

Block Diffusion: Interpolating Between Autoregressive and Diffusion Language Models

Ntountounakis Georgios, Markoulidakis Georgios, Vitalis Petros,
Makras Ilias, Kritharidis Konstantinos, Kordas Nikolaos

Pattern Recognition, ECE
National Technical University of Athens

January 2026

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

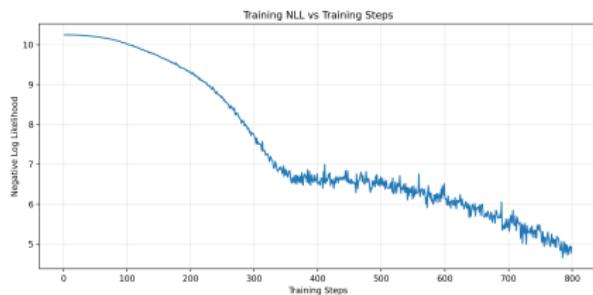
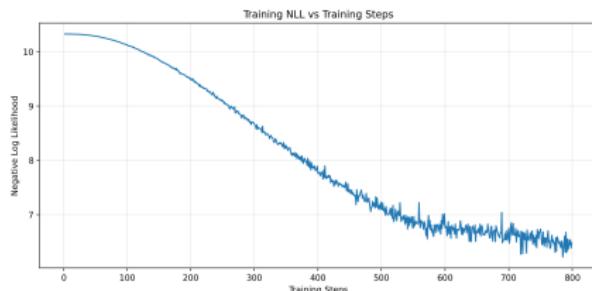
4 Team Organization

5 Retrospection

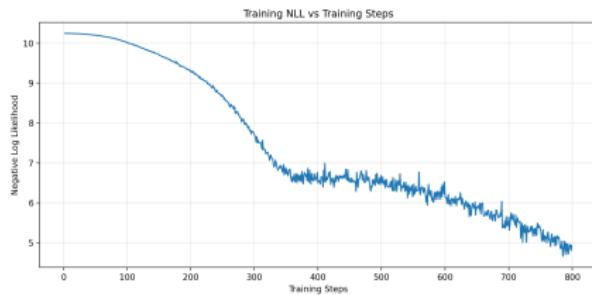
AR vs BD3LM with $L'=1$

Test Perplexities for single token
generation

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



BD3LM



BD3LM + Tuned Schedule

The Effect of Clipped Noise Schedules

L'	U [0, 0.5]			U [0, 1]		
	PPL	Var.	NELBO	PPL	Var.	NELBO
128	1000	1000	1000	1000	1000	1000

L'	U [0.3, 0.8]			U [0, 1]		
	PPL	Var.	NELBO	PPL	Var.	NELBO
16	1000	1000	1000	1000	1000	1000

L'	U [0.5, 1]			U [0, 1]		
	PPL	Var.	NELBO	PPL	Var.	NELBO
4	1226.46	44.41	1225.99	44.41		

Table 3

Table 3 Results

Table 4

Table 4 Results

Table 5

Table 5 Results

Table 6

Table 6 Results

Table 7

Table 7 Results

Table 8

Table 8 Results

Table of Contents

1 Paper Overview

2 Our Results

- Reproduction
- Extensions

3 Conclusion & Future Work

4 Team Organization

5 Retrospection

Exploring New Schedules

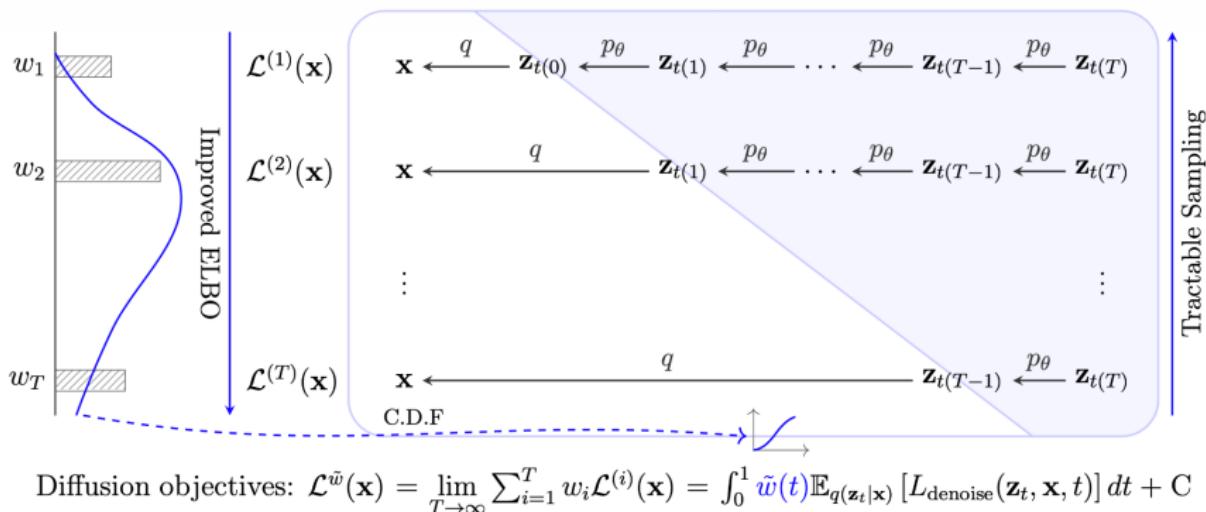
- Motivation for designing alternative noise schedules
- Trade-off between stability and generation quality
- Impact on gradient variance
- Compatibility with block diffusion framework

New Schedules' Results

- Comparison with cosine and clipped schedules
- Effects on perplexity
- Training stability observations
- Sampling behavior differences

Reweighted Losses for Improved Diffusion Objective

Reweighted Losses are Better Variational Bounds



Reweighted Losses for Masked Diffusion

- Initial Reweighted NELBO:

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

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

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

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		$\text{sech}(\frac{\lambda}{2})$	$2\sqrt{\alpha_t(1 - \alpha_t)}$
Sigmoid	$\log \frac{\alpha_t}{1 - \alpha_t}$	$\text{sigmoid}(-\lambda + k)$	$\frac{1 - \alpha_t}{1 - (1 - e^{-k})\alpha_t}$
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 (\downarrow)						
Autoregressive						
Transformer	1221					
Diffusion						
SEDD	1403					
MDLM	1370					
Block diffusion	Base	IDDPBM	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