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

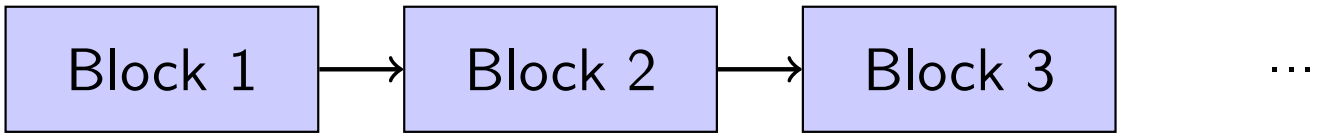
Can we combine the advantages of both approaches?

Core Idea: Block Diffusion

Key Innovation

Split sequence into **blocks** and apply:

- Autoregression **between** blocks
- Diffusion **within** each block



Diffusion within block(parallel)

Autoregressive over blocks

Parameterization: Block size L' controls the trade-off

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

Block Diffusion Training Algorithm

Challenge: To compute the loss $\mathcal{L}_{BD}$ for block b:

- **Noisy Pass:** The model must process $\mathbf{x}_t^b$ to learn denoising.
- **Clean Pass:** The model needs the clean $\mathbf{x}^b$ to provide context for subsequent blocks.

Naive Solution: Every block must pass through $\mathbf{x}_\theta$ at least *twice*.

Algorithm 1 Block Diffusion Training

Input: $\mathbf{x}$, B, q_t, $\mathbf{x}_\theta$, $\mathcal{L}_{BD}$

1: **repeat**
2: Sample $t_1, \ldots, t_B \sim U[0, 1]$
3: $\mathbf{x}_{t_b}^b \sim q_{t_b}(\cdot|\mathbf{x}^b)$
4: $\emptyset, K_{1:B}, V_{1:B} \leftarrow \mathbf{x}_\theta(\mathbf{x})$ ▷ *Clean Pass*
5: $\mathbf{x}_{\text{logit}}^b \leftarrow \mathbf{x}_\theta^b(\mathbf{x}_{t_b}^b, K_{1:b-1}, V_{1:b-1})$ ▷ *Noisy Pass*
6: Grad step $\nabla_\theta \mathcal{L}_{BD}$
7: **until** converged

Why this design?

- **Indep.** t_b**:** Reduces variance
- **KV caching:** 5× speedup
- **Vectorized:** FlexAttention parallelism

Block Diffusion Sampling Algorithm

Challenge: Standard diffusion models cannot generate variable-length sequences.

Algorithm 2 Block Diffusion Sampling

Input: # blocks B, model $\mathbf{x}_\theta$, diffusion sampling algorithm SAMPLE

1: $\mathbf{x}, K, V \leftarrow \emptyset$ ▷ *Initialize output & cache*
2: **for** $b = 1$ to B **do**
3: $\quad \mathbf{x}^b \leftarrow \text{SAMPLE}(\mathbf{x}_\theta^b, K_{1:b-1}, V_{1:b-1})$ ▷ *Parallel block production*
4: $\quad (K, V) \leftarrow (K \oplus K_b, V \oplus V_b)$ ▷ *Extend cache for new block*
5: **end for**
6: **return** $\mathbf{x}$

Why this design?

- **Autoregressive over blocks:** Generate arbitrary length sequences
- **Diffusion within blocks:** Parallel token generation $\rightarrow$ faster text generation
- **KV caching:** Reuse computation from previous blocks $\rightarrow$ inference efficiency
- **Result:** 40$\times$ fewer steps than SSD-LM with better quality

The Problem: Perplexity Gap

Question: Why do diffusion models have worse perplexity?

Observation

For $L' = 1$ (block size $= 1$), the diffusion objective is equivalent to the AR objective in expectation.

But in practice:

Model	**PPL** ($\downarrow$)
AR	**22.88**
$+$ random batch size	24.37
BD3-LM $L' = 1$	$\leq$ 25.56
$+$ tuned schedule	**22.88**

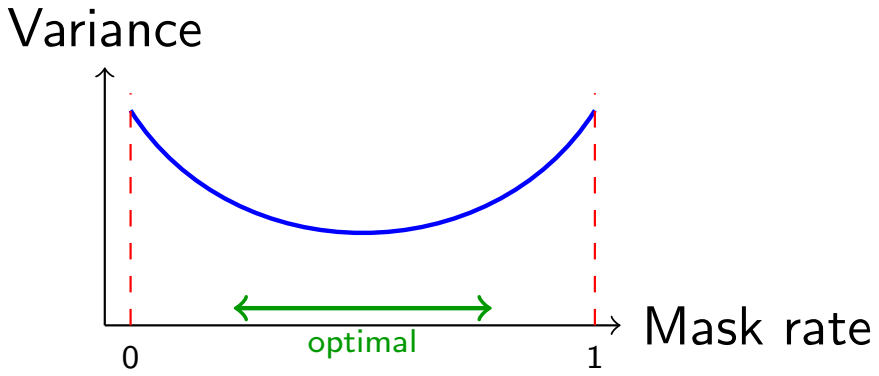
Masking $\Rightarrow$ diffusion training estimates loss gradients with 2x fewer tokens.
Conclusion: The problem is not the objective, but the **variance**!

The Solution: Clipped Noise Schedules

Goal: Design schedules that minimize gradient variance (Section 5)

Why extreme mask rates are bad:

- Too few masked (near 0): Easy task, no learning signal
- All masked (near 1): Predict marginals, doesn't help generation
- Both cause **high variance gradients**



The Solution: Clipped Noise Schedules

Clipped Schedules

$$1 - \alpha_t \sim U[\beta, \omega]$$

- β: Min mask rate, ω: Max mask rate
- Avoids extremes near 0 or 1

Examples:

- $U[0, 1]$: Standard linear
- $U[0.3, 0.8]$: Clipped
- $U[0.45, 0.95]$: Heavy masking (best for $L' = 4$)

Key Finding

There exists a unique distribution for each block size, that minimizes both the variance of the NELBO and the PPL.

Main Experimental Results

Table: Test perplexities (PPL; ↓) on OWT for models trained for 524B tokens. Best diffusion value is bolded.

	PPL (↓)
AR	17.54
SEDD	$\leq$ 24.10
MDLM	$\leq$ 22.98
BD3-LMs $L' = 16$	$\leq$ 22.27
$L' = 8$	$\leq$ 21.68
$L' = 4$	$\leq$ **20.73**

Table: Generation length statistics from sampling 500 documents from models trained on OWT.

	Median # tokens	Max # tokens
OWT train set	717	131K
AR	4008	131K
SEDD	1021	1024
BD3-LM $L' = 16$	798	9982

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Implementation Phases

Phase	Description	Weeks
1	Paper & codebase study	1-2
2	Environment & data setup	2-3
3	Initial reproduction	3-5
4	Final reproduction	5-6
5	Extension experiments	6-7
6	Analysis & Writing	7-8

Current Status

Phase 3 (Initial reproduction): running a small-scale setup (tiny model + reduced dataset) to validate the full pipeline.

Reproduction

Goal: Reproduce the paper's training/inference pipeline in a *controlled* setting.

Training datasets and tokenizers

Training dataset	**Tokenizer**
LM1B	`bert-base-uncased`
OWT	`GPT2`

Reproduction (experimental setup)

Experimental Setup (Small-scale)

Configuration	Choice
Training Samples	500
Training Steps	800
Evaluation Samples	100
Model Size	`tiny`
Context Length	128

What we will report:

- Training loss curves and evaluation perplexity (PPL)
- Sampling sanity checks: coherence vs. speed (block size trade-off)

Expected outcome: correct trends and stable training (not necessarily paper-level absolute PPL due to limited resources)

Potential Extensions

Extension 1: Diffusion Optimization

- Optimize elements of the diffusion process to improve quality and/or performance.

Extension 2: Adaptive Block Size

- Adaptively change the block size according to the need for fine-grained detail of each block.

Extension 3: Training / Fine-tuning on new, resource-friendly datasets

- **AG News**: news-domain text for domain adaptation
- **LAMBADA**: long-range dependency evaluation
- **Penn Treebank (`ptb`)**: classic language modeling benchmark
- **BabyLM Corpus**: child-language data for acquisition modeling

Experimental Results (Reproduction)

Table 3 Initial Reproduction: Test Perplexities

	PPL (↓)
Autoregressive	
Transformer	1221
Diffusion	
SEDD	$\leq$ 1403
MDLM	$\leq$ 1370
Block diffusion (Ours)	
BD3-LMs $L' = 16$	$\leq$ 1345
$L' = 8$	$\leq$ 1210
$L' = 4$	$\leq$ **1176**

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Computational Resources & Data

Computational Resources:

- Google Colab (Primary environment)
- Kaggle Notebooks
- our GPUs

Datasets:

- LM1B
- OWT

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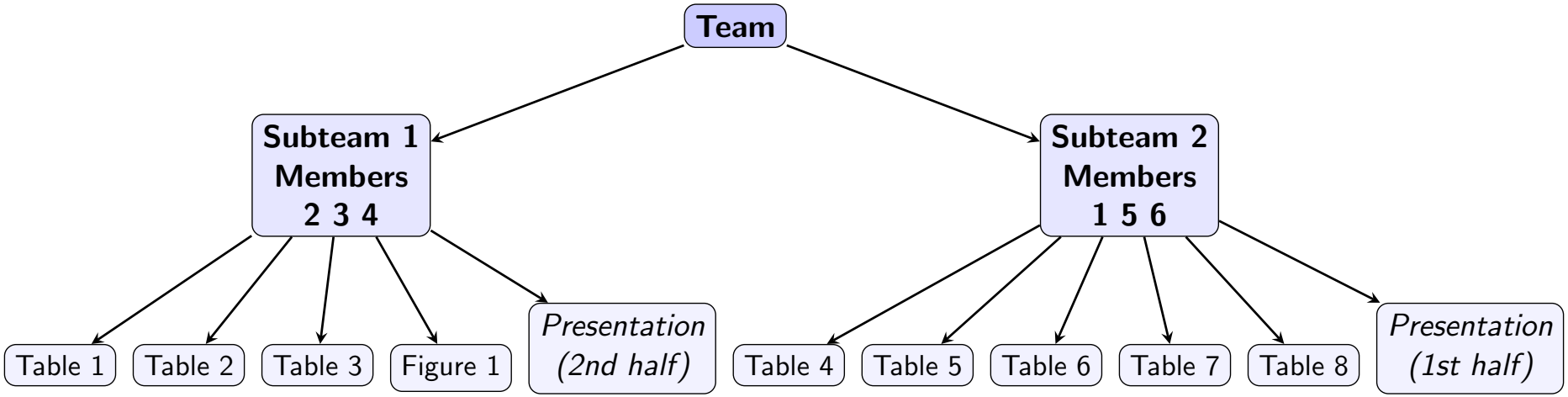
Team Organization and Structure



Coordination:

- Weekly team meetings
- Subteams internal coordination
- GitHub repo
- Discord server

Member Roles

Phase	Description	Members
1	Paper & codebase study	Everyone
2	Environment & data setup	Georgios M., Petros
3	Initial reproduction	Georgios M., Petros, Ilias
4	Final reproduction	Georgios Nt., Konstantinos, Nikolaos
5	Extension experiments	Everyone
6	Analysis & Writing	Everyone

Thank You!

Questions?

Paper: Block Diffusion (ICLR 2025)
Code: `https://github.com/kuleshov-group/bd3lms`
Our Repo: `https://github.com/ntua-el21050/bd3lms`
Authors: Arriola, Gokaslan, Chiu, Yang, Qi, Han, Sahoo, Kuleshov