dInfer: An Efficient Inference Framework for Diffusion Language Models

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Abstract

Diffusion-based large language models (dLLMs) have emerged as a promising alternative to autoregressive (AR) LLMs, leveraging denoising-based generation to enable inherent parallelism. Even more and more open-sourced dLLM models emerge, yet their widespread adoption remains constrained by the lack of a standardized and efficient inference framework. We present dInfer, an efficient and extensible framework for dLLM inference. dInfer decomposes the inference pipeline into four modular components—model, diffusion iteration manager, decoding strategy, and KV-cache manager—and integrates novel algorithms for each component alongside system-level optimizations. Through this combination of algorithmic innovations and system enhancements, dInfer achieves substantial efficiency gains without compromising output quality on LLaDA-MoE. At batch size 1, it surpasses 1,100 tokens per second on HumanEval and averages over 800 tokens per second across six benchmarks on 8× H800 GPUs. Compared to prior systems, dInfer delivers 10× speedup over Fast-dLLM while maintaining similar model performance. Even compared with AR models (with a comparable number of activation parameters and performance) QWen2.5-3B, which is highly optimized with latest vLLM inference engine, dInfer still deliverers 2–3× speedup. The implementation of dInfer is open-sourced at https://github.com/inclusionAI/dInfer.

1 Introduction

Over the past year, diffusion-based large language models (dLLMs) have gained increasing attention in both academia and industry. Unlike conventional autoregressive (AR) models that generate tokens sequentially, dLLMs refine entire sequences in parallel through iterative denoising. This intrinsic parallelism opens new opportunities for faster decoding and enables better utilization of GPU hardware. Combined with rapid algorithmic progress, these properties make dLLMs a compelling alternative to AR LLMs. Recent work has shown that models such as LLaDA(-MoE) Nie et al. (2025); Zhu et al. (2025) can reach performance levels comparable to strong AR baselines, including Llama Grattafiori et al. (2024) and Qwen Yang et al. (2024).

Despite these advantages, the practical deployment of dLLMs still faces three critical bottlenecks. First, dLLMs are substantially more computationally expensive than AR models due to iterative denoising steps, making efficiency improvements at both the algorithm and system level essential. Second, while dLLMs have inherent parallelism, scaling parallel decoding remains challenging—larger parallel spans often degrade output quality. Third, the field lacks a unified inference framework and standardized evaluation protocol. This gap hinders consistent benchmarking and often leads to incomparable acceleration claims, such as reporting tokens per second (TPS) under varying batch sizes or hardware.

To address these challenges, we propose dInfer, an efficient and extensible inference framework for dLLMs. dInfer modularizes inference into four components—model, diffusion iteration manager, decoding strategy, and KV-cache management—and provides well-designed APIs for flexible combinations of algorithms in each component. It supports multiple dLLM variants, including LLaDA Nie et al. (2025), LLaDA-MoE Zhu et al. (2025), and LLaDA-MoE-TD (Section C.1). dInfer introduces an iteration smoothing algorithm for smoother denoising, hierarchical and credit decoding for enhanced parallel decoding, and a vicinity refresh strategy for KV-cache management to mitigate cache staleness.

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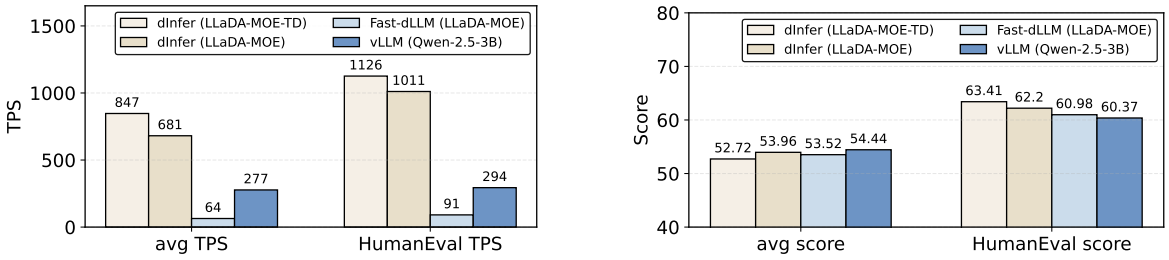

(a). TPS

(b). Model performance

Figure 1: Benchmark results. We compare dInfer on LLaDA-MoE and LLaDA-MoE-TD with Fast-dLLM and vLLM across six benchmarks and show their average inference speed in tokens per second (TPS) on the six benchmarks and the highest inference speed on the HumanEval dataset. When achieving similar model performance on the benchmarks, dInfer is about $10\times$ faster than Fast-dLLM on the same model and is about $2-3\times$ faster than vLLM on Qwen-2.5-3B.

Beyond algorithmic improvements, dInfer integrates several system-level optimizations. It supports both tensor parallelism (TP) and expert parallelism (EP) to maximize GPU utilization even at batch size 1. It leverages PyTorch compilation and NVIDIA CUDA Graphs for efficient kernel execution, and introduces a loop unrolling mechanism to eliminate CUDA stream bubbles across diffusion iterations.

We evaluate inference efficiency using tokens per second (TPS) per sequence, shown in Figure 1. On HumanEval, dInfer achieves over 1,100 TPS at batch size 1, and averages more than 800 TPS across six benchmarks on a single node with $8\times$ H800 GPUs. Compared to Fast-dLLM Wu et al. (2025), dInfer delivers more than a $10\times$ speedup while maintaining accuracy; on LLaDA-MoE it provides a $2-3\times$ speedup over QWen2.5-3B on vLLM with comparable quality.

Our contributions are summarized as follows:

- We present dInfer, the first modularized dLLM inference framework that integrates algorithmic innovations with system-level optimizations to deliver substantial efficiency gains.
- We provide the first open-source demonstration that dLLM inference can surpass AR models at batch size 1, establishing a new milestone for inference efficiency. The implementation is available at `https://github.com/inclusionAI/dInfer`.

2 Framework Design

A key advantage of dLLMs lies in their ability to perform parallel decoding within each iteration. To fully exploit this capability, advances are required in model design, diffusion iteration strategies, and decoding algorithms. At the same time, dLLMs introduce unique computational challenges. Unlike AR models—where previously computed keys and values can be cached—dLLMs employ bidirectional attention, meaning that decoding a single token can affect the representations of all tokens in the sequence. This makes straightforward KV-cache reuse infeasible and necessitates specialized cache management for efficient inference.

To address these issues, we design dInfer, an inference framework that accelerates dLLMs through four modular components: model, diffusion iteration manager, decoding strategy, and KV-cache management (Figure 2). This modular architecture enables flexible combinations of algorithms across components, allowing users to construct cus-

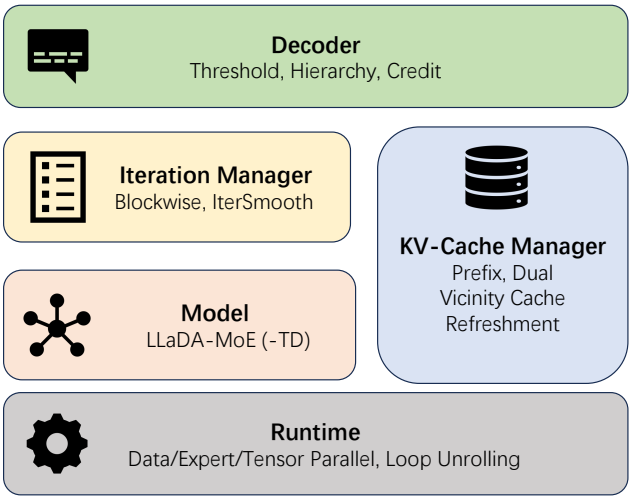

Figure 2: The architecture of the dInfer framework

tomized inference pipelines that maximize the benefits of parallel decoding while improving computational efficiency.

Algorithm 1 Blockwise dLLM Inference

Require: Input tokens $X \in \mathbb{Z}^{B\times L}$ (undecided positions marked as *mask_id*); block size S; model $\mathcal{M}$; decoder $\mathcal{D}$; KV-cache manager $\mathcal{K}$; block iteration manager $\mathcal{I}$
Ensure: Completed tokens $\widehat{X} \in \mathbb{Z}^{B\times L}$

$\mathcal{K}$.CREATE(B, L) ▷ Create KV cache
while $\mathcal{I}$.HASNEXT$()$ **do**
  # 1) Iterator: pick next block (blockwise order)
  $[start:end] \leftarrow \mathcal{I}$.NEXTBLOCK$()$ ▷ Get next block
  undecided $\leftarrow (X[start:end] = mask\_id)$ ▷ Boolean mask of undecided positions
  while any(undecided) **do**
    # 2) KV update policy
    if $\mathcal{K}$.SHOULDUPDATE(loop_context, $start:end$) **then**
      $\mathcal{K}$.UPDATE$(X, start:end)$
    end if
    # 3) Model forward on this region (with KV Cache)
    logits $\leftarrow \mathcal{M}$.FORWARD$(X, \mathcal{K}, start:end)$ ▷ logits $\in \mathbb{R}^{B\times L\times V}$
    # 4) Decoder: tokens to commit in this block
    $(X,\ undecided) \leftarrow \mathcal{D}$.DECODE(logits, X, undecided, $start:end$)
  end while
end while
return X ▷ $\widehat{X}$

2.1 Diffusion Iteration Manager

The diffusion iteration manager acts as the controller of the iterative denoising process, with three main responsibilities: 1) determining the next region of tokens to decode, 2) interacting with the model to obtain outputs such as logits and hidden states, 3) maintaining historical predictions to provide a richer context for future decoding.

dInfer currently implements two algorithms in this component. The **block-wise diffusion iteration** algorithm performs decoding in fixed-size spans and serves as a baseline (Algorithm 1). The **iteration smoothing** algorithm improves upon this by retaining token representations from the previous iteration and fusing them with the next iteration's embeddings. This enables cross-iteration information flow, enriches contextual cues, and empirically boosts token confidence while mitigating the performance degradation typically caused by KV-cache deployment. A detailed description is provided in Appendix A.1.

2.2 Decoding Strategy

dInfer supports three strategies for parallel decoding:

- Threshold decoding (from Fast-dLLM Wu et al. (2025)): commits tokens whose confidence exceeds a preset threshold.
- Hierarchical decoding (ours): recursively partitions masked spans, ensuring at least one token is decoded per region, thereby reducing local dependencies and improving efficiency.
- Credit decoding (ours): accumulates historical confidence scores as *credits* and preferentially commits tokens with consistently stable predictions, improving reliability across iterations.

These algorithms allow dInfer to achieve higher decoding efficiency without retraining the underlying model. Detailed formulations are included in Appendix B.1 and B.2.

2.3 KV-cache management

A central challenge in dLLM inference is KV-cache incompatibility. In AR models, causal attention allows KV states to be computed once and reused; in dLLMs, however, token representations evolve across denoising steps, making static reuse infeasible. Without caching, inference must perform Transformer computations over the entire sequence, creating heavy computational overhead.

Earlier approaches introduced training-free strategies such as block-wise caching and Dual Cache Wu et al. (2025), which reuse KV states for decoded tokens or suffixes of masked tokens. However, these methods treat cached states as static, neglecting updates from newly decoded tokens, which often degrades accuracy.

To balance cost and performance, dInfer introduces **vicinity KV-cache refresh**. This method exploits semantic locality by selectively updating a small window of tokens adjacent to the current decoding block. During denoising, K and V states are recomputed for both masked tokens and their immediate neighbors; once a block is fully decoded, a full cache update ensures global consistency.

2.4 Model support

dInfer is designed to be model-agnostic and currently supports state-of-the-art dLLMs such as LLaDA-MoE, LLaDA-1.5, and LLaDA-Instruct, with plans for continued extension. Beyond compatibility, we also explore improving the parallel decoding capability of dLLMs through training. Specifically, we introduce Trajectory Distillation, applied to LLaDA-MoE, yielding the enhanced LLaDA-MoE-TD variant (see Section C.1). This method fine-tunes models using effective decoding trajectories identified from their own generation process, significantly boosting parallel decoding efficiency.

2.5 An example of the orchestration of the algorithms in dInfer

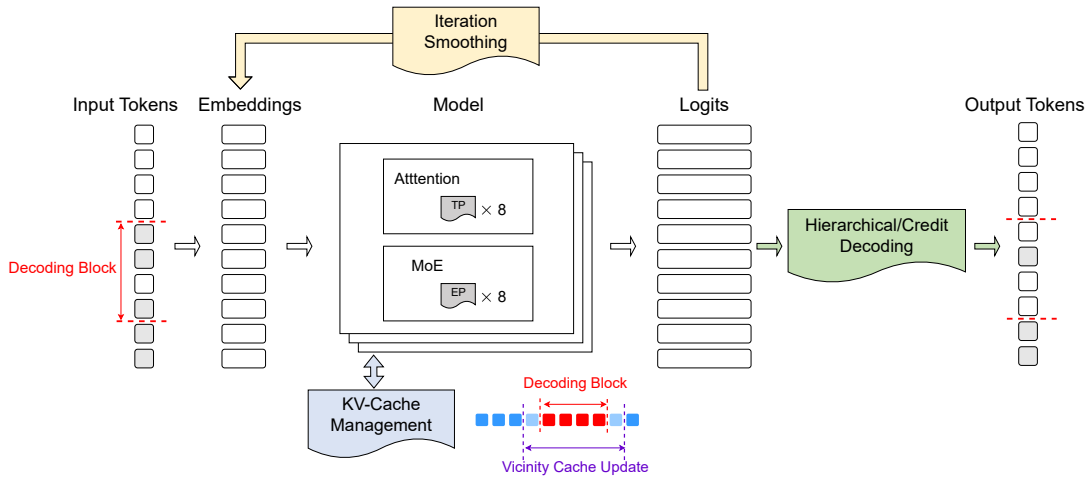

Figure 3: Orchestration of the algorithms in different dInfer components.

Figure 3 shows how the algorithms interact within dInfer. In each iteration, the framework tries to identify the [MASK] tokens in the active decoding block. The sequence is first embedded (potentially leveraging context from previous iterations), followed by a forward pass through the model using tensor/expert parallelism to produce logits. During the forward pass, the previous KV cache that does not hit the vicinity refresh strategy will remain unchanged and be reused. After getting the logits, the hierarchical/credit decoding algorithm will decide which [MASK] tokens to decode and predict their identities. In addition, the iteration smoothing algorithm will retain the logit-weighted embeddings of the sequence and incorporate them as part of the embedding for the next iteration, ensuring continuity across steps. Together, these components enable dInfer to achieve both efficiency and stability in dLLM inference.

3 Implementation Details

To deliver fast inference speed, dInfer provides system-level optimizations on the components of dInfer.

Model computations dInfer builds on vLLM's backend to exploit two complementary forms of parallelism. Tensor parallelism is applied to the linear layers preceding attention modules, distributing dense computations efficiently across multiple GPUs. Expert parallelism is applied to the LLaDA-MoE model and is effective even at a batch size of one—unlike in AR models, where expert parallelism typically requires large batch sizes. By combining tensor and expert parallelism, dInfer achieves more than a 100% improvement in inference efficiency.

To further optimize single-sequence inference, dInfer uses PyTorch's just-in-time (JIT) compiler `torch.compile` to fuse CUDA kernels and execute them within NVIDIA CUDA Graphs, thereby eliminating

PyTorch execution overhead. This compilation technique improves inference efficiency by over 200% when TP and EP are enabled.

Diffusion iterations Diffusion iterations can suffer from CUDA stream bubbles—idle gaps of consecutive kernel launches between diffusion iterations—which waste GPU cycles and reduce throughput. To address this, dInfer applies a loop unrolling strategy that allows Python to launch CUDA kernels continuously without being blocked by stream synchronization. This reduces launch latency, keeps GPU pipelines fully occupied, and boosts iteration efficiency by about 5-10%.

We also introduce an early termination mechanism for block-wise decoding. Once an end-of-sequence (EOS) token is generated within a block, subsequent decoding steps on the remaining blocks become redundant. dInfer therefore halts the diffusion loop and fills all remaining blocks with EOS, avoiding unnecessary computation. This optimization improves inference efficiency by 15-40%.

Parallel decoding To make loop unrolling effective in diffusion iterations, decoding algorithms in dInfer are implemented without control-flow operations, and data transfer from PyTorch tensors to Python code is eliminated. This design ensures compatibility with system-level optimizations to achieve high decoding throughput.

4 Evaluations

4.1 Datasets and Configurations

Datasets. We select six datasets from diverse domains with sufficient response lengths: CRUX-O (Gu et al., 2024), LiveCodeBenchv6 (Jain et al., 2024)(denoted as LCB V6), MBPP (Austin et al., 2021), and HumanEval (Chen et al., 2021) for code generation; GSM8K (Cobbe et al., 2021) for mathematical reasoning; and IFEval (Zhou et al., 2023) for instruction-following agent tasks.

Evaluation Metric. To evaluate the efficiency of the dInfer framework, we use **tokens per forward (TPF) per sequence** to measure the parallel decoding capability within a single diffusion iteration, and **tokens per second (TPS) per sequence** to assess overall inference efficiency. To be more specific, TPF can be formally described as $TPF = \frac{T_i}{F_i}$ where T_i and F_i are the number of tokens generated before the first `EOS` and the number of diffusion iterations that run on a sequence i to generate tokens. TPS can be described as $TPS = \frac{T_i}{t_i}$ where t_i is the time cost to generate tokens for sequence i.

Configurations. We compare dInfer with Fast-dLLM (Wu et al., 2025) to demonstrate the effectiveness of both system optimizations and algorithmic innovations in dInfer. Without KV cache, Fast-dLLM employs parallel decoding with a threshold of 0.9, a setting used in their paper, while dInfer further incorporates *credit decoding* and *iteration smoothing* to validate the effectiveness of the proposed decoder. When KV cache is enabled, Fast-dLLM adopts Dual Cache, whereas dInfer integrates the *vicinity KV-Cache refresh* method with *iteration smoothing* and threshold decoding. In addition, we evaluate the effectiveness of LLaDA-MoE-TD in dInfer. We report its results under the dInfer optimal setting, which integrates dual-cache, *hierarchical decoding*, *vicinity KV-Cache refresh*, and *iteration smoothing*. Please see more details about the configurations of the experiments in Appendix D.

All experiments are conducted on a server equipped with 8× NVIDIA H800 GPUs, with PyTorch 2.9.0.dev20250831 and vLLM 0.10.1. We use a batch size of one, a generation length of 1024 and a block size of 64 for all experiments.

4.2 Performance

As shown in Table 1, it can be clearly observed that LLaDA-MoE have comparable or higher performance than Qwen2.5-3B over six diverse datasets. Under the "Without KV Cache" setting, dInfer achieves an average accuracy of 54.33, which is higher than Fast-dLLM and is comparable to the performance of QWen2.5-3B in vLLM and LLaDA-MoE reported in its paper Zhu et al. (2025), while achieving 6.5× speedup over Fast-dLLM. When KV cache is enabled, dInfer achieves higher accuracy than Fast-dLLM (53.96 vs. 52.15) and delivers 6× speedup over Fast-dLLM. When achieving similar model performance, dInfer achieves over 10× speedup (a TPS of 680.71) over Fast-dLLM (a TPS of 63.61) across the six benchmarks. dInfer is also 2.5× faster than Qwen-2.5 3B (a TPS of 277.45) in vLLMs.

As shown in Table 2, the LLaDA-MoE model trained by the trajectory distillation technique substantially improves inference efficiency on the six benchmarks. Coupled with the full set of dInfer algorithmic

Table 1: Evaluations of different framework and configurations in terms of performance, TPF, and TPS on LLaDA-MoE. We can observe that dInfer achieves a $2-3\times$ improvement over vLLM (680.71 vs. 277.45). Furthermore, we can see that dInfer provides more than a tenfold enhancement over Fast-dLLM (680.71 vs. 63.61) while achieving similar results (53.96 vs. 53.52).

Config.	Frame.	Metric	Avg.	CRUX-O	GSM8K	HumanEval	IFEval	MBPP	LCB V6
LLaDA-MoE	-	Perf	54.83	42.38	82.41	61.59	59.33	70.02	13.27
QWen2.5-3B	vLLM	Perf	54.44	46.75	86.28	60.37	58.2	65.81	9.2
		TPF	1	1	1	1	1	1	1
		TPS	277.45	289.53	294.15	294.05	296.7	290.15	200.12
Without KV Cache	Fast-dLLM	Perf	53.52	43.75	82.79	60.98	54.53	66.5	12.56
		TPF	2.82	2.9	2.28	3.87	2.42	3.01	2.46
		TPS	63.61	59.79	56.19	90.8	60.25	70.2	44.4
	dInfer	Perf	**54.33**	42.38	82.26	63.41	57.49	67.21	13.22
		TPF	**4.29**	4.26	3.76	6.17	2.79	4.82	3.92
		TPS	**407.36**	379.62	379.63	606.85	285.49	475.23	317.36
With KV Cache	Fast-dLLM	Perf	52.15	40.75	79.9	60.37	53.97	65.11	12.78
		TPF	2.46	2.68	2.09	3.24	2.02	2.55	2.19
		TPS	110.98	120.57	97.5	143.9	95.23	112.9	95.8
	dInfer	Perf	**53.96**	41.38	80.97	62.2	58.78	67.45	13
		TPF	**3.87**	4.02	3.42	5.52	2.32	4.54	3.38
		TPS	**680.71**	765.3	682.9	1011.12	444.51	757.55	422.88

Table 2: Evaluations of different framework and configurations in terms of performance, TPF, and TPS on LLaDA-MoE-TD. With the introduction of Trajectory Distillation, the TPS for various benchmarks has significantly improved. The average TPS exceeds that of vLLM by more than threefold.

Config.	Frame.	Metric	Avg.	CRUX-O	GSM8K	HumanEval	IFEval	MBPP	LCB V6
LLaDA-MoE	-	Perf	54.83	42.38	82.41	61.59	59.33	70.02	13.27
QWen2.5-3B	vLLM	Perf	54.44	46.75	86.28	60.37	58.2	65.81	9.2
		TPF	1	1	1	1	1	1	1
		TPS	277.45	289.53	294.15	294.05	296.7	290.15	200.12
With KV Cache	dInfer	Perf	**52.72**	40.12	79.15	63.41	56.19	65.11	12.33
		TPF	**5.67**	6.06	6.12	7.10	2.98	6.61	5.18
		TPS	**847.22**	976.66	1,011.22	1,125.67	496.92	906.98	562.87

optimizations, the distilled model achieves an average TPS of 847.22, significantly higher than the 680.71 TPS of the non-distilled baseline, which is more than **3x** speedup over Qwen2.5-3B in vLLM.

5 Conclusion

In this work, we presented dInfer, an efficient and extensible inference framework for dLLMs. By decomposing inference into modular components and incorporating optimizations such as hierarchical decoding, credit decoding, iteration smoothing, and vicinity KV-cache refresh, dInfer effectively addresses the key bottlenecks of high computation cost and limited parallel decoding efficiency of dLLMs. Extensive experiments on LLaDA-MoE demonstrate that dInfer achieves state-of-the-art throughput—exceeding 1,100 TPS on $8\times$H800 GPUs—while maintaining output quality. We believe dInfer provides both a practical toolkit and a standardized platform to accelerate research and development in the rapidly growing field of dLLMs.

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A Diffusion iteration

A.1 IterSmooth: Iteration Smoothing

In conventional dLLM decoding, only a small subset of positions is updated at each step by selecting argmax tokens, while the logits for all other positions are discarded. IterSmooth reuses this otherwise wasted information: for positions that remain masked, it converts the logits distribution into an expected embedding and injects it into the corresponding mask-token embedding. This allows uncertain positions to be enriched with dense, distribution-level signals. In our setting, since the output projection and input embedding matrices are not weight-tied, the expected embeddings are computed using the input embedding matrix together with the token probability distribution.

We operate only on masked positions to avoid shifting the training distribution elsewhere. Let $z_t[i]$ be the logits at step t and position i, W_{emb} the input embedding matrix, and e_{mask} the standard mask embedding. Without temperature scaling, we use:

$$p_t[i] = \text{softmax}(z_t[i]), \quad \Delta e_t[i] = p_t[i]\, W_{\text{emb}}, \quad e_{t+1}[i] = e_{\text{mask}} + \alpha_t\, \Delta e_t[i], \quad \alpha_t = min(\alpha_{init} + \alpha_{growth} t, \alpha_{preset})$$

The mixing weight α_t increases from a small initial value (e.g., 0.1) over decoding steps toward a preset maximum(e.g., 0.2–0.4), ensuring conservative behavior early. In addition, we adopt a decode-threshold schedule that decays from 1.0 toward a preset target across steps, decoding only high-confidence positions early while progressively relaxing the criterion; which stabilizes inputs early and increases the contribution of distribution-level guidance later. Our method does not introduce new parameters or retraining, and W_{emb} is reused directly.

The approach increases per-step information by leveraging the full distribution instead of only argmax tokens. Our empirical study shows that this method can increase the average number of tokens decoded in a diffusion iteration by $30-40\%$, and improves the final quality of generated texts.

B Decoding strategy

B.1 Hierarchical decoding

While dLLMs theoretically allow parallel decoding by predicting multiple tokens at once, naive implementations often suffer from quality degradation. This stems from the violation of the conditional independence assumption among simultaneously generated tokens, which frequently leads to semantic inconsistencies.

To overcome this limitation, we propose Hierarchical Decoding, a training-free strategy inspired by the divide-and-conquer paradigm. The method recursively partitions masked spans into smaller sub-regions and decodes tokens based on their confidence, attempting to resolve at least one token in each region during every forward pass whenever confidence permits. The key insight is that the spatial distribution of masked tokens has a critical impact on prediction stability.

This approach provides two notable advantages. First, by promoting non-contiguous decoding, it increases the spacing between masked tokens, thereby reducing local dependencies and improving semantic consistency. Second, when decoding positions are preferentially selected near the center of each span, the undecoded regions shrink recursively, enabling the process to approach $O(logn)$ complexity in the ideal case. Together, these properties allow Hierarchical Decoding to generate more tokens per forward pass than vanilla decoding without fine-tuning the base model.

B.2 Credit decoding

In standard dLLM inference, text is generated through repeated *predict–sample–re-mask* cycles across multiple denoising steps. Existing parallel decoding strategies typically commit tokens based solely on their *current* confidence at each step. In practice, however, many tokens that are ultimately correct stabilize early in the generation process but remain below the confidence threshold. These tokens are repeatedly re-masked and re-evaluated, leading to unnecessary computation. We present *CreditDecoding*, a training-free acceleration algorithm for dLLMs that reduces redundant computation and accelerates convergence in parallel decoding.

During decoding, we maintain a *credit* $C_t^{i,v}$ for each position i and token $v \in \mathcal{V}$. This credit which quantifies how consistently a token has been favored along the generation process, serving as a temporal prior for its likelihood of being correct. Give the input x_t, let $p_\theta^i(v \mid x_t) = \text{Softmax}(f_\theta(x_t)_v^i)$ denote the model's current predictive distribution, where $f_\theta(x_t)$ are the logits. Let $v^* = \arg\max_v p_\theta^i(v \mid x_t)$ be the top candidate token at

position i. The credit is updated as follows:

$$C_t^{i,v} = \begin{cases} \beta\, C_{t-1}^{i,v} + \big(p_\theta^i(v \mid x_t)\big)^\gamma & v = v^*, \\ \beta\, C_{t-1}^{i,v} & \text{otherwise,} \end{cases} \qquad \beta \in (0,1),\ \gamma \in (0,1). \tag{1}$$

Here β discounts the earlier confidece and prevents errors from accumulating and influencing future predcion. The concave transformation $(\cdot)^\gamma$ (with $\gamma < 1$) provides relatively larger boosts to tokens with low or moderate confidence, helping correct but underconfident predictions stabilize earlier.

Before making a token commitment decision, the accumulated credit is fused with the model's logits as a prior in the log domain:

$$\tilde{f}_\theta(x_t)_v^i = f_\theta(x_t)_v^i + \alpha\, \log\big(1 + C_t^{i,v}\big), \qquad \alpha > 0, \tag{2}$$

which yields an enhanced distribution $\tilde{p}_\theta^i(v \mid x_t) = \mathrm{Softmax}\big(\tilde{f}_\theta(x_t)_v^i\big)$. Intuitively, tokens that have been consistently predicted across steps receive a confidence boost, making them more likely to be committed earlier. In contrast, tokens with fluctuating or transiently high confidence are suppressed. This mechanism enhances decoding stability, particularly in long-sequence and reasoning tasks.

Importantly, CreditDecoding does not change the underlying sampling or decoding policy, but instead simply replaces the original distribution p_θ with the enhanced $\tilde{p}_\theta$. This design ensures the compatibility with standard inference optimizations such as threshold decoding, top-k sampling, KV-cache, and compiler-level optimizations, allowing efficiency gains to accumulate when combined.

To balance efficiency and robustness under varying stability conditions, we default to maintaining and updating credits only within the current decoding block. This limits the influence of uncertain future context, reduces interference from under-informed positions, and improves scalability across different model sizes and context lengths—especially in long-sequence generation scenarios.

C Post-training to enhance models' parallel decoding

C.1 Inference Acceleration via Trajectory Compression

While dLLMs show promise for non-sequential generation, their practical application is often hindered by high inference latency stemming from the iterative, multi-step sampling process. Inspired by the approach in Seed Diffusion Song et al. (2025), which demonstrates the value of training on high-quality generation paths, we propose a novel second-stage fine-tuning method, termed **Trajectory Compression**, to explicitly reduce the number of required sampling steps. The core idea is to train the model to "jump" between non-consecutive states within an optimal generation trajectory, thereby decoding multiple tokens in a single forward pass. We refer to this resulting model as LLaDA-MoE-TD.

Our method consists of two main stages: high-quality trajectory distillation and compressed transition learning.

High-Quality Trajectory Distillation First, we generate a dataset of "golden" trajectories. We use a pre-trained dLLM to sample a large corpus of generation paths, $\mathcal{T}$, on a domain-specific dataset (e.g., 200,000 math problems). A trajectory $\tau = (s_N, s_{N-1}, \ldots, s_0)$ represents the sequence of states from the initial fully masked sequence s_N to the final generated output s_0.

Each trajectory's final output s_0 is evaluated by an external verifier, $V(\cdot)$. For mathematical tasks, we employ a $math_verify$ function to ascertain the correctness of the solution. We then filter the corpus to retain only the trajectories that result in a correct output, forming a high-quality dataset $\mathcal{T}_{\text{gold}}$:

$$\mathcal{T}_{\text{gold}} = \{\tau \in \mathcal{T} \mid V(s_0^\tau) = \text{True}\}$$

This process ensures that the subsequent fine-tuning stage learns from effective and valid reasoning paths.

Compressed Transition Learning In the second stage, we fine-tune the dLLM on a new objective. Instead of learning the standard single-step transition $p_\theta(s_{t-1}|s_t)$, we train the model to predict a multi-step transition from an early state s_i to a later state s_j, where $i > j$.

For each trajectory $\tau \in \mathcal{T}_{\text{gold}}$, we construct a training instance by randomly sampling two timestamps, i and j, where $N \geq i > j \geq 0$. The pair (s_i, s_j) serves as the input and target, respectively. Since tokens, once revealed, are fixed in subsequent steps, the model's task is to predict the tokens that are '[MASK]' in s_i but are revealed

in s_j. Let M_t be the set of indices of '[MASK]' tokens in state s_t. The model learns to predict the tokens at indices $\Delta_{i \to j} = M_i \setminus M_j$.

The fine-tuning objective is to minimize the negative log-likelihood of this compressed transition. The loss function is defined as:

$$\mathcal{L}_{\text{compress}}(\theta) = -\mathbb{E}_{\tau \in \mathcal{T}_{\text{gold}}, i,j \sim U(\tau)} \left[\sum_{k \in \Delta_{i \to j}} \log p_\theta(x_k = s_j[k] \mid s_i) \right]$$

where $s_j[k]$ is the ground-truth token at position k in the target state s_j. To handle variable-length sequences, both s_i and s_j are padded to the model's maximum context length.

This fine-tuning process endows the model with the ability to execute large *jumps* during inference, significantly accelerating generation. We measure this improvement using Tokens Per Forward (TPF). Our experiments show that this method yields a 99.8% increase in TPF for mathematical reasoning and an average TPF improvement of 45.3% across other domains, including code generation, confirming Trajectory Compression as an effective technique for reducing dLLM inference latency.

D Detailed Configuration of Experiments

To achieve an optimal balance between efficiency and generation quality, different experimental settings adopt distinct combinations of decoding and optimization methods, as summarized in Table 3. Each configuration is tuned for its best trade-off between model performance and inference efficiency given the model's characteristics and cache usage. We thus employ tailored algorithms for each setting, based on the ablation results provided in Table 4, Table 5, and Table 6, respectively.

The hyperparameter settings for the corresponding methods are as follows: the threshold decoding uses a confidence threshold of 0.8; the hierarchical decoding adopts a decoding threshold of 0.92 and a lower boundary threshold of 0.62; the iteration smoothing employs a continuation weight (cont_weight) of 0.3; and the vicinity KV-Cache refreshment strategy uses a prefix look and after look of 16, with warmup_times = 4.

Table 3: Experimental settings and enabled methods. A checkmark (✓) indicates the method is applied.

dInfer Setting	**Threshold**	**Hier.**	**Credit**	**IterSmooth.**	**Vicinity KV-Ref.**
LLaDA-MoE w/o KV-Cache	×	×	✓	✓	×
LLaDA-MoE with KV-Cache	✓	×	×	✓	✓
LLaDA-MoE-TD with KV-Cache	×	✓	×	✓	✓

Table 4: Ablation study of decoding algorithm on LLaDA-MoE w/o KV-Cache setting.

Config.	Metric	Avg.	CRUX-O	GSM8K	HumanEval	IFEval	MBPP	LCB V6
Threshold	Perf	54.01	42.62	82.41	60.98	55.64	67.21	15.2
	TPF	3.67	3.03	3.11	5.40	2.64	4.44	3.37
Hierarchy	Perf	53.68	39.75	80.97	64.02	57.67	65.81	13.88
	TPF	3.89	3.28	3.55	5.80	2.34	4.75	3.64
Credit	Perf	54.33	42.38	82.26	63.41	57.49	67.21	13.22
	TPF	4.29	4.26	3.76	6.17	2.79	4.82	3.92

Table 5: Ablation study of decoding algorithm on LLaDA-MoE with KV-Cache setting.

Config.	Metric	Avg.	CRUX-O	GSM8K	HumanEval	IFEval	MBPP	LCB V6
Threshold	Perf	53.96	41.38	80.97	62.2	58.78	67.45	13
	TPF	3.87	4.02	3.42	5.52	2.32	4.54	3.38
Hierarchy	Perf	53.90	48.82	79.3	64.02	53.97	66.28	11.01
	TPF	3.15	3.20	2.91	4.39	1.92	3.68	2.80
Credit	Perf	51.56	37.88	80.14	61.59	53.97	63.93	11.87
	TPF	3.4	3.01	3.19	5.01	2.08	3.99	3.12

Table 6: Ablation study of decoding algorithm on LLaDA-MoE-TD with KV-Cache setting.

Config.	Metric	Avg.	CRUX-O	GSM8K	HumanEval	IFEval	MBPP	LCB V6
Threshold	Perf	49.56	35.25	76.88	57.93	56.93	60.89	9.47
	TPF	5.83	6.26	6.33	7.27	3.14	6.73	5.23
Hierarchy	Perf	52.72	40.12	79.15	63.41	56.19	65.11	12.33
	TPF	5.67	6.06	6.12	7.09	2.98	6.60	5.18
Credit	Perf	48.89	34.5	77.18	57.32	50.83	62.53	10.96
	TPF	5.17	4.75	5.9	6.77	2.77	6.07	4.73