



# Elucidating the Exposure Bias in Diffusion Models

ICLR, 2024

Miao's Group - Paper Reading



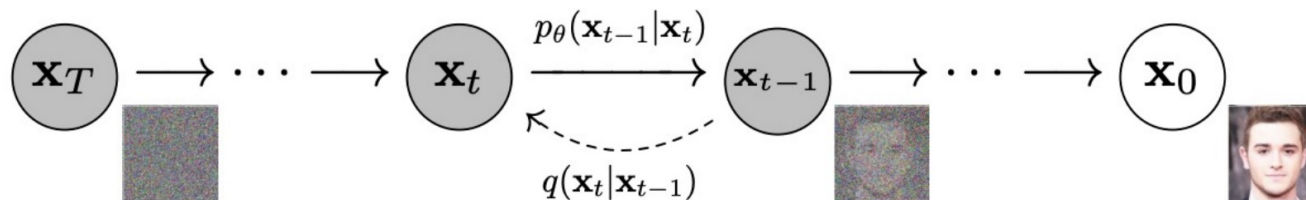
时间 : 2024.4.9





# **Recall Denoising Diffusion Probability Models**

# Recall Denoising Diffusion Probability Models



$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t}\mathbf{x}_{t-1}, \beta_t \mathbf{I})$$

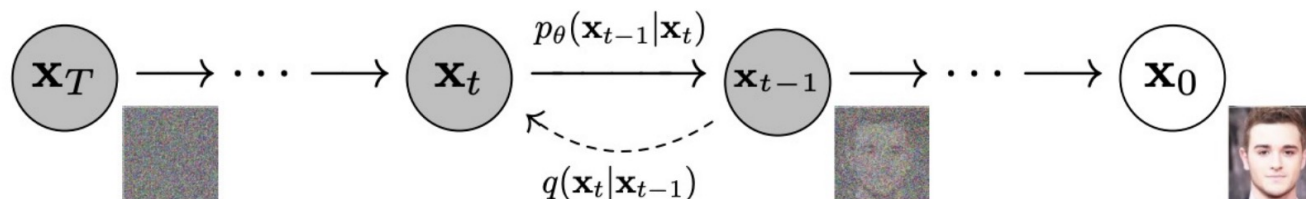
$$q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0), \tilde{\boldsymbol{\beta}}_t \mathbf{I})$$

$$\tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1 - \bar{\alpha}_t} \mathbf{x}_0 = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \boldsymbol{\epsilon}_t \right)$$

$$\tilde{\boldsymbol{\beta}}_t = \frac{1 - \bar{\alpha}_{t-1}}{1 - \bar{\alpha}_t} \cdot \beta_t$$

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

# Recall Denoising Diffusion Probability Models



$$\alpha_t = 1 - \beta_t, \bar{\alpha}_t = \prod_{i=1}^t \alpha_i$$

$$\begin{aligned} \mathbf{x}_t &= \sqrt{\alpha_t} \mathbf{x}_{t-1} + \sqrt{1 - \alpha_t} \boldsymbol{\epsilon}_{t-1} \\ &= \sqrt{\alpha_t \alpha_{t-1}} \mathbf{x}_{t-2} + \sqrt{1 - \alpha_t \alpha_{t-1}} \bar{\boldsymbol{\epsilon}}_{t-2} \\ &= \dots \\ &= \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\epsilon} \end{aligned}$$

$$q(\mathbf{x}_t|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t} \mathbf{x}_0, (1 - \bar{\alpha}_t) \mathbf{I})$$

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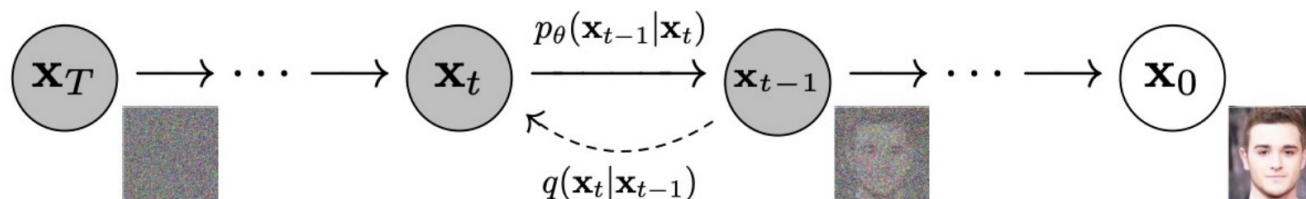
## Algorithm 1 Training

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- 1: **repeat**
  - 2:  $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
  - 3:  $t \sim \text{Uniform}(\{1, \dots, T\})$
  - 4:  $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
  - 5: Take gradient descent step on  

$$\nabla_{\theta} \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\epsilon}, t) \right\|^2$$
  - 6: **until** converged
-

# Recall Denoising Diffusion Probability Models



$$p_{\theta}(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_{\theta}(\mathbf{x}_t, t), \boldsymbol{\Sigma}_{\theta}(\mathbf{x}_t, t))$$

$$\tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0) = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \boldsymbol{\epsilon}_t \right)$$

$$\tilde{\beta}_t = \frac{1 - \bar{\alpha}_{t-1}}{1 - \bar{\alpha}_t} \cdot \beta_t$$

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## Algorithm 2 Sampling

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- 1:  $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
  - 2: **for**  $t = T, \dots, 1$  **do**
  - 3:    $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$
  - 4:    $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \boldsymbol{\epsilon}_{\theta}(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$
  - 5: **end for**
  - 6: **return**  $\mathbf{x}_0$
-



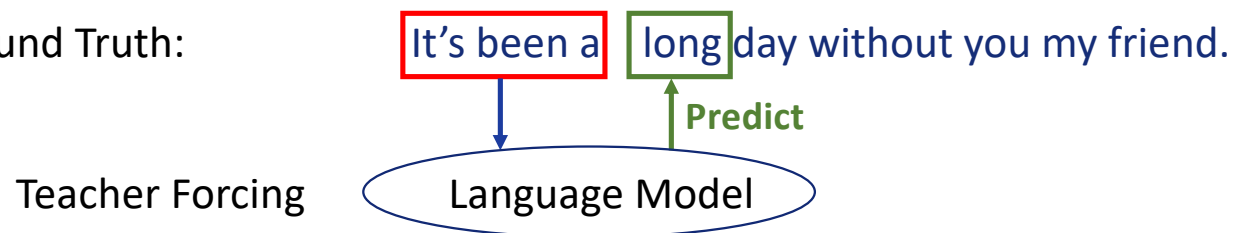
# **Elucidating the Exposure Bias in Diffusion Models**

# Elucidating the Exposure Bias in Diffusion Models

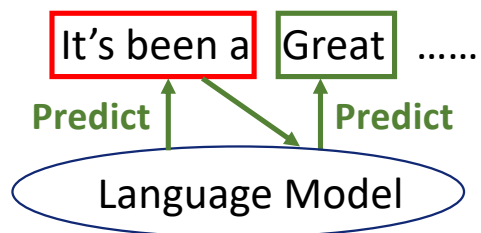
- What is Exposure Bias?

- Example: Train a Language Model

- Ground Truth:



Autoregressive



Exposure Bias  
Accumulative Error

# Elucidating the Exposure Bias in Diffusion Models

- Exposure Bias in Diffusion Models

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## Algorithm 1 Training

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```
1: repeat  
2:    $\mathbf{x}_0 \sim q(\mathbf{x}_0)$   
3:    $t \sim \text{Uniform}(\{1, \dots, T\})$   
4:    $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$   
5:   Take gradient descent step on  
      $\nabla_{\theta} \|\epsilon - \epsilon_{\theta}(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t}\epsilon, t)\|^2$   
6: until converged
```

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Teacher Forcing

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## Algorithm 2 Sampling

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```
1:  $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$   
2: for  $t = T, \dots, 1$  do  
3:    $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$   
4:    $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_{\theta}(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$   
5: end for  
6: return  $\mathbf{x}_0$ 
```

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Exposure Bias  
Accumulative Error



# Elucidating the Exposure Bias in Diffusion Models

- Exposure Bias in Diffusion Models

Sampling Distribution

$$q(\hat{\mathbf{x}}_t | \mathbf{x}_{t+1}, \mathbf{x}_\theta^{t+1})$$

采样阶段看到的  $\hat{\mathbf{x}}_t$

Training Distribution

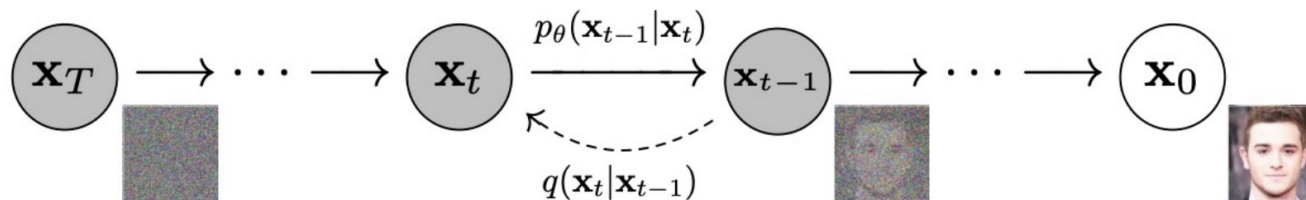
$$q(\mathbf{x}_t | \mathbf{x}_0)$$

训练时在时间步  $t$  看到的  $\mathbf{x}_t$

接下来看  $\hat{\mathbf{x}}_t$  和  $\mathbf{x}_t$  的区别

$$q(\mathbf{x}_t | \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t} \mathbf{x}_0, (1 - \bar{\alpha}_t) \mathbf{I})$$

# Elucidating the Exposure Bias in Diffusion Models



$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t}\mathbf{x}_{t-1}, \beta_t \mathbf{I})$$

$$q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0), \tilde{\boldsymbol{\beta}}_t \mathbf{I})$$

$$\tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1 - \bar{\alpha}_t} \mathbf{x}_0 = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \boldsymbol{\epsilon}_t \right)$$

$$\tilde{\boldsymbol{\beta}}_t = \frac{1 - \bar{\alpha}_{t-1}}{1 - \bar{\alpha}_t} \cdot \beta_t$$

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

$\mathbf{x}_\theta^t$

# Elucidating the Exposure Bias in Diffusion Models

$$q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0), \tilde{\boldsymbol{\beta}}_t \mathbf{I})$$

$$\tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1 - \bar{\alpha}_t} \mathbf{x}_0 = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \boldsymbol{\epsilon}_t \right)$$

$\mathbf{x}_\theta^t$

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

Sampling:  $\mathbf{x}_\theta^t - \mathbf{x}_0 \neq 0$

# Elucidating the Exposure Bias in Diffusion Models

$$q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0), \tilde{\boldsymbol{\beta}}_t \mathbf{I})$$

$$\tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\bar{\alpha}_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1 - \bar{\alpha}_t} \mathbf{x}_0 = \frac{1}{\sqrt{\bar{\alpha}_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \boldsymbol{\epsilon}_t \right)$$

$$p_{\theta}(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_{\theta}(\mathbf{x}_t, t), \boldsymbol{\Sigma}_{\theta}(\mathbf{x}_t, t))$$

$\mathbf{x}_{\theta}^t$

Modeling

$$p_{\theta}(\mathbf{x}_0|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{\theta}^t; \mathbf{x}_0, e_t^2 \mathbf{I}), \quad \mathbf{x}_{\theta}^t = \mathbf{x}_0 + e_t \boldsymbol{\epsilon}_0 \quad (\boldsymbol{\epsilon}_0 \sim \mathcal{N}(0, \mathbf{I}))$$

$$\hat{\mathbf{x}}_t = \frac{\sqrt{\bar{\alpha}_t}\beta_{t+1}}{1 - \bar{\alpha}_{t+1}} \mathbf{x}_{\theta}^{t+1} + \frac{\sqrt{\bar{\alpha}_{t+1}}(1 - \bar{\alpha}_t)}{1 - \bar{\alpha}_{t+1}} \mathbf{x}_{t+1} + \sqrt{\tilde{\beta}_{t+1}} \boldsymbol{\epsilon}_1$$

$$\hat{\mathbf{x}}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t + \left( \frac{\sqrt{\bar{\alpha}_t}\beta_{t+1}}{1 - \bar{\alpha}_{t+1}} e_{t+1} \right)^2} \boldsymbol{\epsilon}_3$$

# Elucidating the Exposure Bias in Diffusion Models

- Exposure Bias in Diffusion Models

Training Distribution

$$q(\mathbf{x}_t | \mathbf{x}_0)$$

训练时在时间步  $t$  看到的  $\mathbf{x}_t$

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$$

Sampling Distribution

$$q(\hat{\mathbf{x}}_t | \mathbf{x}_{t+1}, \mathbf{x}_\theta^{t+1})$$

采样阶段看到的  $\hat{\mathbf{x}}_t$

$$\hat{\mathbf{x}}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t + \left( \frac{\sqrt{\bar{\alpha}_t} \beta_{t+1}}{1 - \bar{\alpha}_{t+1}} e_{t+1} \right)^2} \epsilon_3$$

mean	$\sqrt{\bar{\alpha}_t} \mathbf{x}_0$	$\sqrt{\bar{\alpha}_t} \mathbf{x}_0$
variance	$(1 - \bar{\alpha}_t) \mathbf{I}$	$\left( 1 - \bar{\alpha}_t + \left( \frac{\sqrt{\bar{\alpha}_t} \beta_{t+1}}{1 - \bar{\alpha}_{t+1}} e_{t+1} \right)^2 \right) \mathbf{I}$ bigger!

# Elucidating the Exposure Bias in Diffusion Models

- Exposure Bias in Diffusion Models

Training Distribution

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$$

Sampling Distribution

$$\hat{\mathbf{x}}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t + \left( \frac{\sqrt{\bar{\alpha}_t} \beta_{t+1}}{1 - \bar{\alpha}_{t+1}} e_{t+1} \right)^2} \epsilon_3$$

bigger!

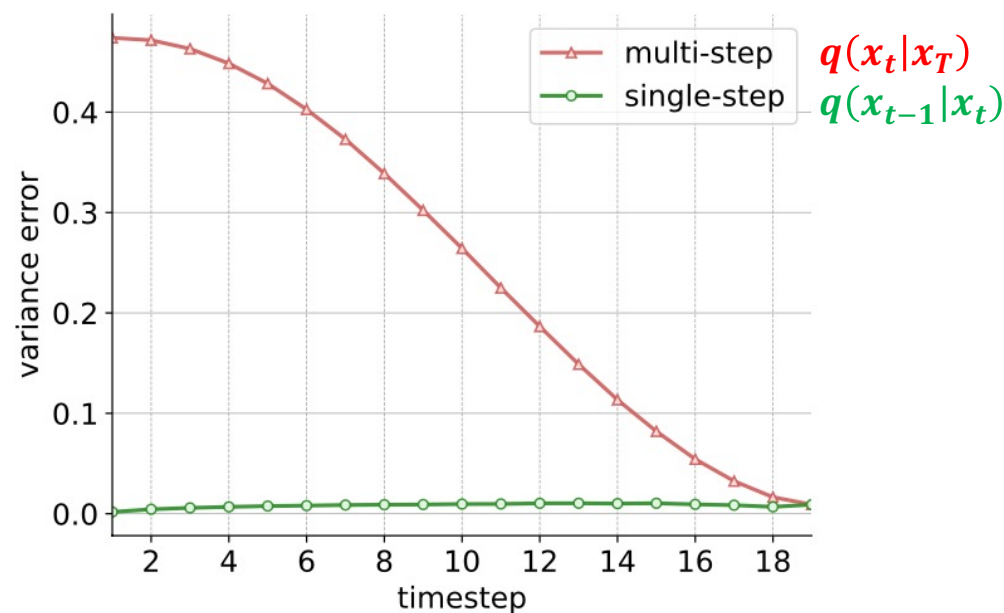


Figure 1: Variance error in single-step and multi-step samplings.

# Elucidating the Exposure Bias in Diffusion Models

- Exposure Bias in Diffusion Models

Training Distribution

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$$

Sampling Distribution

bigger!

$$\hat{\mathbf{x}}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t + \left( \frac{\sqrt{\bar{\alpha}_t} \beta_{t+1}}{1 - \bar{\alpha}_{t+1}} e_{t+1} \right)^2} \epsilon_3$$

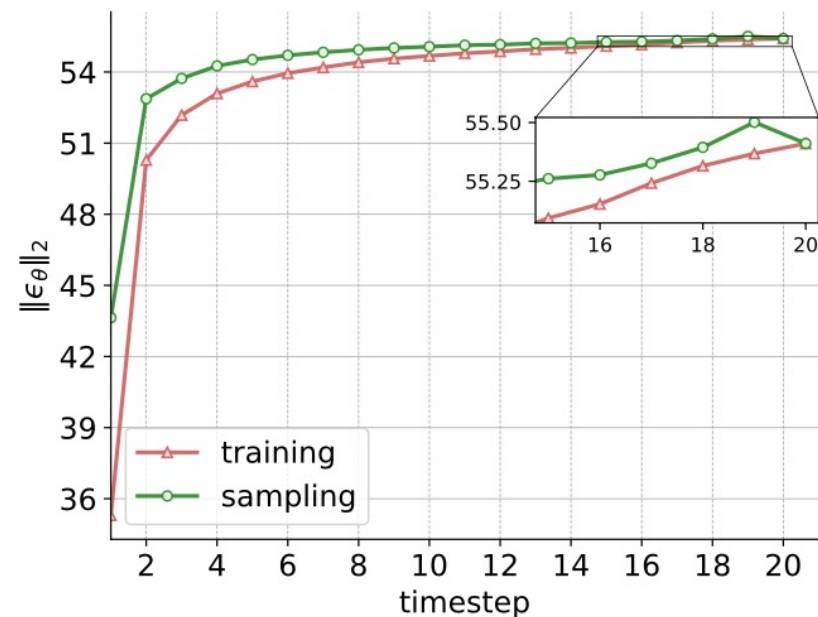


Figure 2:  $\|\epsilon_{\theta}(\cdot)\|_2$  during training and sampling on CIFAR-10. We use 20-step sampling and report the L2-norm using 50k samples at each timestep.

# Elucidating the Exposure Bias in Diffusion Models

- Exposure Bias in Diffusion Models

Training Distribution

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\epsilon}$$

Sampling Distribution

bigger!

$$\hat{\mathbf{x}}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t + \left( \frac{\sqrt{\bar{\alpha}_t} \beta_{t+1}}{1 - \bar{\alpha}_{t+1}} e_{t+1} \right)^2} \boldsymbol{\epsilon}_3$$

**Solution**

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## Algorithm 2 Sampling

---

```
1:  $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
2: for  $t = T, \dots, 1$  do
3:    $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$ 
4:    $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$ 
5: end for
6: return  $\mathbf{x}_0$ 
```

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$$\tilde{\boldsymbol{\mu}}(\mathbf{x}_t, \mathbf{x}_0) = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \frac{\boldsymbol{\epsilon}_t}{\lambda_t} \right)$$



# Elucidating the Exposure Bias in Diffusion Models

- Result

$T'$	Model	Unconditional			Conditional	
		CIFAR-10 32×32	LSUN 64×64	FFHQ 128×128	ImageNet 64×64	ImageNet 128×128
100	ADM	3.37	3.59	14.52	2.71	3.55
	ADM-ES	<b>2.17</b>	<b>2.91</b>	<b>6.77</b>	<b>2.39</b>	<b>3.37</b>
50	ADM	4.43	7.28	26.15	3.75	5.15
	ADM-ES	<b>2.49</b>	<b>3.68</b>	<b>9.50</b>	<b>3.07</b>	<b>4.33</b>
20	ADM	10.36	23.92	59.35	10.96	12.48
	ADM-ES	5.15	8.22	26.14	7.52	9.95
	ADM-ES*	<b>4.31</b>	<b>7.60</b>	<b>24.83</b>	<b>7.37</b>	<b>9.86</b>

# Elucidating the Exposure Bias in Diffusion Models

- Result

$T'$	Model	Unconditional		Conditional	
		Heun	Euler	Heun	Euler
35	EDM	1.97	3.81	1.82	3.74
	EDM-ES (ours)	<b>1.95</b>	<b>2.80</b>	<b>1.80</b>	<b>2.59</b>
21	EDM	2.33	6.29	2.17	5.91
	EDM-ES	<b>2.24</b>	<b>4.32</b>	<b>2.08</b>	<b>3.74</b>
13	EDM	7.16	12.28	6.69	10.66
	EDM-ES	<b>6.54</b>	<b>8.39</b>	<b>6.16</b>	<b>6.59</b>

# Reference

- [What are Diffusion Models? | Lil'Log \(lilianweng.github.io\)](https://lilianweng.github.io/lil-log/)
- Ho, Jonathan, Ajay Jain, and Pieter Abbeel. "Denoising diffusion probabilistic models." NIPS 2020
- Mang Ning, Mingxiao Li, Jianlin Su, Albert Ali Salah, Itir Önal Ertugrul. "Elucidating the Exposure Bias in Diffusion Models" ICLR 2024



**Q&A**





# Thanks

## Elucidating the Exposure Bias in Diffusion Models

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向乾龙



时间 : 2024.4.9

