Block Diffusion: Interpolating Between Autoregressive and Diffusion Language Models

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Table of Contents

1. Paper Overview
2. Our Results
   - Reproduction
   - Extensions
3. Conclusion & Future Work
4. Team Organization
5. Retrospection

Table of Contents

1. Paper Overview
2. Our Results
   - Reproduction
   - Extensions
3. Conclusion & Future Work
4. Team Organization
5. Retrospection

Introduction to the Problem-Motivation

Two main approaches for Language Models:

Autoregressive (AR):

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

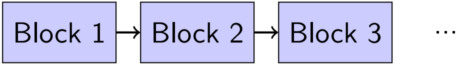
Diffusion:

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

Question

Can we combine the advantages of both approaches?

Core Idea: Block Diffusion



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

Table of Contents

1. Paper Overview
2. Our Results
    - Reproduction
    - Extensions
3. Conclusion & Future Work
4. Team Organization
5. Retrospection

Table of Contents

1. Paper Overview

2. Our Results
   - Reproduction
   - Extensions

3. Conclusion & Future Work

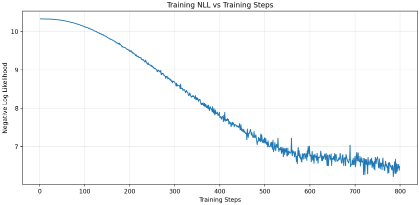
4. Team Organization

5. Retrospection

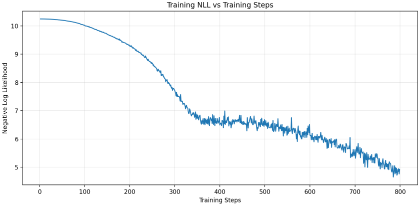
AR vs BD3LM with L'=1

Test Perplexities for single token generation on LM1B dataset (800 Training Steps)

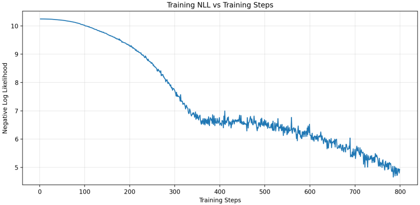
	PPL ($\downarrow$)
Autoregressive	**1893**
BD3LM L'=1	2231
BD3LM L'=1 + Tuned Schedule	2220



AR



BD3LM



BD3LM + Tuned Schedule

The Effect of Clipped Noise Schedules

Test Perplexities for single token generation on LM1B dataset
(400 Pretraining Steps + 100 Fine-tuning Steps)

L'	Clipping	PPL	Var. NELBO
128	$\mathcal{U}[0, 0.5]$	1000	10.00
	$\mathcal{U}[0, 1]$	1000	10.00
16	$\mathcal{U}[0.3, 0.8]$	**1278**	**10.50**
	$\mathcal{U}[0, 1]$	1279	10.51
4	$\mathcal{U}[0.5, 1]$	**1226**	**44.41**
	$\mathcal{U}[0, 1]$	**1226**	**44.41**

Commentary (placeholder)

Key takeaways:

- *???*
- *???*
- *???*

Conclusion...

BD3LMs vs ARs vs Diffusion Models on LM1B

Test perplexities (PPL; ↓) of models on LM1B.
(400 Pretraining Steps + 100 Fine-tuning Steps)

	PPL (↓)
Autoregressive	
Transformer	3042
Diffusion	
SEDD	1447
MDLM	1616
Block diffusion (Ours)	
BD3-LMs $L' = 16$	1278
$L' = 8$	1734
$L' = 4$	**1226**

Commentary (placeholder)

Key takeaways:

- *???*
- *???*
- *???*

Conclusion...

BD3LMs vs ARs vs Diffusion Models on OWT

Test perplexities (PPL; ↓) of models on OWT.
(800 Pretraining Steps + 800 Fine-tuning Steps)

	PPL (↓)
Autoregressive	
Transformer	2036
Diffusion	
SEDD	2120
MDLM	2101
Block diffusion (Ours)	
BD3-LMs $L' = 16$	1939
$L' = 8$	1941
$L' = 4$	**1935**

Commentary (placeholder)

Key takeaways:

- *???*
- *???*
- *???*

Conclusion...

Performance on other Datasets

Zero-shot validation perplexities (↓) of models trained on OWT.(?training steps?)

	LM1B	**Lambada**	**Wikitext**
AR	2388	1550	**2875**
SEDD	2742	1562	3335
MDLM	2722	1556	3283
BD3-LM $L' = 4$	**2196**	**1438**	3143

Commentary (placeholder)

Key takeaways:

- *??? (e.g., BD3-LM improves on . . . compared to diffusion baselines)*
- *??? (e.g., note where AR is still best / gap remains)*
- *??? (e.g., mention that diffusion values are upper bounds if relevant)*

Conclusion...

Variable-Length Sequence Generation

Generation length statistics from sampling 10 documents from models trained on OWT.(?training steps?)

	Median # tokens	Max # tokens
OWT train set	717	131K
AR	4008	131K
SEDD	1021	1024
BD3-LM $L' = 16$	798	2927

Commentary (placeholder)

Key takeaways:

- *??? (e.g., diffusion models are constrained in max length, BD alleviates this)*
- *??? (e.g., compare median vs max lengths across AR/SEDD/BD3)*
- *??? (e.g., mention practical implication for long-form generation)*

Conclusion...

Sample Quality

Generative Perplexity (Gen.PPL;↓) and number of Function Evaluations (NFEs;↓) of 300 samples. All models are trained on OWT. (?training steps?)

	$L = 1024$		$L = 2048$	
Model	Gen. PPL	NFEs	Gen. PPL	NFEs
AR	14.1	1K	13.2	2K
Diffusion				
SEDD	52.0	1K	–	–
MDLM	46.8	1K	41.3	2K
Block Diffusion				
SSD-LM $L' = 25$	37.2	40K	35.3	80K
281.3	1K	281.9	2K	
BD3-LMs $L' = 16$	32.97	1K	31.42	2K
$L' = 8$	29.35	1K	27.42	2K
$L' = 4$	**24.74**	1K	**23.85**	2K

Effect of Different Noise Schedules

Effect of noise schedule on PPL and variance of NELBO for different L' on LM1B. (?training steps?)

Noise schedule	PPL	Var. NELBO
$L' = 4$		
Clipped		
$\mathcal{U}[0.45, 0.95]$	**29.21**	**6.24**
$\mathcal{U}[0.3, 0.8]$	29.38	10.33
Linear $\mathcal{U}[0, 1]$	30.18	23.45
Logarithmic	30.36	23.53
Square root	31.41	26.43
$L' = 16$		
Clipped		
$\mathcal{U}[0.45, 0.95]$	31.42	3.60
$\mathcal{U}[0.3, 0.8]$	**31.12**	**3.58**
Linear $\mathcal{U}[0, 1]$	31.72	7.62
Square	31.43	13.03
Cosine	31.41	13.00

Commentary (placeholder)

Key takeaways:

- *???*
- *???*
- *???*

Conclusion...

Table of Contents

1. Paper Overview
2. Our Results
   - Reproduction
   - Extensions
3. Conclusion & Future Work
4. Team Organization
5. Retrospection

Noise Scheduling in Masked Diffusion (Summary)

Continuous time index:

$$t \sim \mathcal{U}[0,1]$$

Noise schedule ⇒ masked probability:

$$p(t): \text{ masked probability induced by the noise schedule}$$

Keep (no-mask) probability:

$$a(t) = 1 - p(t)$$

Loss scaling induced by the schedule:

$$\text{loss scaling}(t) \;=\; \frac{a'(t)}{1 - a(t)}$$

Intuition

The noise schedule sets *where* the model learns via $p(t)$ (masking rate). When sampling $t \sim \mathcal{U}[0,1]$, loss_scaling$(t) = \frac{a'(t)}{1-a(t)}$ acts as a weight on the per-token log-likelihood term so the discrete estimator matches the continuous-time integral/ELBO and balances low- vs high-noise regions.

Already Implemented Noise Schedules

Schedule	$p(t)$	$\mathbf{loss\_scaling}(t)$
LogLinear	t	$-\frac{1}{t}$
Square	t^2	$-\frac{2}{t}$
Square root	$t^{0.5}$	$-\frac{1}{2t}$
Logarithmic	$\frac{\log(1+t)}{\log 2}$	$-\frac{1}{(1+t)\,\log(1+t)}$
Cosine	$1-(1-\varepsilon)\cos\left(\frac{\pi t}{2}\right)$	$-\frac{\left(\frac{\pi}{2}\right)(1-\varepsilon)\sin\left(\frac{\pi t}{2}\right)}{1-(1-\varepsilon)\cos\left(\frac{\pi t}{2}\right)}$

Gaussian & Bimodal Gaussian Noise Schedules

Goal: sample a masked probability $p(t) \in (0,1)$ from $t \sim \mathcal{U}[0,1]$.

Gaussian schedule (truncated to $(0,1)$):
Let $\alpha = \frac{0-\mu}{\sigma}$, $\beta = \frac{1-\mu}{\sigma}$, $\Phi_\alpha = \Phi(\alpha)$, $\Phi_\beta = \Phi(\beta)$. For $t \in (0,1)$:

$$z(t) = \Phi^{-1}\big(\Phi_\alpha + t(\Phi_\beta - \Phi_\alpha)\big), \qquad p(t) = \mu + \sigma z(t) \in (0,1).$$

With $Z = \Phi_\beta - \Phi_\alpha$ and $\varphi(\cdot)$ the standard normal pdf:

$$\text{loss\_scaling}(t) = \frac{a'(t)}{1-a(t)} = -\frac{p'(t)}{p(t)} = -\frac{\sigma Z}{\varphi(z(t))\, p(t)}.$$

Bimodal Gaussian schedule (mixture):
Choose a split weight $w \in (0,1)$ (denote $w_1 = w$, $w_2 = 1-w$). With probability w use (μ_1, σ_1), otherwise use (μ_2, σ_2):

$$t_1 = \frac{t}{w_1} \ \ (t < w_1), \qquad t_2 = \frac{t - w_1}{w_2} \ \ (t \geq w_1), \qquad p(t) = \begin{cases} \mu_1 + \sigma_1 z_1(t_1), & t < w_1 \\ \mu_2 + \sigma_2 z_2(t_2), & t \geq w_1 \end{cases}$$

where each $z_i(\cdot)$ is defined as above (with its own $\alpha_i, \beta_i, \Phi_{\alpha_i}, \Phi_{\beta_i}$ and Z_i). The resulting scaling is piecewise:

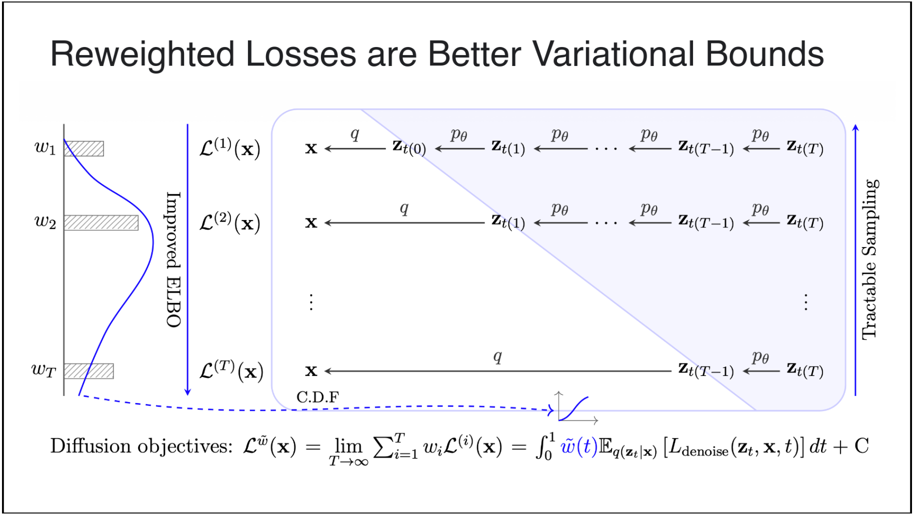
$$\text{loss\_scaling}(t) = -\frac{1}{p(t)} \begin{cases} \frac{1}{w_1} \frac{\sigma_1 Z_1}{\varphi(z_1(t_1))}, & t < w_1 \\ \frac{1}{w_2} \frac{\sigma_2 Z_2}{\varphi(z_2(t_2))}, & t \geq w_1 \end{cases}$$

New Schedules' Results

Perplexities (PPL) and Var. NELBO for implemented vs new schedules on LM1B (400 Pretraining Steps + 100 Fine-tuning Steps). B.G. stands for Bimodal Gaussian

Block Size	Already Implemented			Newly Implemented		
	Noise Schedule	PPL	Var. NELBO	Noise Schedule	PPL	Var. NELBO
128	Loglinear	1000	10.00	Gaussian (μ =0.5)	1000	10.00
	Loglinear $\mathcal{U}[0,\ 0.5]$	1000	10.00	Gaussian (μ =0.6)	1000	10.00
	Cosine	1000	10.00	B.G. ($\mu_1 = 0.3, w_1 = 0.6$)	1000	10.00
	Cosine $\mathcal{U}[0,\ 0.5]$	1000	10.00	B.G. ($\mu_1 = 0.1, w_1 = 0.6$)	1000	10.00
16	Loglinear	1279	10.50	Gaussian (μ =0.5)	1234	10.00
	Loglinear $\mathcal{U}[0.3,\ 0.8]$	1278	10.51	Gaussian (μ =0.6)	1235	10.00
	Cosine	1236	10.00	B.G. ($\mu_1 = 0.3, w_1 = 0.6$)	1254	10.00
	Cosine $\mathcal{U}[0.3,\ 0.8]$	1235	10.00	B.G. ($\mu_1 = 0.1, w_1 = 0.6$)	1295	10.00
4	Loglinear	**1226**	**44.41**	Gaussian (μ =0.5)	1250	46.76
	Loglinear $\mathcal{U}[0.5,\ 1]$	**1226**	**44.41**	Gaussian (μ =0.7)	1252	46.76
	Cosine	1228	45.28	B.G. ($\mu_1 = 0.3, w_1 = 0.6$)	1253	46.84
	Cosine $\mathcal{U}[0.5,\ 1]$	1229	45.26	B.G. ($\mu_1 = 0.1, w_1 = 0.6$)	1243	46.49

Reweighted Losses for Improved Diffusion Objective



Reweighted Losses are Better Variational Bounds

w_1
w_2
w_T
Improved ELBO
$\mathcal{L}^{(1)}(\mathbf{x})$
$\mathbf{x} \xleftarrow{q} \mathbf{z}_{t(0)} \xleftarrow{p_\theta} \mathbf{z}_{t(1)} \xleftarrow{p_\theta} \cdots \xleftarrow{p_\theta} \mathbf{z}_{t(T-1)} \xleftarrow{p_\theta} \mathbf{z}_{t(T)}$
$\mathcal{L}^{(2)}(\mathbf{x})$
$\mathbf{x} \xleftarrow{q} \mathbf{z}_{t(1)} \xleftarrow{p_\theta} \cdots \xleftarrow{p_\theta} \mathbf{z}_{t(T-1)} \xleftarrow{p_\theta} \mathbf{z}_{t(T)}$
$\vdots$
$\vdots$
$\mathcal{L}^{(T)}(\mathbf{x})$
$\mathbf{x} \xleftarrow{q} \mathbf{z}_{t(T-1)} \xleftarrow{p_\theta} \mathbf{z}_{t(T)}$
C.D.F
Tractable Sampling

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	$\log \frac{\alpha_t}{1-\alpha_t}$	$p_{\mathcal{N}(2.4,2.4^2)}(\lambda) \frac{e^{-\lambda}+0.5^2}{0.5^2}$	$w(\lambda(t))$
IDDPM		$\mathrm{sech}(\frac{\lambda}{2})$	$2\sqrt{\alpha_t(1-\alpha_t)}$
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

Table of Contents

1. Paper Overview
2. Our Results
   - Reproduction
   - Extensions
3. Conclusion & Future Work
4. Team Organization
5. Retrospection

Table of Contents

1. Paper Overview

2. Our Results
   - Reproduction
   - Extensions

3. Conclusion & Future Work

4. Team Organization

5. Retrospection

Table of Contents

1. Paper Overview
2. Our Results
   - Reproduction
   - Extensions
3. Conclusion & Future Work
4. Team Organization
5. Retrospection