14/11/23

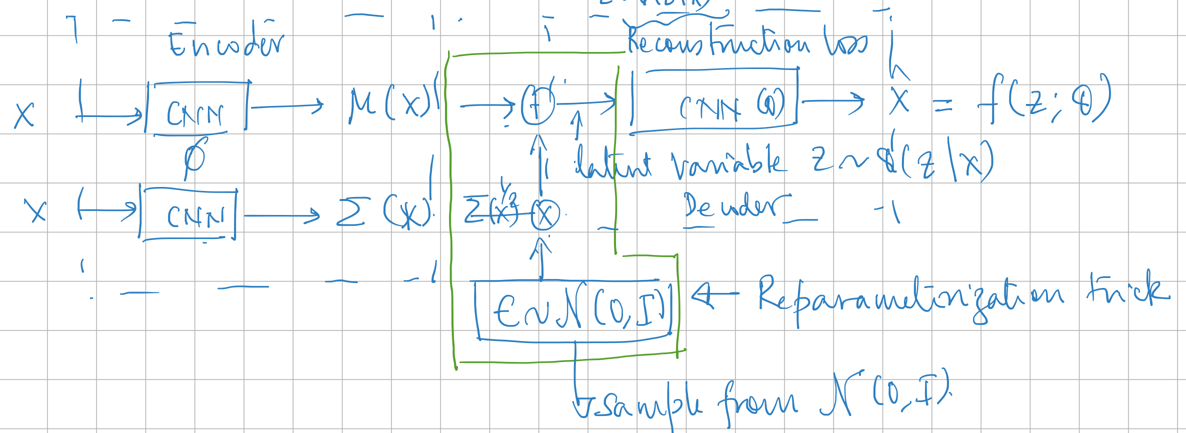
Deep Learning

- Recap: VAE

- Diffusion Models

- VAE: $D(Q(z|x)\,\|\,P(z|x)) \rightarrow \underbrace{\log P(x)} - D(Q(z|x)\,\|\,P(z|x)) =$

$$\underset{z\sim Q(z|x)}{E}\log[P(x|z)] - D(Q(z|x)\,\|\,P(z))$$



- $\underset{x\sim P(x)}{E}\left[\log P(x) - D(Q(z|x)\,\|\,P(z|x))\right]$ is the term that we ideally want to maximize.

- This is approximated using sample average.

- Diffusion models: Latent variable approach.

  $q(x^{(0)})$: distribution of the input RV i.e. the data distribution (→ time step; ↳ input RV)

  $q(x^{(0)}, x^{(1)}, \ldots, x^{(T)})$: joint distribution.

  $q(x^{(T)})$: $\mathcal{N}(0, I)$

  $x^{(0)} \rightarrow x^{(T)}$ (Input space → Latent space) — Inference process

  } Inference path

- $p(x^{(T)})$: $\mathcal{N}(0, I)$

  $p(x^{(0)})$: approximation of $q(x^{(0)})$

  $p(x^{(0)}, \ldots, x^{(T)})$: Joint dist. of RVs in the generative path

  $x^{(T)} \rightarrow x^{(0)}$ (latent space → Input space) — generative process

  } Generative path.

- Loss: $L = \int \log p(x^{(0)}) \cdot q(x^{(0)}) \, dx^{(0)}$