





LLaDA-MoE: A Sparse MoE Diffusion Language Model

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Abstract

We introduce LLaDA-MoE, a large language diffusion model with the Mixture-of-Experts (MoE) architecture, trained from scratch on approximately 20T tokens. LLaDA-MoE achieves competitive performance with significantly reduced computational overhead by maintaining a 7B-parameter capacity while activating only 1.4B parameters during inference. Our empirical evaluation reveals that LLaDA-MoE achieves state-of-the-art performance among diffusion language models with larger parameters, surpassing previous diffusion language models LLaDA, LLaDA 1.5, and Dream across multiple benchmarks. The instruct-tuned model LLaDA-MoE-7B-A1B-Instruct demonstrates capabilities comparable to Qwen2.5-3B-Instruct in knowledge understanding, code generation, mathematical reasoning, agent and alignment tasks, despite using fewer active parameters. Our results show that integrating a sparse MoE architecture into the training objective of masked diffusion language models still brings out MoE's strengths under efficient inference with few active parameters, and opens ample room for further exploration of diffusion language models. LLaDA-MoE models are available at Huggingface¹.

1 Introduction

Large Language Models (LLMs) (Zhao et al., 2023) have advanced rapidly and are now widely used across a wide range of tasks. Alongside the dominant autoregressive (AR) paradigm (Radford et al., 2018; 2019; Brown et al., 2020; Ouyang et al., 2022), Masked Diffusion Models (MDMs) (Austin et al., 2021a; Lou et al., 2023; Ou et al., 2024; Nie et al., 2025) provide an alternative modeling paradigm with comparable scaling properties and performance (Lou et al., 2023; Ou et al., 2024; Nie et al., 2024; Nie et al., 2024; Nie et al., 2025). These trends make diffusion language modeling a promising direction.

Despite these achievements, work on MDMs has largely relied on dense Transformer backbones (Vaswani et al., 2017), and, to the best of our knowledge, no prior work has pretrained MDMs from scratch with a sparse MoE architecture (Jacobs et al., 1991; Shazeer et al., 2017; Lepikhin et al., 2020; Fedus et al., 2022; Shen et al., 2023; Jiang et al., 2024). By contrast, the MoE architecture has been widely validated for AR models (Liu et al., 2024a;b; Comanici et al., 2025; Bai et al., 2023; Yang et al., 2025a), achieving performance comparable to larger dense models while activating only a small subset of parameters per token via sparse expert routing. These observations provide a basis for studying sparse MoE architectures for MDMs.

In this work, we introduce LLaDA-MoE, a diffusion language model with a sparse MoE architecture that maintains a small number of active parameters during inference while delivering strong overall performance. With only 1B active parameters, LLaDA-MoE surpasses prior dense 8B diffusion language models (Nie et al., 2025; Zhu et al., 2025; Ye et al., 2025). After instruction tuning, it achieves performance comparable to Qwen2.5-3B-Instruct (Bai et al., 2023) across knowledge understanding, code generation, mathematical reasoning, agent, and alignment tasks. Taken together, these results provide initial evidence that a sparse MoE architecture is a viable path toward more efficient MDMs.

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¹ https://huggingface.co/collections/inclusionAI/llada-68c141bca386b06b599cfe45

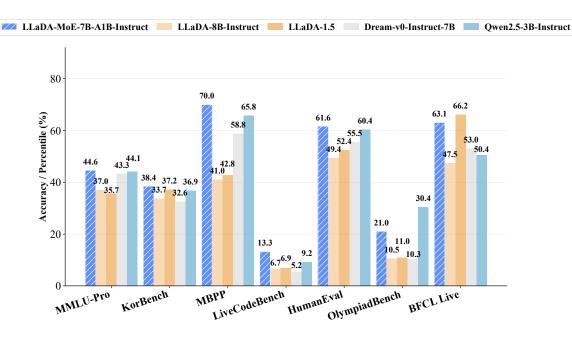


Figure 1: **Benchmark results.** We compare LLaDA-MoE with larger MDMs and Qwen2.5-3B-Instruct across key tasks in knowledge, reasoning, mathematics, coding, and agent tasks. Despite using fewer activated parameters, LLaDA-MoE consistently outperforms other diffusion language models and achieves performance comparable to Qwen2.5-3B-Instruct.

We summarize our contributions as follows:

- We introduce LLaDA-MoE, a diffusion language model with a sparse MoE architecture trained from scratch. It combines masked diffusion modeling with MoE to deliver strong performance while keeping the active-parameter budget small during inference.
- We demonstrate that LLaDA-MoE achieves state-of-the-art performance in diffusion language models: it surpasses prior 8B-parameter diffusion language models while activating only 1.4B parameters, and matches the performance of Qwen2.5-3B-Instruct across diverse tasks, including knowledge understanding, code generation, mathematical reasoning, agent, and alignment tasks.

2 Related Work

2.1 Diffusion Language Models

Recent studies investigate diffusion modeling for discrete data (Austin et al., 2021a; Campbell et al., 2022; Chen et al., 2022; He et al., 2022; Gong et al., 2022; Li et al., 2022; Dieleman et al., 2022; Gulrajani & Hashimoto, 2023), with MDMs receiving increasing attention for simplicity and strong results. MDMs generate text by iteratively refining partially masked sequences, in contrast to widely used AR models that decode tokens from left to right (Radford et al., 2018; 2019; Brown et al., 2020; Ouyang et al., 2022). As illustrated in Figure 2, an MDM repeatedly predicts the currently masked tokens and progressively unmasks them during inference. During training, MDMs optimize a variational lower bound on the log-likelihood by reconstructing masked tokens from partially observed context (Lou et al., 2023; Ou et al., 2024; Sahoo et al., 2024; Shi et al., 2024), thereby learning to recover the original sequence from incomplete inputs.

LLaDA (Nie et al., 2025) exemplifies the scaling behavior of MDMs (Nie et al., 2024): trained from scratch with 8B parameters, it achieves performance comparable to LLaMA3 8B across a range of benchmarks (Dubey et al., 2024). Building on this, subsequent work has expanded the scope and practicality of diffusion language models by extending them to multimodal (You et al., 2025; Yang et al., 2025b; Li et al., 2025; Yu et al., 2025), improving inference efficiency through caching and parallel decoding strategies (Wu et al., 2025; Ma et al., 2025; Liu et al., 2025; Wei et al., 2025), and strengthening reasoning and coding capabilities (Zhu et al., 2025; Gong et al., 2025; Zhao et al., 2025; Tang et al., 2025; Huang et al., 2025; Wang et al., 2025). These developments underscore the substantial potential of diffusion language models.

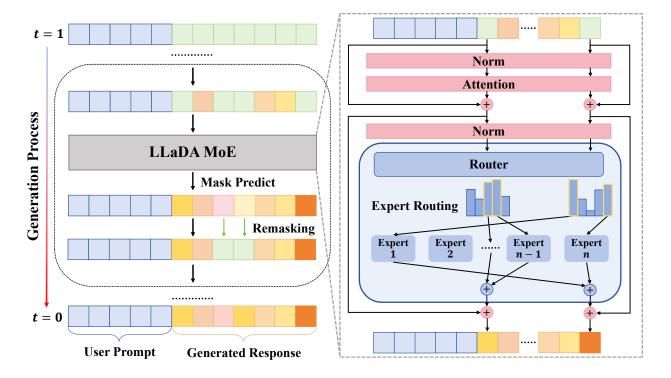


Figure 2: **Overview of the generation process and architecture. Left:** The iterative generation process from fully masked (t=1) to fully unmasked (t=0). Blue blocks are fixed user prompt tokens, green blocks are mask tokens. The model iteratively predicts and remasks tokens until generation completes. **Right:** The MoE architecture with router selecting top-2 experts per token. The histogram shows expert routing distribution, and outputs are weighted combinations of selected experts, enabling efficient sparse activation.

2.2 The MoE Architecture

The MoE architecture improves parameter efficiency by activating only a small subset of parameters for each token: instead of a single dense feed-forward block, it maintains a large pool of expert networks and uses a learned router to select which experts to run per token (Jacobs et al., 1991; Shazeer et al., 2017; Lepikhin et al., 2020; Fedus et al., 2022; Shen et al., 2023; Jiang et al., 2024). In a typical MoE layer, the router assigns each token to the top k experts, and only those experts are activated. This directs computation to token-relevant parameters and allows the model to keep a much larger total parameter pool without activating all of it for every token. To prevent routing collapse and maintain balanced expert usage, MoE models typically add auxiliary load-balancing losses and enforce per-expert capacity limits. The integration of MDMs and MoE may provide the diffusion language modeling paradigm with a more resource-efficient and capacity-scalable framework.

3 LLaDA-MoE

3.1 Overview

Model Architecture. LLaDA-MoE employs RMSNorm for normalization, SwiGLU as the activation function, rotary positional embeddings for position encoding, and incorporates QK-layernorm within its multi-head attention blocks (Zhang & Sennrich, 2019; Shazeer, 2020; Su et al., 2024). Key architectural parameters are summarized in Table 2.

Training pipeline. As shown in Figure 3, our training pipeline comprises multiple phases. Pretrain Stage 1 trains the model from scratch for 10T tokens on a large mixed text corpus. Pretrain Stage 2 then continues for another 10T tokens resampled from the same underlying corpus, with sampling reweighted to increase the fraction of mathematics and code. For Annealing Stage 1, we initialize from the checkpoint with the best average evaluation metrics from Pretrain Stage 2 and continue training on 500B tokens of high-quality text.

Table 1: Comparison among LLaDA-MoE-7B-A1B-Base with other MDMs and AR baselines.

	LLaDA-MoE-7B-A1B-Base	LLaDA-8B-Base	Dream-v0-Base-7B	Qwen2.5-3B-Base				
Architecture	МоЕ	Dense	Dense	Dense				
Model	Diffusion	Diffusion	Diffusion	AR				
Method	Pretrain	Pretrain	Continue Pretrain	Pretrain				
# Total Params	7B	8B	7B	3B				
# Activated Params	1B	8B	7B	3B				
General Tasks								
MMLU	64.59	65.90	69.50	<u>67.98</u>				
MMLU-Pro	39.16	41.80	48.15	35.50				
CEval	65.56	<u>70.50</u>	59.18	75.00				
CMMLU	65.65	<u>69.90</u>	60.87	73.65				
RACE	84.96	88.37	44.70	<u>87.88</u>				
	Rea	asoning Tasks						
BBH	52.71	49.80	57.90	<u>56.50</u>				
Drop	65.86	<u>72.93</u>	75.16	51.61				
KorBench	31.20	<u>33.68</u>	37.44	27.44				
	1	Math Tasks						
GSM8K	66.41	70.70	<u>77.79</u>	78.17				
MATH	36.10	27.30	<u>39.60</u>	40.94				
OlympiadBench	<u>10.07</u>	6.85	10.22	9.33				
Coding Tasks								
CRUX-O	39.00	31.00	<u>37.75</u>	35.62				
MBPP	52.40	38.20	<u>56.20</u>	69.56				
MultiPL-E	41.13	23.61	27.60	<u>40.80</u>				
HumanEval	45.73	33.50	<u>57.90</u>	57.93				
LiveCodeBench v6	<u>16.18</u>	2.53	14.87	16.99				
BigCodeBench-Full	<u>21.23</u>	13.42	18.33	30.88				
Avg	<u>46.94</u>	43.53	46.66	50.34				



Figure 3: **Training pipeline.** LLaDA-MoE is trained through Pretrain stage 1 (10T tokens), pretrain stage 2 (10T tokens), annealing stage 1 (500B tokens), annealing stage 2 (500B tokens with 8k context length), followed by SFT on curated prompt–answer pairs.

Annealing Stage 2 resumes from the last Annealing Stage 1 checkpoint, raises the RoPE base from 10,000 to 50,000, expands the context length from 4k to 8k to support longer sequences, and trains for 500B tokens. Finally, the SFT Stage performs supervised tuning on high-quality question—answer pairs according to Eq. 5; the resulting checkpoint serves as our Instruct model.

3.2 Training and Inference for LLaDA-MoE

We follow the standard formulation of MDMs to present the modeling, training objective, and inference procedure, and then describe pretrain, supervised fine-tuning (SFT), and related methods (Austin et al., 2021a; Lou et al., 2023; Sahoo et al., 2024; Shi et al., 2024; Ou et al., 2024; Nie et al., 2025).

Forward Process. Let $y \in \{0, 1, ..., K-1\}^L$ be a clean sequence of length L over a vocabulary of size K. We first draw a noise level $t \sim \mathcal{U}[0,1]$, then independently decide for each position whether to keep the original

Table 2: The LLaDA-MoE Architecture

Layers	16
Hidden Dimension	2048
Attention Heads	16
Total Experts	64
Activated Experts	8
Expert Dimension	1024
RoPE Base	50,000
Active Parameters	1.4B
Non-embedding Parameters	7B

token or replace it by M, where M denotes the mask token. Formally,

$$q(y_t \mid t, y) = \prod_{i=1}^{L} q(y_t^i \mid t, y^i), \qquad q(y_t^i \mid t, y^i) = \begin{cases} 1 - t, & y_t^i = y^i, \\ t, & y_t^i = \mathbf{M}, \\ 0, & \text{otherwise.} \end{cases}$$
(1)

Mask predictor and objective. A parametric mask predictor $p_{\theta}(\cdot \mid y_t)$ outputs token distributions for all positions. The training objective of LLaDA-MoE is

$$\mathcal{L}_{\text{Pretrain}}(\theta) = -\mathbb{E}_{y \sim p_{\text{data}}} \mathbb{E}_{t \sim \mathcal{U}[0,1]} \mathbb{E}_{y_t \sim q(y_t|t,y)} \left[\frac{1}{t} \sum_{i=1}^{L} \mathbf{1}[y_t^i = \mathbf{M}] \log p_{\theta}(y^i \mid y_t) \right], \tag{2}$$

 $\mathcal{L}_{Pretrain}$ upper-bounds the negative log-likelihood of the model distribution.

LLaDA-MoE employs bidirectional attention and is pretrained with a fixed 4k context, creating a train–test discrepancy: training always sees 4k tokens, whereas inference contexts vary and are often shorter, which degrades performance. To narrow this gap, we adapt variable-length training (Nie et al., 2024) for a small fraction of steps. Specifically, during pretraining, in 1% of steps we sample a target length $\ell \in [8,4096]$ and truncate the input to ℓ tokens; the remaining 99% of steps use the default 4k context. This simple intervention reduces the distribution mismatch and yields substantial gains on evaluation metrics.

MoE Routing. We employ a top-*k* gated MoE layer:

$$p_t = \text{Softmax}(\text{Router}(h_t)), \qquad o_t = \sum_i p_{t,i} E_i(h_t), \qquad \text{where } p_{t,i} \in \text{Topk}(p_t).$$
 (3)

where h_t is the hidden state, Router(·) is a linear router producing per-expert logits, $E_i(\cdot)$ is the i-th expert, and Topk(·) selects the k largest entries; the corresponding softmax scores $p_{t,i}$ weight the selected experts' outputs.

To mitigate expert-load imbalance, we adopt the standard auxiliary losses (Shazeer et al., 2017; Zoph et al., 2022):

$$\mathcal{L}_{LB} = N \sum_{i=1}^{N} f_i P_i, \qquad \mathcal{L}_{Z} = \frac{1}{T} \sum_{t=1}^{T} \left(\log \sum_{j=1}^{N} e^{z_{t,j}} \right)^2,$$
 (4)

where $z_t = \operatorname{Router}(h_t)$, $p_t = \operatorname{Softmax}(z_t)$, P_i denotes the average routing probability assigned to expert i across tokens, f_i denotes the frequency of expert i being selected across all tokens, N is the number of experts, and T is the number of tokens. In practice, we set loss weights of 0.01 for \mathcal{L}_{LB} and 0.001 for \mathcal{L}_{Z} , which yields stable expert-routing training. Figure 4 shows the training dynamics of LLaDA-MoE's auxiliary losses over the first 1T training tokens, where both the Z-Loss and the load-balancing loss decrease rapidly early in pre-training and then stabilize at low magnitudes.

Supervised Fine-Tuning. SFT is a special case of the pretraining objective: we apply the corruption kernel in Eq. 1 only to the response y while keeping the prompt x clean. Given a pair (x, y), sample $t \sim \mathcal{U}[0, 1]$, form y_t by masking each token in y with probability t, and train the model to recover masked tokens in y conditioned on x:

$$\mathcal{L}_{SFT}(\theta) = -\mathbb{E}_{(x,y) \sim p_{\text{data}}} \mathbb{E}_{t \sim \mathcal{U}[0,1]} \mathbb{E}_{y_t \sim q(y_t \mid t,y)} \left[\frac{1}{t} \sum_{i=1}^{|y|} \mathbf{1}[y_t^i = \mathbf{M}] \log p_{\theta}(y^i \mid x, y_t) \right]. \tag{5}$$

Table 3: Comparison among	LLaDA-MoE-7B-A1B-Instruct with	other MDMs and AR baselines.

	LLaDA-MoE-7B-A1B-Instruct	LLaDA-8B-Instruct	LLaDA-1.5	Dream-v0-Instruct-7B	Qwen2.5-3B-Instruct		
Architecture	MoE	Dense	Dense	Dense	Dense		
Model	Diffusion	Diffusion	Diffusion	Diffusion	AR		
Method	Pretrain + SFT	Pretrain + SFT	Pretrain + SFT + DPO	Continue Pretrain + SFT	Pretrain + SFT + RL		
# Total Params	7B	8B	8B	7B	3B		
# Activated Params	1B	8B	8B	7B	3B		
General Tasks							
MMLU	<u>67.18</u>	65.50	66.00	67.00	69.11		
MMLU-Pro	44.64	37.00	35.70	43.30	<u>44.13</u>		
CMMLU	64.30	55.21	58.72	58.82	65.62		
CEval	<u>63.93</u>	54.48	58.41	57.98	68.20		
		Reasonin	g Tasks				
Drop	79.77	83.09	84.89	76.25	68.56		
KorBench	38.40	33.68	<u>37.20</u>	32.56	36.88		
		Math 7	Tasks				
GSM8K	82.41	78.60	83.30	81.00	86.28		
MATH	58.68	42.20	42.60	39.20	67.02		
OlympiadBench	21.04	10.52	10.96	10.44	30.41		
		Coding	Tasks				
CRUX-O	42.38	28.50	29.12	40.12	46.75		
MBPP	70.02	41.00	42.80	58.80	<u>65.81</u>		
MultiPL-E	<u>52.53</u>	29.08	29.04	29.86	54.92		
HumanEval	61.59	49.40	52.40	55.50	<u>60.37</u>		
LiveCodeBench v6	13.27	6.66	6.94	5.23	<u>9.20</u>		
BigCodeBench-Full	<u>20.44</u>	11.32	11.93	19.04	27.81		
Agent & Alignment Tasks							
IFEval Strict Prompt	<u>59.33</u>	51.39	58.23	62.50	58.20		
BFCL-Live	63.09	47.47	66.20	53.03	50.40		
Avg	53.12	42.65	45.56	46.51	53.51		

To enable variable-length generation, we pad shorter responses with |EOS| tokens to the maximum length in the batch, consistent with LLaDA (Nie et al., 2025). The appended |EOS| tokens are treated as part of the response: they are masked and included in the loss in Eq. 5. For multi-turn dialogs $D = [(x_1, y_1), \ldots, (x_T, y_T)]$, we sample a target turn $\tau \in [1, T]$. The visible prompt is $[x_1, y_1, \ldots, x_T]$. We apply the corruption kernel in Eq. 1 only to the target response y_τ to obtain $y_{\tau,t}$. We then train using Eq. 5 to recover the masked tokens in y_τ given the visible prompt and $y_{\tau,t}$. Any |EOS| tokens appended after y_τ are included in the target segment and handled in the same way.

As noted previously, LLaDA-MoE's context window is expanded from 4k to 8k during Annealing Stage 2. However, during SFT, we limit each sample to 4k tokens because most SFT samples are shorter than 4k; masking and training on sequences padded to 8k with |EOS| token may cause the model to generate too many |EOS| tokens and degrade performance.

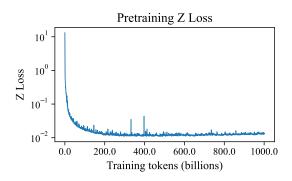
Inference. Starting from the fully masked sequence \mathbf{M}^L , we iteratively reduce the noise level and sample tokens at masked positions using the mask predictor. For $0 \le s < t \le 1$,

$$q(y_{s} \mid s, t, y_{t}) = \prod_{i=1}^{L} q(y_{s}^{i} \mid s, t, y_{t}), \qquad q(y_{s}^{i} \mid s, t, y_{t}) = \begin{cases} \frac{t-s}{t} p_{\theta}(y^{i} \mid y_{t}), & y_{t}^{i} = \mathbf{M}, y_{s}^{i} \neq \mathbf{M}, \\ \frac{s}{t}, & y_{t}^{i} = \mathbf{M}, y_{s}^{i} = \mathbf{M}, \\ 1, & y_{t}^{i} \neq \mathbf{M}, y_{s}^{i} = y_{t}^{i}, \\ 0, & \text{otherwise.} \end{cases}$$
(6)

Beyond the sampling scheme above, prior work adopts a semi-autoregressive sampling strategy (Arriola et al., 2025; Nie et al., 2025). Specifically, a sequence of length L is partitioned into K = L/B blocks, each containing B tokens. At block k, all B masked positions are predicted in parallel using the same reverse dynamics as above; once block k is fully unmasked, decoding proceeds to block k+1. In other words, autoregression operates at the block level. Semi-autoregressive sampling is often combined with low-confidence remasking. At each decoding step, we record the chosen token's probability as its confidence and then remask the tokens with the lowest confidence to refine the output results.

4 Experiments

We evaluate LLaDA-MoE on a broad suite of benchmarks spanning knowledge (Hendrycks et al., 2020; Wang et al., 2024; Li et al., 2023; Huang et al., 2023; Lai et al., 2017), reasoning (Suzgun et al., 2022; Dua et al., 2019;



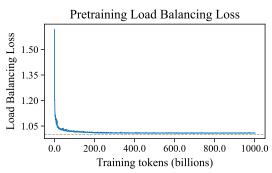


Figure 4: Training dynamics of auxiliary losses over training tokens. LLaDA-MoE pre-training results over the first 1T tokens. Left: Z-Loss; right: Load-Balancing Loss.

Ma et al., 2024), mathematics (Cobbe et al., 2021; Hendrycks et al., 2021; He et al., 2024), coding (Gu et al., 2024; Austin et al., 2021b; Cassano et al., 2022; Chen et al., 2021; Jain et al., 2024; Zhuo et al., 2024), agent (Patil et al.), and alignment (Zhou et al., 2023).

For MDMs (Nie et al., 2025; Zhu et al., 2025; Ye et al., 2025) with reported results, we cite the published numbers directly. For all other generative benchmarks, we use semi-autoregressive sampling (Arriola et al., 2025; Nie et al., 2025) with a generation length of 1024 and a block length of 64 to ensure a fair and robust comparison.

Table 1 and Table 3 report the evaluation results for LLaDA-MoE-Base and LLaDA-MoE-Instruct. Overall, despite activating only 1B parameters, LLaDA-MoE-7B-A1B is highly competitive. On average, both the Base and Instruct outperform the previous larger dense MDM baselines—LLaDA-8B and Dream-7B—as well as LLaDA-1.5. After instruction tuning, LLaDA-MoE-7B-A1B-Instruct trails Qwen2.5-3B-Instruct by only a small margin.

In summary, LLaDA-MoE shows that masked diffusion language modeling works well with a sparse MoE architecture, delivering strong and parameter-efficient performance and opening a broad design space for future exploration.

5 Conclusion

We introduce LLaDA-MoE, a diffusion language model trained from scratch with a MoE architecture enabling efficient inference. With 1.4B active parameters, LLaDA-MoE surpasses prior 8B-parameter diffusion language models. After instruction tuning, it is comparable to Qwen2.5-3B-Instruct across all benchmarks. These results establish MoE as an effective foundation for efficient MDMs and open the door to further research and improvements.

This study is potentially constrained by the current model size; in future work, we plan to scale LLaDA-MoE and address any challenges that accompany scaling up.

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