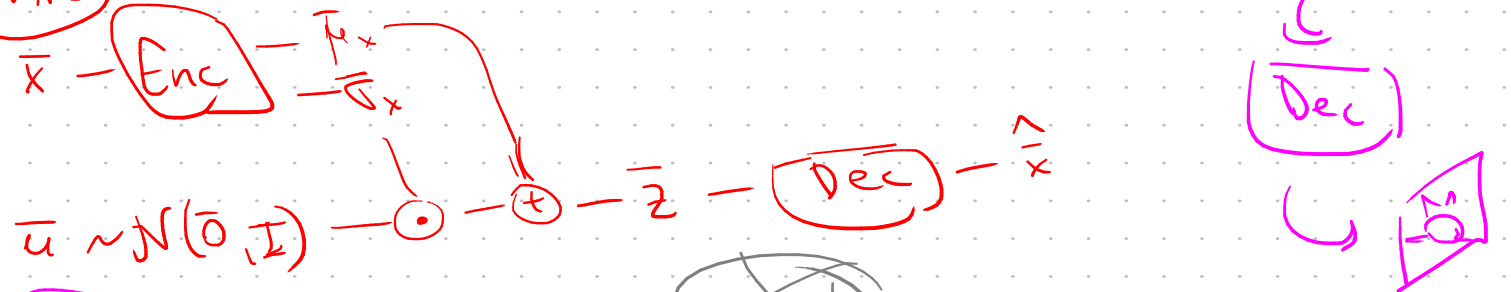


① dVAE



VAE

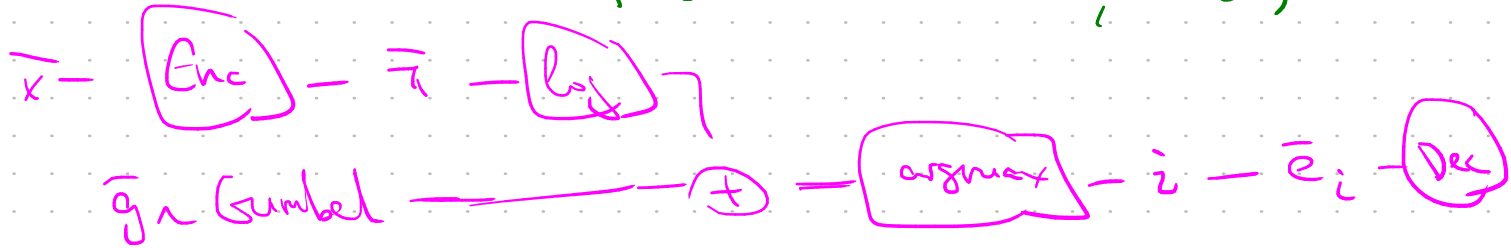


dVAE



Gumbel - Max trick:

$z \sim \text{Mult}(\bar{\pi})$
 $\bar{\pi} = (\pi_k, \pi_l)$
 $z = \underset{i}{\text{argmax}} (g_i + \log \pi_i)$, $g_i \sim \text{Gumbel}$
 $p(g_i) = e^{-g_i} e^{-e^{-g_i}}$, $F(g_i) = e^{-e^{-g_i}}$



Proof
 $p(z=k) = p(g_k + \log \pi_k \geq g_j + \log \pi_j \forall j) =$
 $= \int_{-\infty}^{\infty} p(\forall j \neq k, g_j + \log \pi_j \leq g_k + \log \pi_k) p(g_k) dg_k =$
 $\prod_{j \neq k} p(g_j \leq g_k + \log \pi_k - \log \pi_j | g_k) = \prod_{j \neq k} F(g_k + \log \frac{\pi_k}{\pi_j})$

$$= \int_{-\infty}^{\infty} \left(\prod_{j \neq k} e^{-g_k - \log \pi_k + \log \pi_j} \right) \cdot e^{-(g_k + e^{-g_k})} dg_k =$$

$$= \int_{-\infty}^{\infty} \underbrace{\prod_{j \neq k} e^{-\tau_j}}_{\pi_k} \cdot e^{-g_k - \log \pi_k} \cdot e^{-(g_k + e^{-g_k})} dg_k =$$

$$= \int_{-\infty}^{\infty} e^{-g_k - \log \pi_k} \left(\sum_{j \neq k} \pi_j \right)^{\tau_k - \tau_k} \cdot e^{-g_k - e^{-g_k}} dg_k$$

$$= \int_{-\infty}^{\infty} e^{-g_k - \log \pi_k} + \pi_k \cdot e^{-g_k - \log \pi_k} - g_k - e^{-g_k} dg_k$$

$$- e^{-(g_k + \log \pi_k)} - (g_k + \log \pi_k) + g_k + \log \pi_k + \pi_k e^{-g_k - \log \pi_k} - g_k - e^{-g_k}$$

$$= e^{\log \pi_k} \int_{-\infty}^{\infty} e^{-(g_k + \log \pi_k)} - e^{-(g_k + \log \pi_k)} dg_k = \pi_k$$

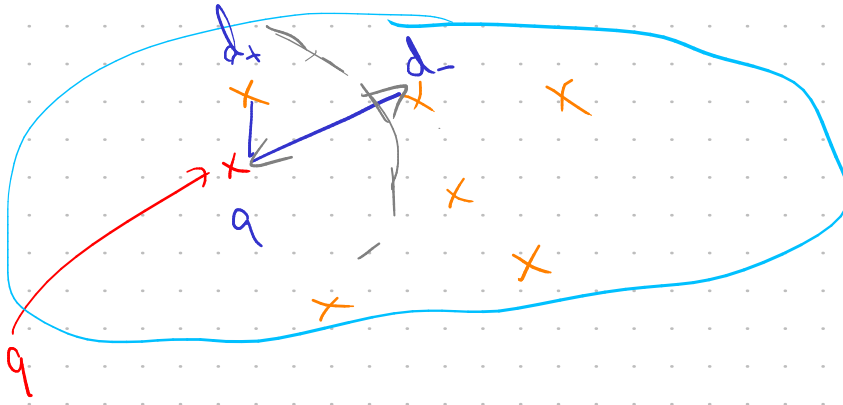
Gumbel-softmax:

$$\bar{x} = \text{E}(\bar{x}) = \bar{\pi} + \log \tau \quad \bar{g} \sim \text{Gumbel} \quad \text{softmax} \quad \bar{x} = \sum_i \alpha_i \bar{x}_i$$

$$\alpha_i = \text{softmax} \left(\frac{1}{\tau} (\bar{g}_i + \log \tau_i) \right)_i = \frac{e^{\frac{1}{\tau} (g_i + \log \tau_i)}}{\sum_j e^{\frac{1}{\tau} (g_j + \log \tau_j)}}$$

temperature

Contrastive learning



$$L(\bar{q}, d_+, d_-) = \bar{q}^T d_+ - \bar{q}^T d_-$$

triplet loss