

20/01/25

# Computer Vision

## • Recap

- Diffusion Process  $\rightarrow$  fwd and bwd trajectories have the same dist func form
- Maximizing log likelihood  $\checkmark$
- Markov chain assumption  $\checkmark$
- Conditional dist Gaussian  $\rightarrow$  closed form expression for bound

## • Lower bound on the expected log likelihood

• Recap: 
$$\mathcal{L}(\theta) = \int q(x^{(0)}) \cdot \log p_{\theta}(x^{(0)}) dx^{(0)} \quad - (1)$$

$$\theta^* = \arg \max_{\theta \in \Theta} \mathcal{L}(\theta) \quad - (2)$$

$$p_{\theta}(x^{(0)}) = \int p_{\theta}(x^{(0:-T)}) \cdot dx^{(0:-T)}$$

$$= \int p_{\theta}(x^{(T)}) \cdot \frac{\prod_{t=1}^T p_{\theta}(x^{(t+1)} | x^{(t)})}{\prod_{t=1}^T q(x^{(t)} | x^{(t+1)})} dx^{(1:-T)}$$

$$p_{\theta}(x^{(0)}) = \int p_{\theta}(x^{(T)}) \cdot q(x^{(1:-T)} | x^{(0)}) \frac{\prod_{t=1}^T p_{\theta}(x^{(t+1)} | x^{(t)})}{\prod_{t=1}^T q(x^{(t)} | x^{(t+1)})} dx^{(1:-T)}$$

(3)

Plug (3) into (1)

$$\mathcal{L}(\theta) = \int q(x^{(0)}) \cdot \log \left[ \int p_{\theta}(x^{(T)}) \cdot q(x^{(1:-T)} | x^{(0)}) \frac{\prod_{t=1}^T p_{\theta}(x^{(t+1)} | x^{(t)})}{\prod_{t=1}^T q(x^{(t)} | x^{(t+1)})} dx^{(1:-T)} \right] dx^{(0)}$$

We will apply the Jensen's inequality. For a concave function  $\varphi(x)$ ,  $\varphi(E[x]) \geq E[\varphi(x)]$

$\mathcal{L}(\theta) \geq k$ , where

$$k = \int q(x^{(0)}) \cdot q(x^{(1:T)} | x^{(0)}) \log p_{\theta}(x^{(T)}) \cdot \frac{\prod p_{\theta}(x^{(t+1)} | x^{(t)})}{\prod q(x^{(t)} | x^{(t+1)})}$$

$$= \int q(x^{(0:T)}) \cdot \log p_{\theta}(x^{(T)}) \cdot \frac{\prod p_{\theta}(x^{(t+1)} | x^{(t)})}{\prod q(x^{(t)} | x^{(t+1)})} dx^{(0:T)} \quad (4)$$

Since the forward trajectory is a Markov chain,

$$q(x^{(t)} | x^{(t-1)}) = q(x^{(t)} | x^{(t-1)}, x^{(0)}) \quad \rightarrow \text{Since } x^{(0)} \text{ is the image RV}$$

$$= q(x^{(t+1)} | x^{(t)}, x^{(0)}) \cdot \frac{q(x^{(t)} | x^{(0)})}{q(x^{(t+1)} | x^{(0)})} \quad (5)$$

Plug (5) into (4)

$$k = \int q(x^{(0:T)}) \cdot \log p_{\theta}(x^{(T)}) \cdot \frac{\prod p_{\theta}(x^{(t+1)} | x^{(t)}) \cdot q(x^{(t+1)} | x^{(0)})}{\prod q(x^{(t+1)} | x^{(t)}, x^{(0)}) \cdot q(x^{(t)} | x^{(0)})} dx^{(0:T)} \quad (6)$$

Check: we want to express  $\tilde{J}$  as a sum of KL divergence terms and entropy terms.

$$K = \int q(x^{(0:\tau)}) \cdot \log p_\theta(x^{(\tau)}) dx^{(0:\tau)} +$$

$$\int q(x^{(0:\tau)}) \cdot \log \left[ \frac{\prod p_\theta(x^{(t)} | x^{(t-1)})}{\prod q(x^{(t-1)} | x^{(t-2)}, x^{(0)})} \frac{q(x^{(t-1)} | x^{(0)})}{q(x^{(t)} | x^{(0)})} \right] dx^{(0:\tau)}$$