



Siddhant Mishra-Sharma (MIT/AI FI) Summer School



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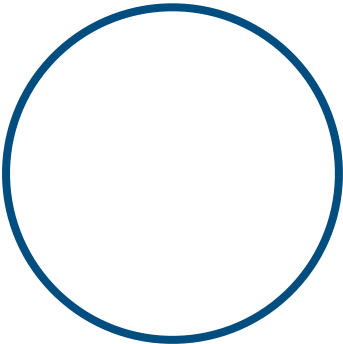
36

The forward process and diffusion kernel

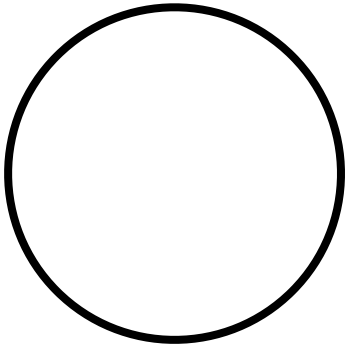
$$\sum_{t=2}^T \left\langle D_{\text{KL}} \left( q \left( z_{t-1} \mid z_t, x \right) \parallel p_{\theta} \left( z_{t-1} \mid z_t \right) \right) \right\rangle_{q(z_t|x)}$$



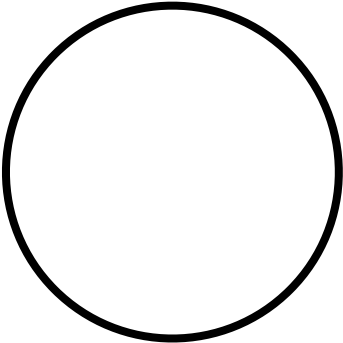




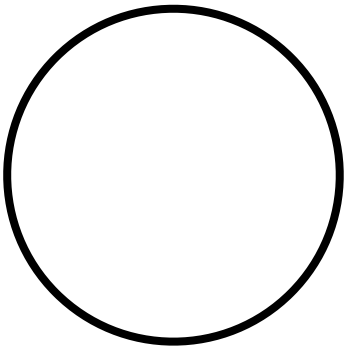
**Z1**



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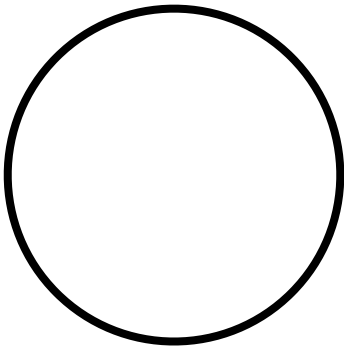




*Z*

*T*









$q(x)$



## Variance-preserving noise schedule

$$q(z_t | z_{t-1}) = \mathcal{N}(\sqrt{1 - \beta_t} \cdot z_{t-1}, \beta_t)$$

$$z_t = \sqrt{1 - \beta_t} \cdot z_{t-1} + \sqrt{\beta_t} \cdot \varepsilon$$

Predict arbitrary time steps without Markovian sampling

$$q(z_t | x)$$


Diffusion kernel

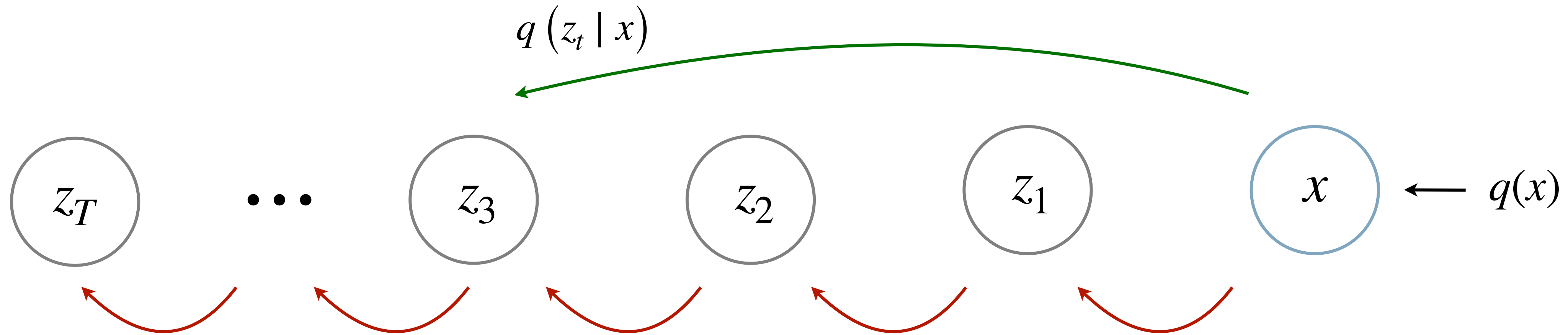
$$q(z_t | x) = \mathcal{N}\left(\sqrt{\bar{\alpha}_t} \cdot x, \sqrt{1 - \bar{\alpha}_t}\right)$$

$$\bar{\alpha}_t = \prod_{i=1}^t \alpha_i$$

# The forward process and diffusion kernel

Predict arbitrary timestep without Markovian sampling

$$\sum_{t=2}^T \left\langle D_{\text{KL}} \left( q(z_{t-1} | z_t, x) \parallel p_{\theta}(z_{t-1} | z_t) \right) \right\rangle_{q(z_t|x)}$$



Variance-preserving noise schedule

$$q(z_t | z_{t-1}) = \mathcal{N} \left( \sqrt{1 - \beta_t} \cdot z_{t-1}, \beta_t \right)$$

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Diffusion kernel

$$q(z_t | x) = \mathcal{N} \left( \sqrt{\bar{\alpha}_t} \cdot x, \sqrt{1 - \bar{\alpha}_t} \right)$$

$$\bar{\alpha}_t = \prod_{i=1}^t \alpha_i$$



# The denoising objective

Given the nature of the forward (noising) process,  $q(z_{t-1} | z_t, x)$  can be computed analytically

$$q(z_{t-1} | z_t, x) = \mathcal{N}\left(z_{t-1}; \mu_q(x_t, x_0), \sigma_q(t)\right)$$

$$\sum_{t=2}^T \left\langle D_{\text{KL}}\left(q(z_{t-1} | z_t, x) \parallel p_{\theta}(z_{t-1} | z_t)\right) \right\rangle_{q(z_t|x)}$$