Block Diffusion: Interpolating Between Autoregressive and Diffusion Language Models

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Introduction to the Problem-Motivation

Two main approaches for Language Models:

Autoregressive (AR):

- Token-by-token generation
- High quality
- KV caching
- Variable length

Diffusion:

- Parallel generation
- Better controllability
- Fixed length (limitation)
- Lower quality (Perplexity Gap)

Question

Can we combine the advantages of both approaches?

Core Idea: Block Diffusion

Block 1 $\rightarrow$ Block 2 $\rightarrow$ Block 3 $\cdots$

Diffusion within each block(parallel)
Autoregressive over blocks

Parameterization: Trade-off through block size L':

- $L' = 1 \rightarrow$ Pure AR
- $L' = L \rightarrow$ Pure Diffusion

Technical Contribution:

- Optimized training and sampling algorithms
- Introduced clipped noise schedules for reduced gradient variance during training
- SoTA PPL among diffusion models + Variable length generation capabilities

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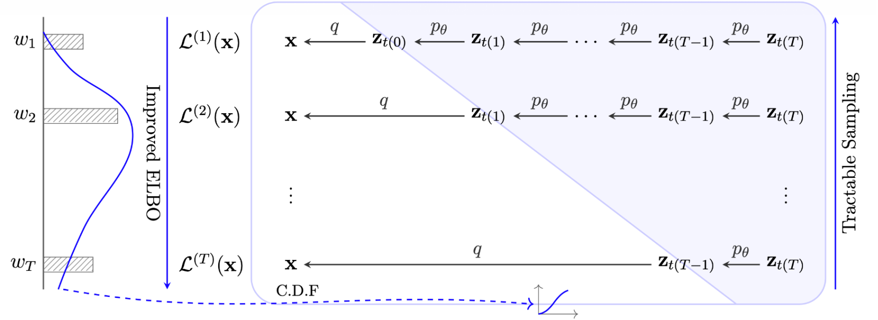
Reweighted Losses for Improved Diffusion Objective

Reweighted Losses are Better Variational Bounds



Diffusion objectives: $\mathcal{L}^{\tilde{w}}(\mathbf{x}) = \lim_{T\to\infty} \sum_{i=1}^{T} w_i \mathcal{L}^{(i)}(\mathbf{x}) = \int_0^1 \tilde{w}(t) \mathbb{E}_{q(\mathbf{z}_t|\mathbf{x})} \left[L_{\text{denoise}}(\mathbf{z}_t, \mathbf{x}, t)\right] dt + \mathrm{C}$

Reweighted Losses for Masked Diffusion

- Initial Reweighted NELBO:

$$\mathcal{L}^{\tilde{w}}(\mathbf{x}) = -\int_0^1 \tilde{w}(t) \frac{\alpha_t'}{1-\alpha_t} \mathbb{E}_{q(\mathbf{z}_t|\mathbf{x})}\left[\delta_{\mathbf{z}_t,m} \cdot \mathbf{x}^\top \log \mu_\theta(\mathbf{z}_t)\right] \mathrm{d}t$$

- Reparameterization trick: $\lambda(t) = \log \frac{\alpha_t}{1-\alpha_t}$:

$$\mathcal{L}^{\hat{w}}(\mathbf{x}) = -\int_0^1 \hat{w}(\lambda(t)) \frac{\alpha_t'}{1-\alpha_t} \mathbb{E}_{q(\mathbf{z}_t|\mathbf{x})}\left[\delta_{\mathbf{z}_t,m} \cdot \mathbf{x}^\top \log \mu_\theta(\mathbf{z}_t)\right] \mathrm{d}t$$

Name	$\lambda(t)$	$\hat{w}(\lambda)$	$\tilde{w}(t)$
EDM		$p_{\mathcal{N}(2.4,2.4^2)}(\lambda)\frac{e^{-\lambda}+0.5^2}{0.5^2}$	$w(\lambda(t))$
IDDPM	$\log \frac{\alpha_t}{1-\alpha_t}$	$\mathrm{sech}(\frac{\lambda}{2})$	$2\sqrt{\alpha_t(1-\alpha_t)}$
Sigmoid		$\mathrm{sigmoid}(-\lambda+k)$	$\frac{1-\alpha_t}{1-(1-e^{-k})\alpha_t}$
FM		$e^{-\frac{\lambda}{2}}$	$\sqrt{\frac{1-\alpha_t}{\alpha_t}}$
Simple		-	$-\frac{1-\alpha_t}{\alpha_t'}$

Reweighted Losses Results

Extended Table 3: Test Perplexities

	PPL (↓)					
Autoregressive						
Transformer	1221					
Diffusion						
SEDD	1403					
MDLM	1370					
Block diffusion	**Base**	**IDDPM**	**EDM**	**Sigmoid (k = 0)**	**FM**	**Simple**
BD3-LMs $L' = 16$	1345	252	49.88	36.06	76213	53070
$L' = 8$	1210	249	49.14	35.79	109169	36010741760
$L' = 4$	1176	246	49.01	**35.08**	67332	2396260

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