Sampling From Masked Diffusion Models

September 2025

February 2025

Large Language Diffusion Models

Shen Nie [1 * †] Fengqi Zhu [1 * †] Zebin You [1 †] Xiaolu Zhang [2 ‡] Jingyang Ou [1] Jun Hu [2 ‡] Jun Zhou [2]
Yankai Lin [1 ‡] Ji-Rong Wen [1] Chongxuan Li [1 ‡ ¶]

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What is now proved was once only imagined.
—William Blake

5. Conclusion and Discussion

In the middle of difficulty lies opportunity.
—Albert Einstein

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- “A nice direction to go in, we’ll see if it becomes useful (I’m not convinced)”
- “Unlikely that many people other than these authors (who clearly have tons of compute) will be willing to keep scaling these up”

Now

LLaDA 1.5: Variance-Reduced Preference Optimization for Large Language Diffusion Models

Fengqi Zhu[1, *, §], Rongzhen Wang[1, *], Shen Nie[1], Xiaolu Zhang[3], Chunwei Wu[3], Jun Hu[3], Jun Zhou[3], Jianfei Chen[2], Yankai Lin[1, †], Ji-Rong Wen[1], Chongxuan Li[1, †, ‡]

[1]Renmin University of China, [2]Tsinghua University, [3]Ant Group

[*] Equal contribution, [§] Work done during an internship at Ant Group, [†] Project leader,

[‡] Corresponding author

Paper | Code | Model

inception

Products | Resources | Company | Try Our API

FEB 26, 2025 | COMPANY

Introducing Mercury, the World's First Commercial-Scale Diffusion Large Language Model.

Stefano Ermon
CEO

Dream 7B: Diffusion Large Language Models

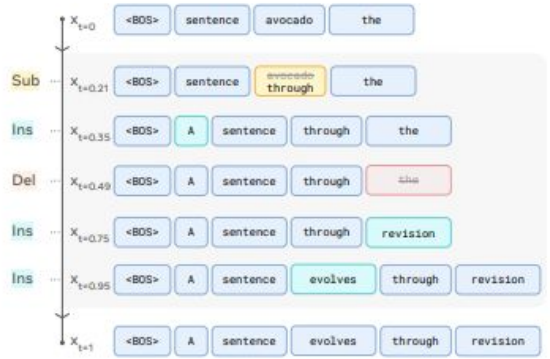
Jiacheng Ye[1*] Zhihui Xie[1*] Lin Zheng[1*] Jiahui Gao[2*] Zirui Wu
Xin Jiang[2] Zhenguo Li[2] Lingpeng Kong[1]
[1]The University of Hong Kong [2] Huawei Noah's Ark Lab

DreamLM/Dream Dream-7B

April 2, 2025

Edit Flows: Flow Matching with Edit Operations

Marton Havasi[1], Brian Karrer[1], Itai Gat[1], Ricky T. Q. Chen[1]
[1]FAIR at Meta



Gemini Diffusion

Our state-of-the-art, experimental text diffusion model

Join the waitlist

Recap

Autoregressive models (ARMs) are the current standard for LLMS

$$\underbrace{p_\theta(x) = p_\theta(x^1) \prod_{i=2}^{L} p_\theta(x^i \mid x^1, \ldots, x^{i-1})}_{\text{Autoregressive formulation}}$$

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But other paradigms, e.g. diffusion, should (theoretically) be able to work just as well at generative modelling:

$$\underbrace{\max_\theta \mathbb{E}_{p_{\text{data}}(x)} \log p_\theta(x) \Leftrightarrow \min_\theta \mathbf{KL}(p_{\text{data}}(x) || p_\theta(x))}_{\text{Generative modeling principles}}$$

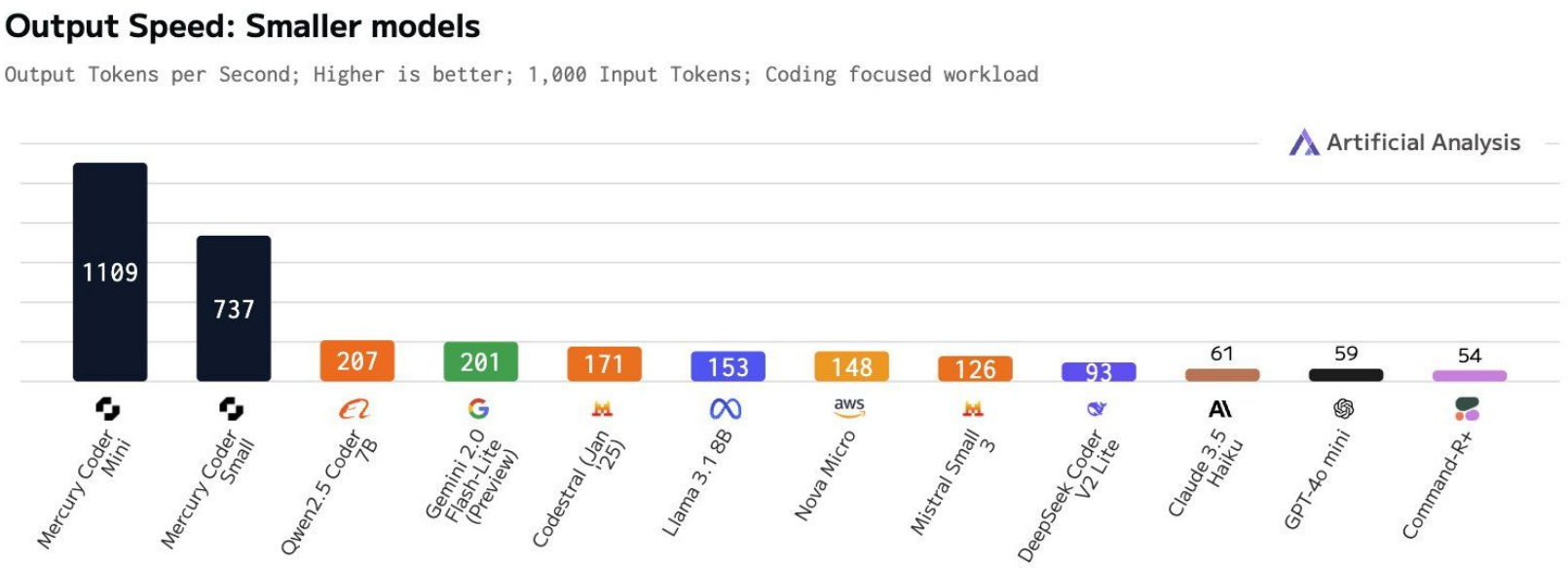
It’s kind of weird…

Table 4. **Visualization of the Sampling Process and a Generated Multi-round Dialogue.** In the response of LLaDA, darker colors indicate tokens predicted in the later stages of sampling, while lighter colors correspond to earlier predictions.

Sampling Process	
User	Lily can run 12 kilometers per hour for 4 hours. After that, she runs 6 kilometers per hour. How many kilometers can she run in 8 hours?
LLaDA	In 4 hours , Lily runs 12 * 4 = 48 kilometers . After 4 hours she runs 6 * 4 = 24 kilometers . In total she runs 48 + 24 = 72 kilometers in 8 hours . Result 72

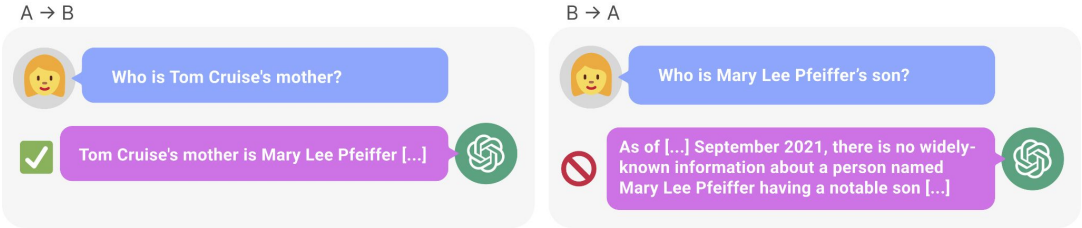
But very fast!

(You can sample multiple tokens in one denoising step)



Autoregressive strategies aren’t always ideal

- Reversal curse



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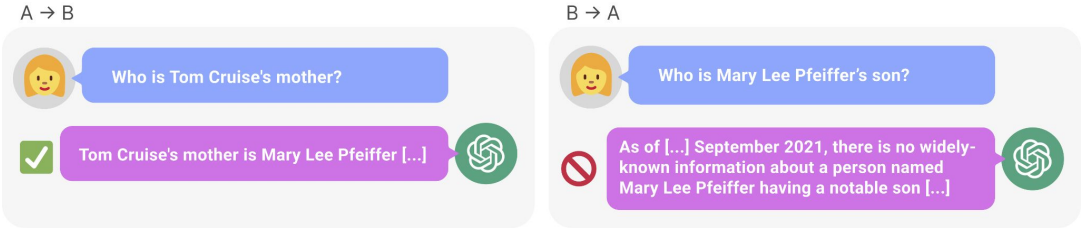

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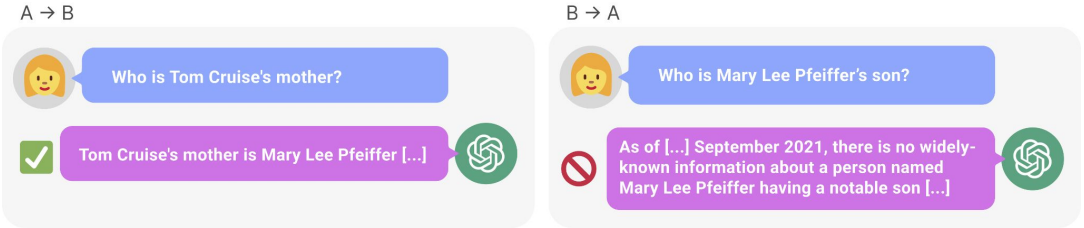
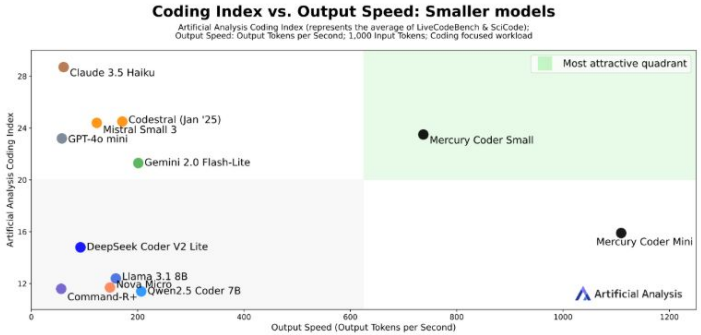


- Global-context in-filling tasks e.g. Sudoku
- Coding…?



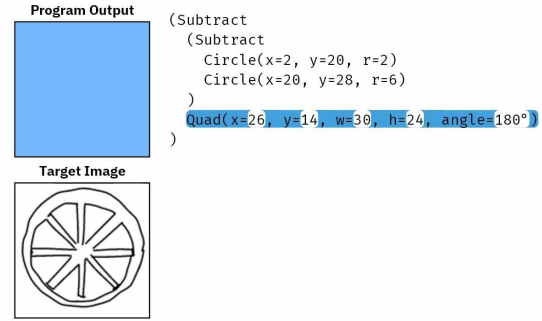
Autoregressive strategies aren't always ideal

ICLR 2025

Diffusion On Syntax Trees For Program Synthesis

Shreyas Kapur, Erik Jenner, Stuart Russell

University of California, Berkeley



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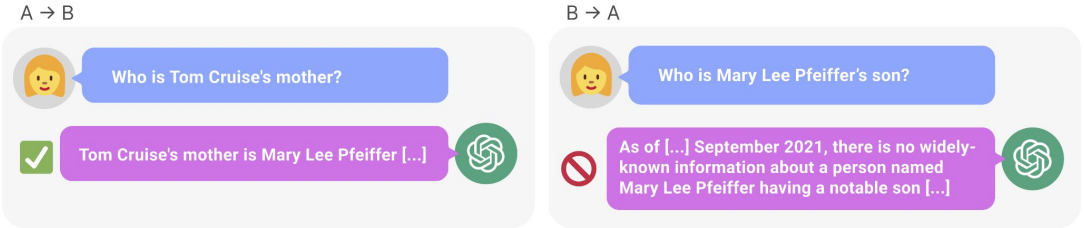

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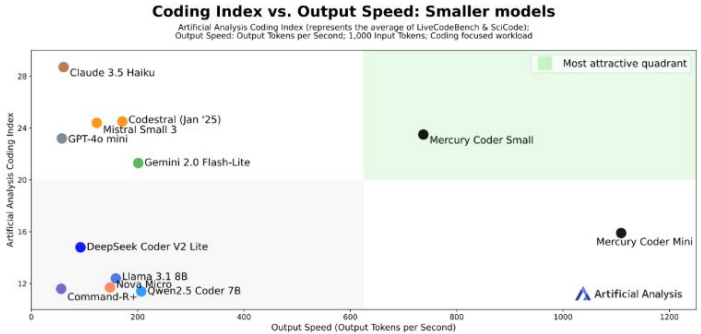

…although, a properly scaled ARM can probably do most of these things correctly – part of the pull here is doing them well with way fewer params

Masked Diffusion Model (MDM)

- Fixed length generation, N tokens

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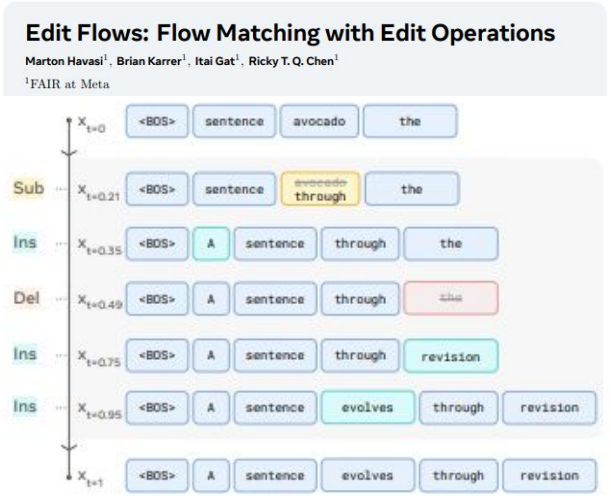

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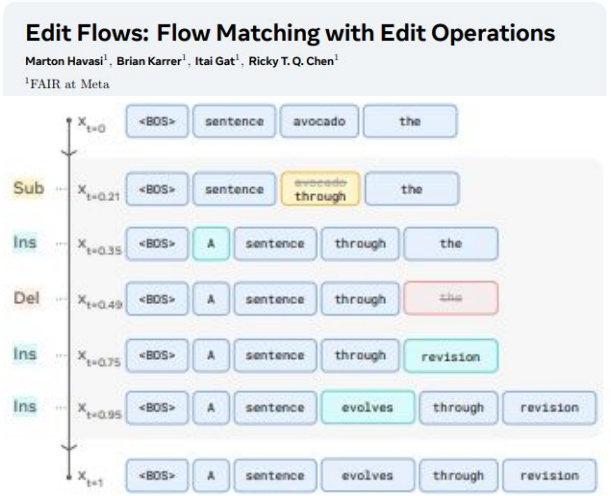

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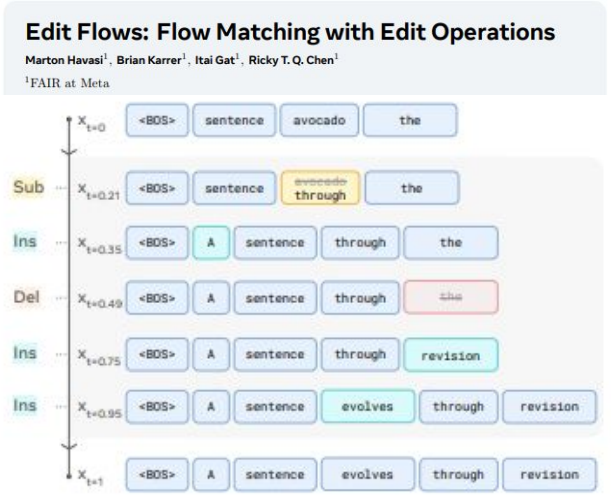

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- Many ways to learn/model $p_\theta(\cdot, x_t)$ but LLaDA still has the simplest explanation imo
  - (FYI: a good in-depth mathematical explanation is given in ‘Simplified and Generalized Masked Diffusion for Discrete Data’ by Shi et al. 2025)

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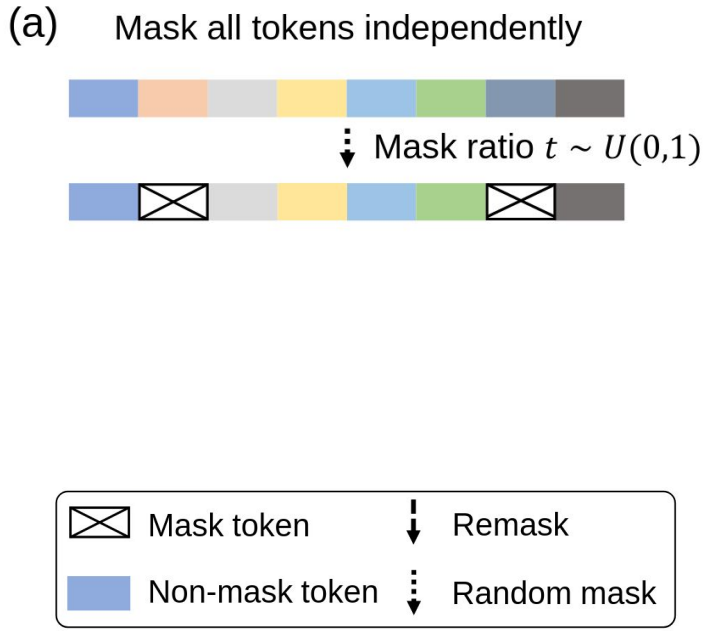

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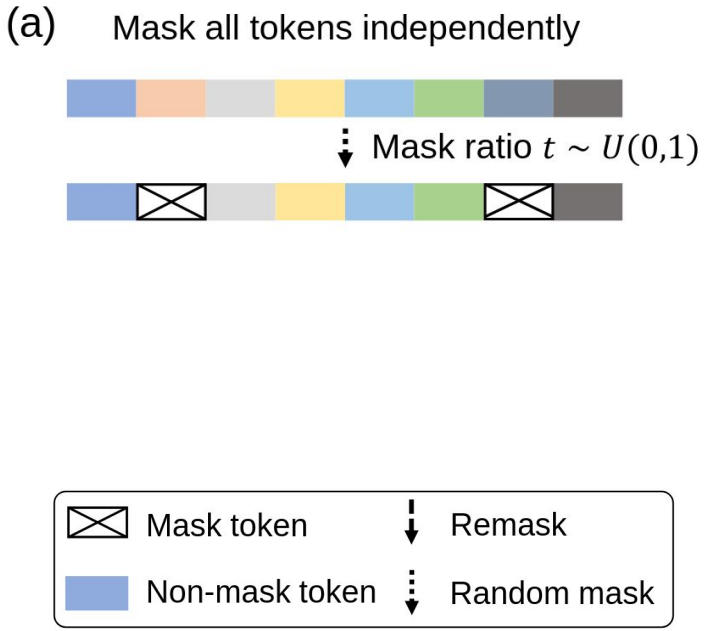

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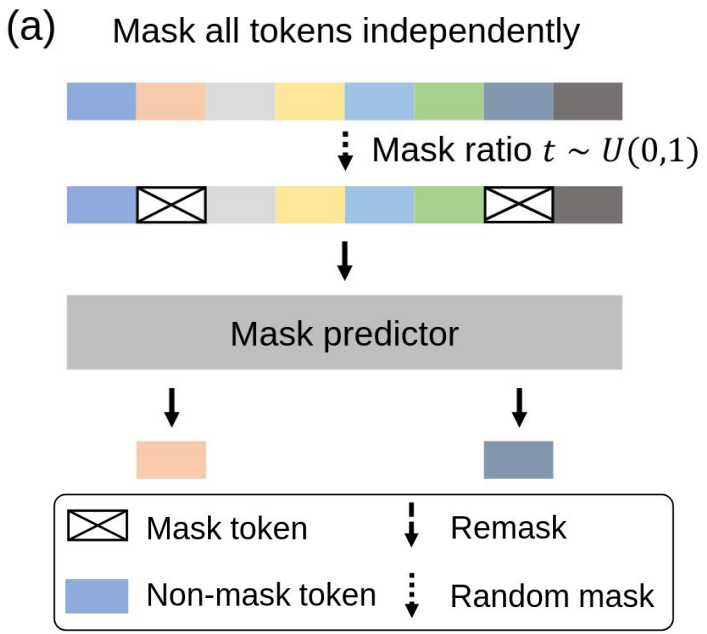

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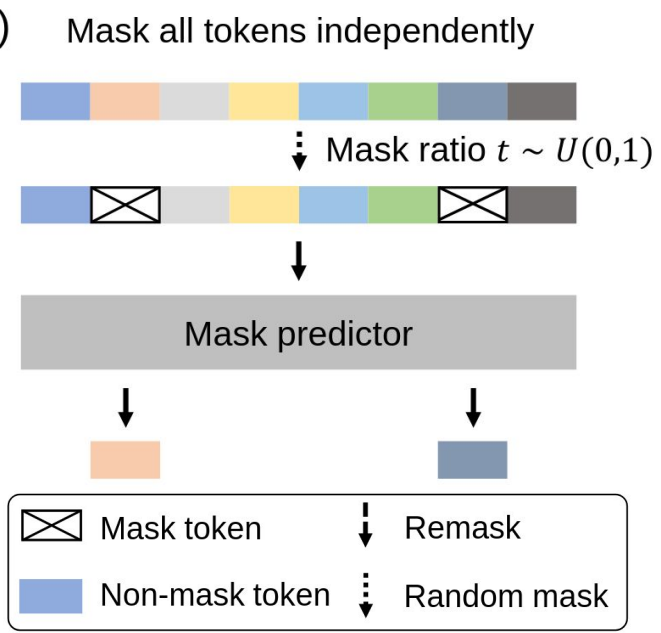
  - Based on a *mask predictor* $p_\theta(\cdot, x_t)$ trained with cross-entropy loss only on the masked tokens:

$$\mathcal{L}(\theta) \triangleq -\mathbb{E}_{t,x_0,x_t}\left[\frac{1}{t}\sum_{i=1}^{L}\mathbf{1}[x_t^i = \mathrm{M}]\log p_\theta(x_0^i|x_t)\right]$$

where $x_0 \sim \mathcal{D}_{\text{train}}, t \sim \text{Uniform}[0, 1]$, and x_t is sampled from the forward process.



How do we apply the standard LLM pipeline?

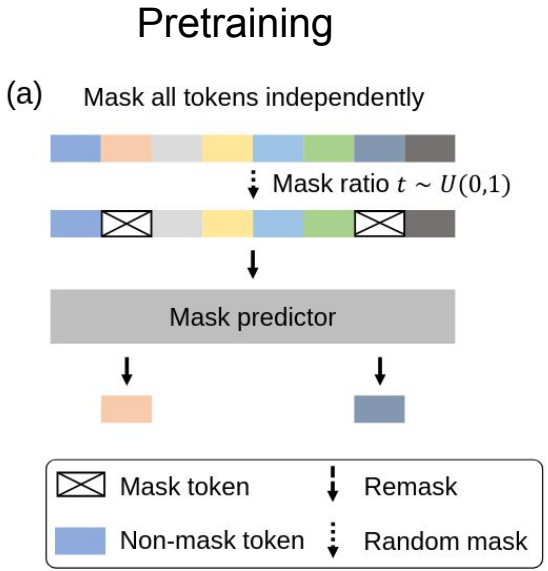


Figure 2. **A Conceptual Overview of LLaDA.** (a) Pre-training. LLaDA is trained on text with random masks applied independently to all tokens at the same ratio $t \sim U[0, 1]$. (b) SFT. Only response tokens are possibly masked. (c) Sampling. LLaDA simulates a diffusion process from $t = 1$ (fully masked) to $t = 0$ (unmasked), predicting all masks simultaneously at each step with flexible remask strategies.

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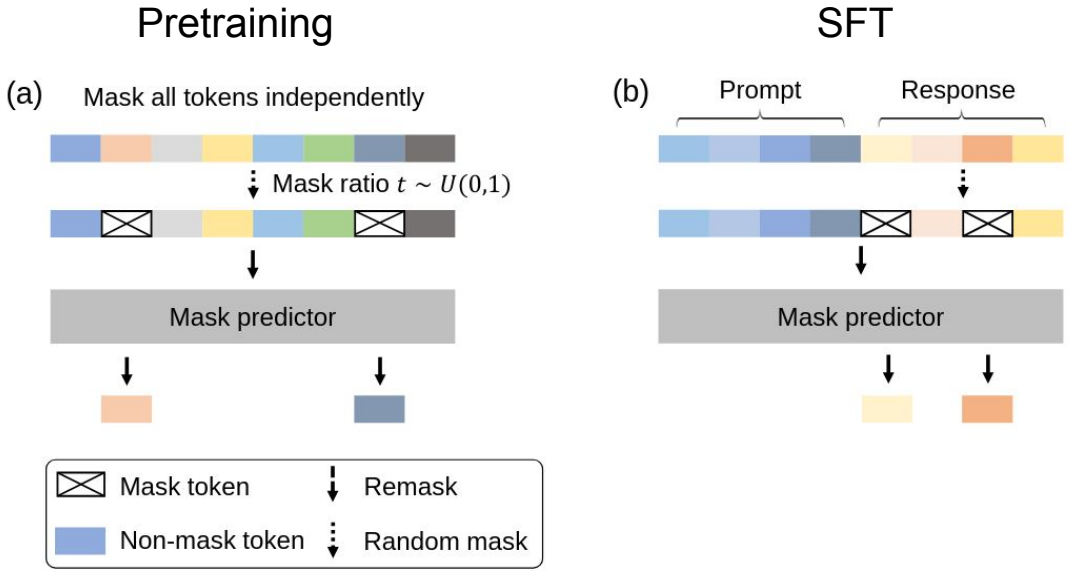

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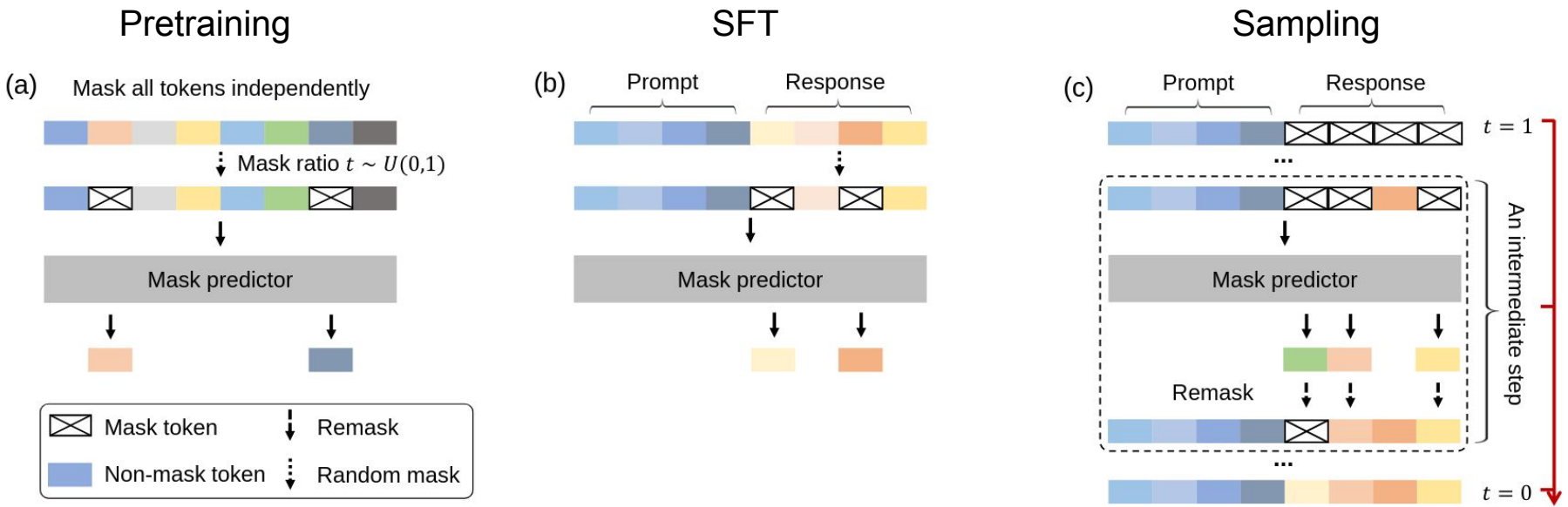

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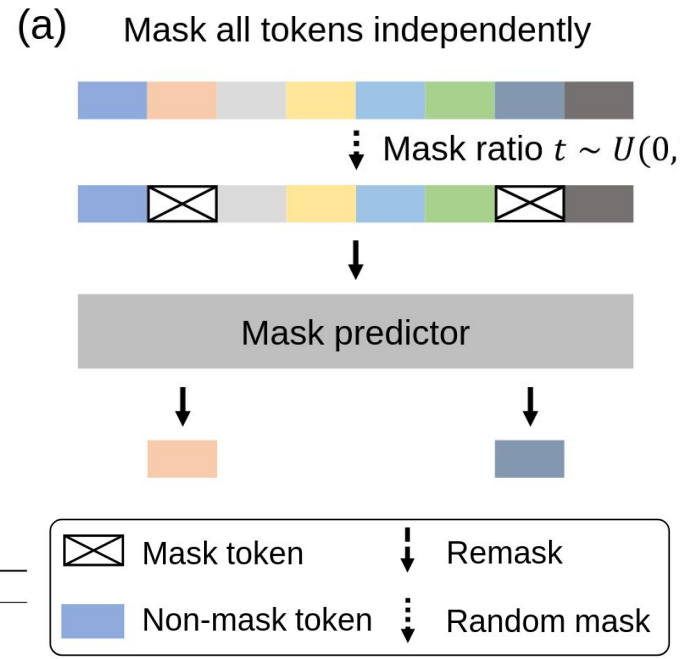
Pretraining

Train the mask predictor $p_\theta(\cdot, x_t)$ as we just described:

$$\mathcal{L}(\theta) \triangleq -\mathbb{E}_{t,x_0,x_t}\left[\frac{1}{t}\sum_{i=1}^{L}\mathbf{1}[x_t^i = \mathrm{M}]\log p_\theta(x_0^i|x_t)\right]$$



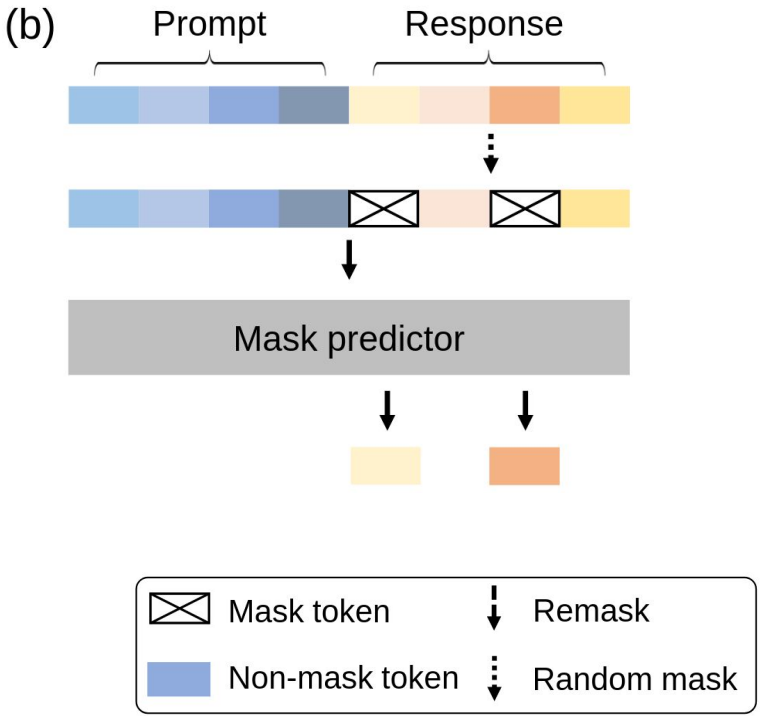
Algorithm 1 Pre-training of LLaDA

Require: mask predictor p_θ, data distribution p_{data}

1: **repeat**
2: $x_0 \sim p_{\text{data}}$, $t \sim \mathrm{U}(0,1]$ # with a probability of 1%, the sequence length of x_0 follows $\mathrm{U}[1, 4096]$
3: $x_t \sim q_{t|0}(x_t|x_0)$ # $q_{t|0}$ is defined in Eq. (7)
4: Calculate $\mathcal{L} = -\frac{1}{t*L}\sum_{i=1}^{L}\mathbf{1}[x_t^i = \mathrm{M}]\log p_\theta(x_0^i|x_t)$ # L is the sequence length of x_0
5: Calculate $\nabla_\theta \mathcal{L}$ and run optimizer.
6: **until** Converged
7: **Return** p_θ

SFT

Slightly different loss (only care about response r_0 given prompt p_0 and intermediate response r_t):



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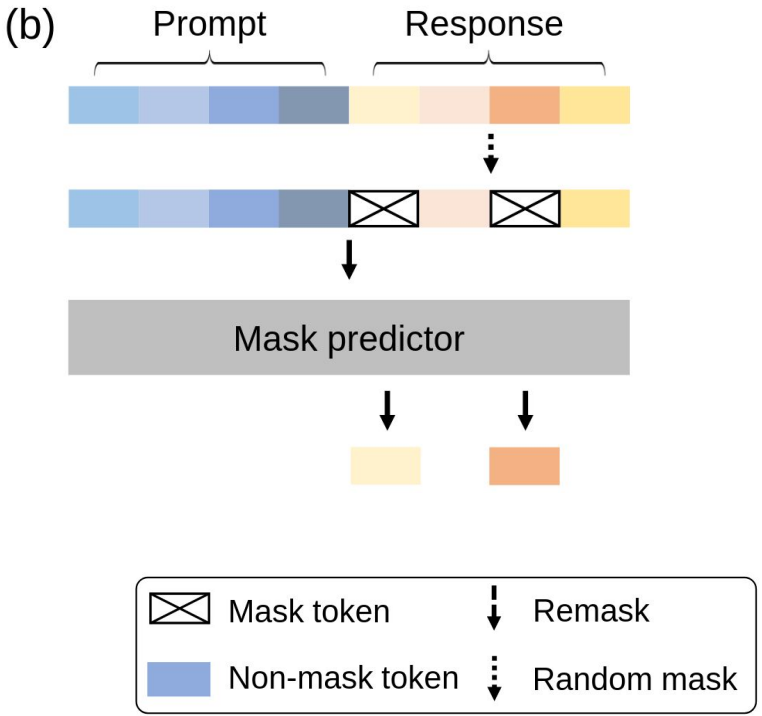
$$-\mathbb{E}_{t,p_0,r_0,r_t}\left[\frac{1}{t}\sum_{i=1}^{L'}\mathbf{1}[r_t^i=\mathrm{M}]\log p_\theta(r_0^i|p_0,r_t)\right]$$



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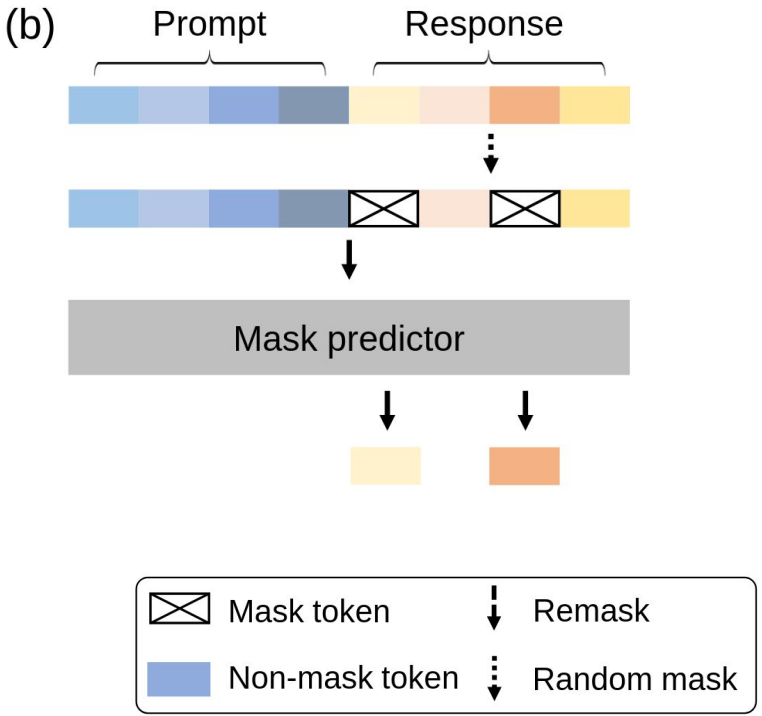
Where L' is a dynamic length:



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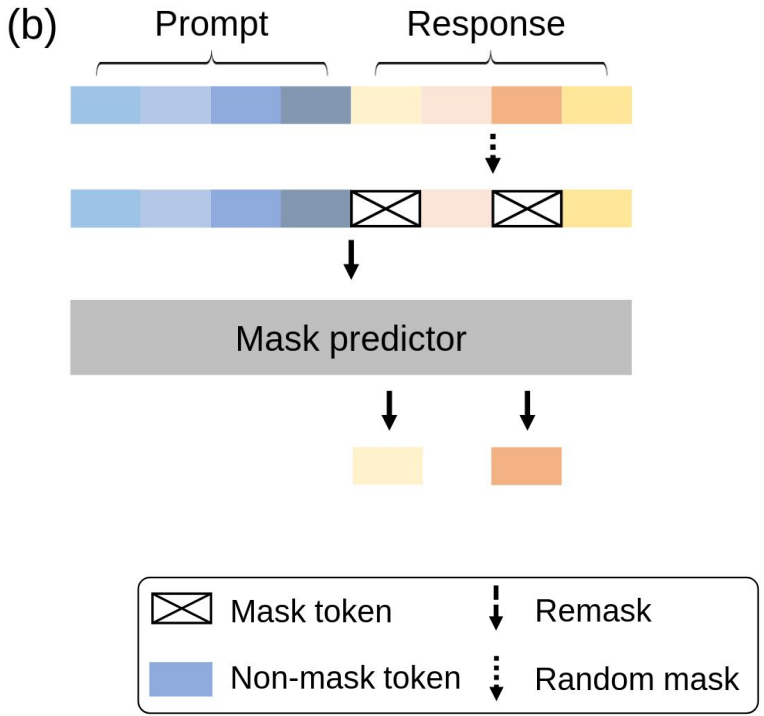
- SFT training examples padded with |EOS| to get to 4096 tokens



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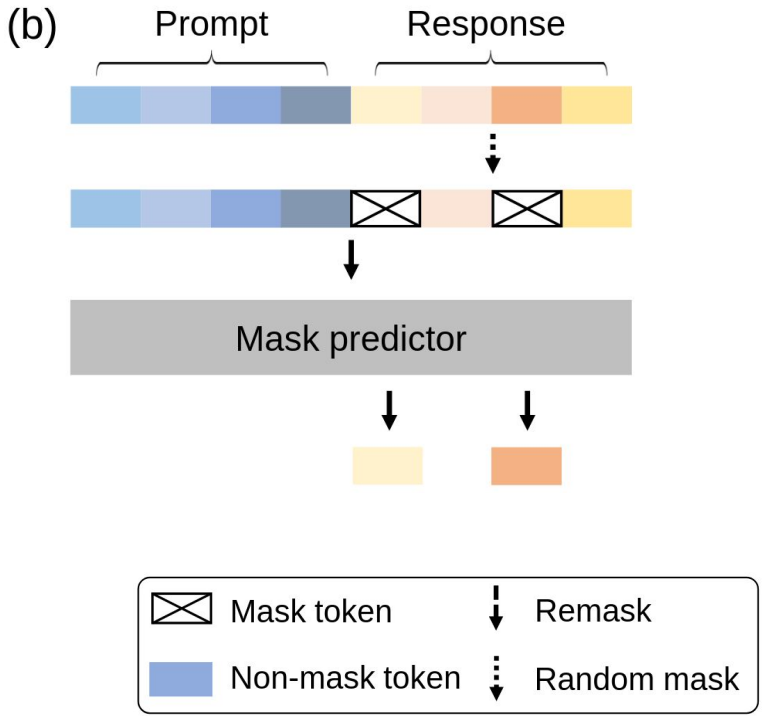

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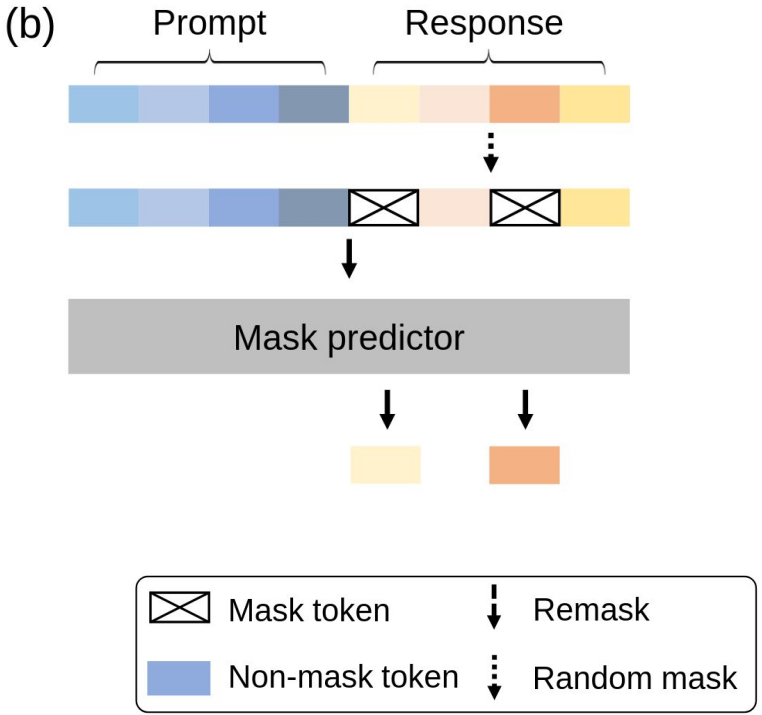
- When |EOS| sampled in reverse process for token i, we delete it and decrease L' by 1.



SFT

Algorithm 2 Supervised Fine-Tuning of LLaDA

Require: mask predictor p_θ, pair data distribution p_{data}

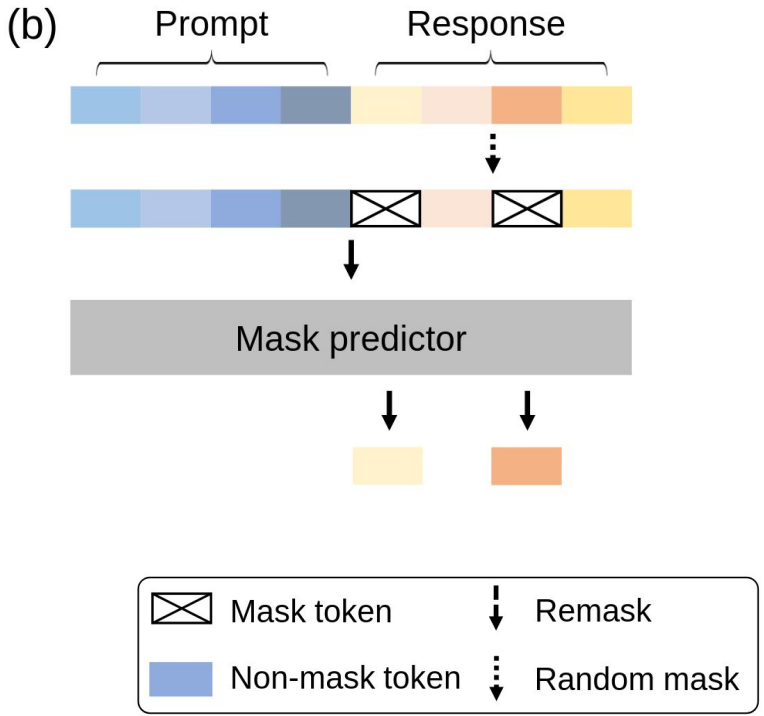
repeat
  $p_0, r_0 \sim p_{\text{data}}, t \sim \text{U}(0, 1]$ # please refer to Appendix B.1 for details on the SFT data processing.
  $r_t \sim q_{t|0}(r_t|r_0)$ # $q_{t|0}$ is defined in Eq. (7)
  Calculate $\mathcal{L} = -\frac{1}{t*L'} \sum_{i=1}^{L'} \mathbf{1}[r_t^i = \text{M}] \log p_\theta(r_0^i|p_0, r_t)$ # L' is the sequence length of r_0
  Calculate $\nabla_\theta \mathcal{L}$ and run optimizer.
until Converged
Return p_θ

Slightly different loss (only care about response r_0 given prompt p_0 and intermediate response r_t):

$$-\mathbb{E}_{t,p_0,r_0,r_t}\left[\frac{1}{t}\sum_{i=1}^{L'}\mathbf{1}[r_t^i = \text{M}]\log p_\theta(r_0^i|p_0, r_t)\right]$$

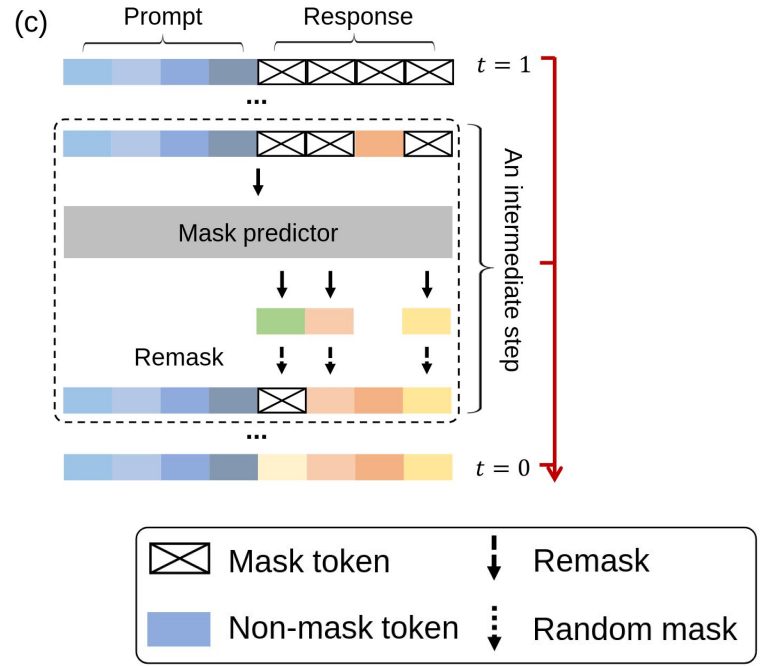
Where L' is a dynamic length:

- SFT training examples padded with |EOS| to get to 4096 tokens
- Model is trained to generate these |EOS| tokens (they get masked in forward process)
- When |EOS| sampled in reverse process for token i, we delete it and decrease L' by 1.



Sampling

1. Choose T sampling steps (tradeoff between efficiency and sample quality) between 1 and 0.



Sampling

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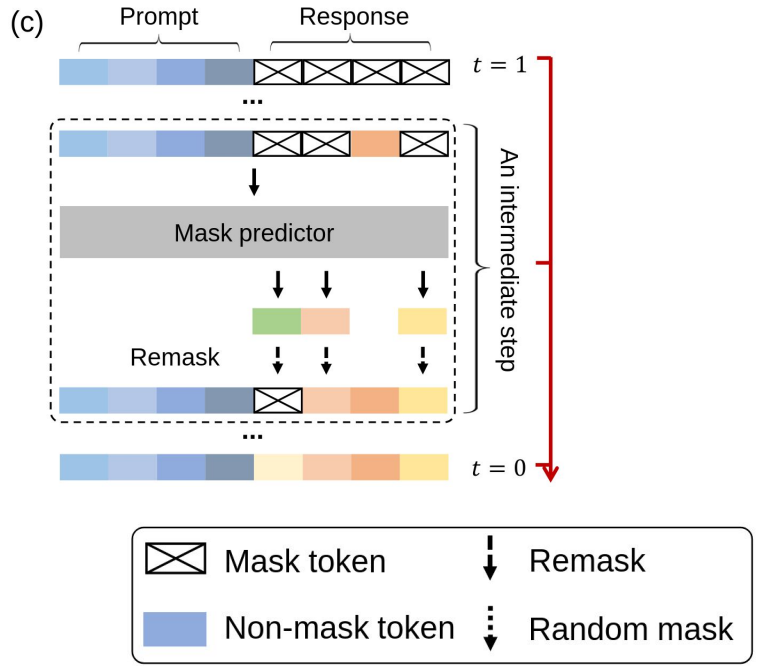
2. For each $t \in \{1, 1-1/T, \ldots, 1/T\}$ predict x_t then ("at time $s = t - 1/T$"), remask the tokens with probability $\frac{s}{t}$.



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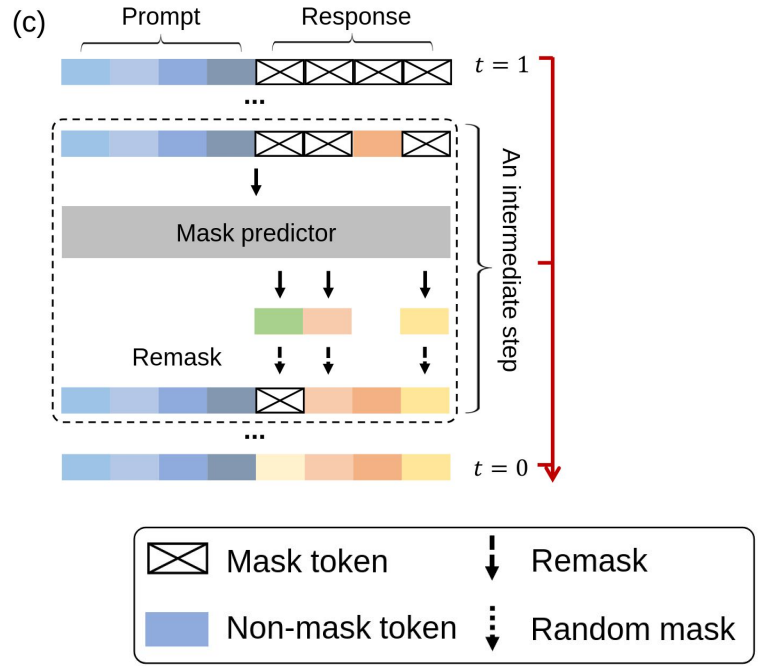
   a. Either remask each token independently
   b. Or remask the $N\frac{s}{t}$ tokens with lowest logits.



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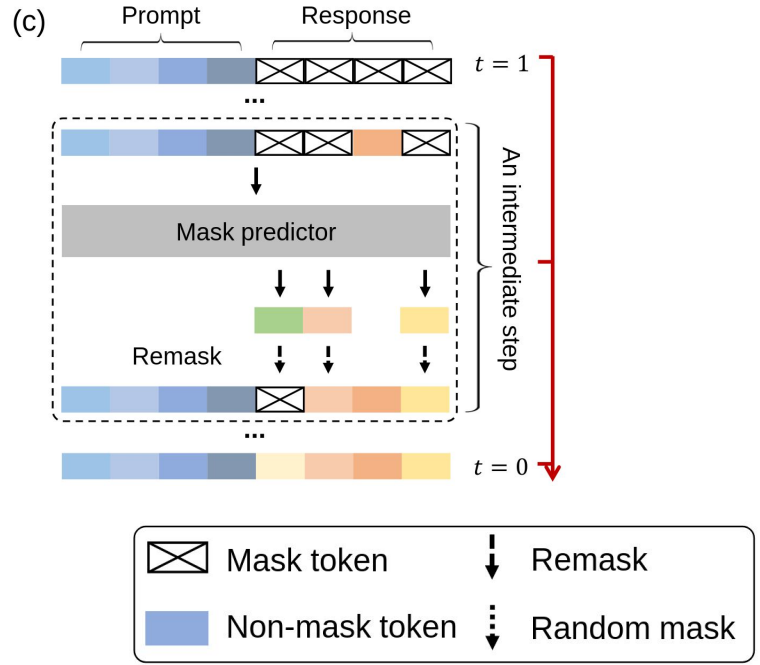
Algorithm 4 Reverse Process of LLaDA

Require: mask predictor p_θ, prompt p_0, answer length L, sampling steps N

Set r_1 is a fully masked sequence of length L.
for $t \leftarrow 1$ **down to** $\frac{1}{N}$ **step** $\frac{1}{N}$ **do**
  $s = t - \frac{1}{N}$
  $r_0 = \arg\max_{r_0} p_\theta(r_0 | p_0, r_t)$ # we employ greedy sampling when predicting masked tokens
  for $i \leftarrow 1$ to L **do**
    if $r_t \neq$ M **then**
      $r_0^i = r_t^i$
    else
      With probability $\frac{s}{t}$, r_0^i is set to M
    end if
  end for
  $r_s = r_0$
end for
Return r_0



	LLaDA 8B Base	LLaDA 8B Instruct
Randomly remasking	52.3	72.0
Lowest confidence remasking	**64.7**	12.9
Lowest confidence & semi-autoregressive remasking	64.4	**73.8**

(on GSM8K)

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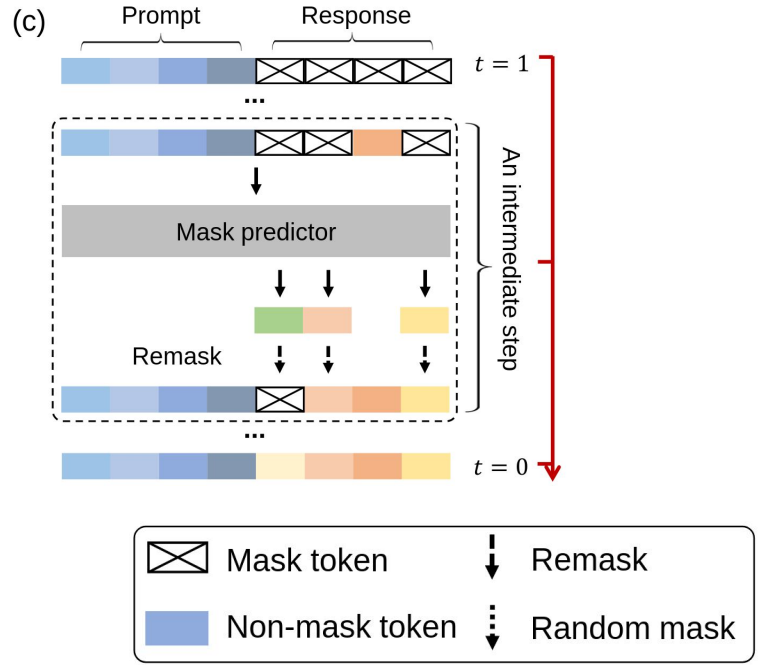

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(on GSM8K)

Semi-autoregressive Sampling

Additionally, we can split the response up into several blocks and generate those from left to right.

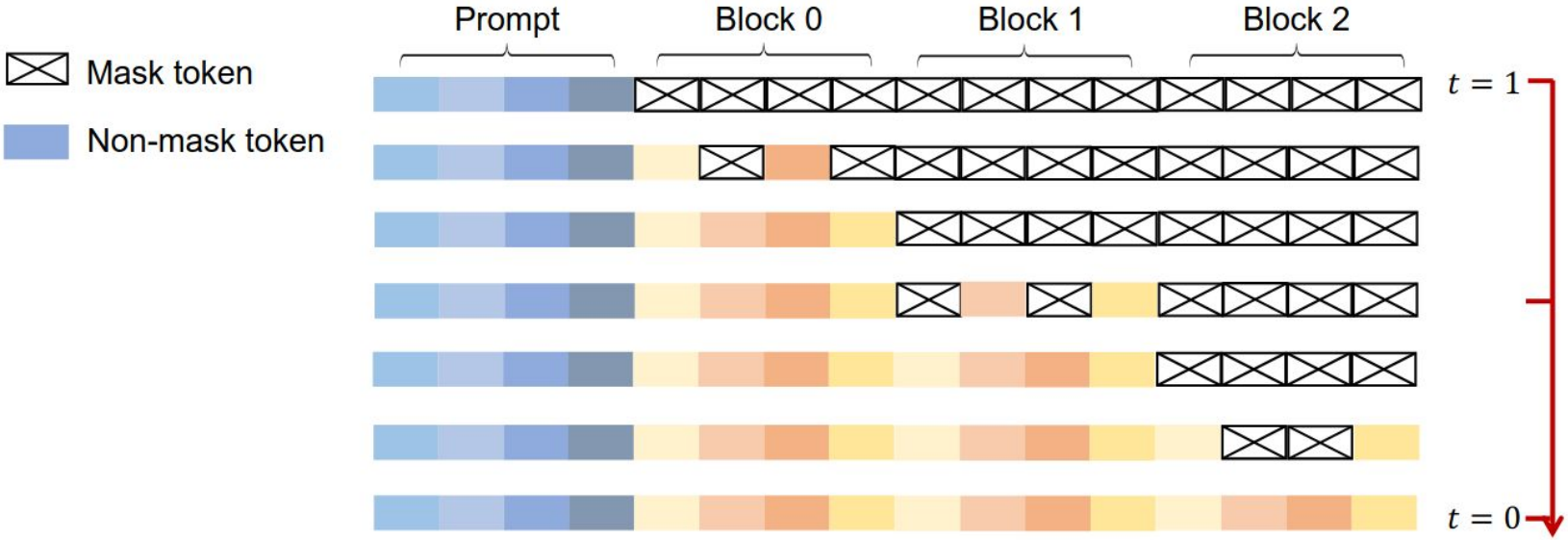

Figure 4. **A Conceptual Overview of the Semi-autoregressive Sampling.**

But the space of possible sampling strategies is HUGE

Train for the Worst, Plan for the Best: Understanding Token Ordering in Masked Diffusions

Jaeyeon Kim [*1] Kulin Shah [*2] Vasilis Kontonis [2] Sham Kakade [1] Sitan Chen [1]

NVIDIA 2025-7-4

Fast-dLLM: Training-free Acceleration of Diffusion LLM by Enabling KV Cache and Parallel Decoding

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Accelerated Sampling from Masked Diffusion Models via Entropy Bounded Unmasking

Heli Ben-Hamu, Itai Gat, Daniel Severo, Niklas Nolte, Brian Karrer
FAIR at Meta

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Unifying Autoregressive and Diffusion-Based Sequence Generation

Nima Fathi, Torsten Scholak & Pierre-André Noël
ServiceNow Research
nima.fathi@mila.quebec, {torsten.scholak,pierre-andre.noel}@servicenow.com

MASKED DIFFUSION MODELS ARE SECRETLY TIME-AGNOSTIC MASKED MODELS AND EXPLOIT INACCURATE CATEGORICAL SAMPLING

Kaiwen Zheng[1*], Yongxin Chen[2], Hanzi Mao[2], Ming-Yu Liu[2], Jun Zhu[1†], Qinsheng Zhang[2]
[1]Department of Computer Science & Technology, Institute for AI, Tsinghua University
[2]NVIDIA

Simplified and Generalized Masked Diffusion for Discrete Data

Jiaxin Shi*, Kehang Han*, Zhe Wang, Arnaud Doucet, Michalis K. Titsias
Google DeepMind

Strategy 0: IID per token (e.g. MD4)

- Go from all-noise at $t = 1$ to noiseless at $t = 0$.

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- Many options are available for the schedule α_t.

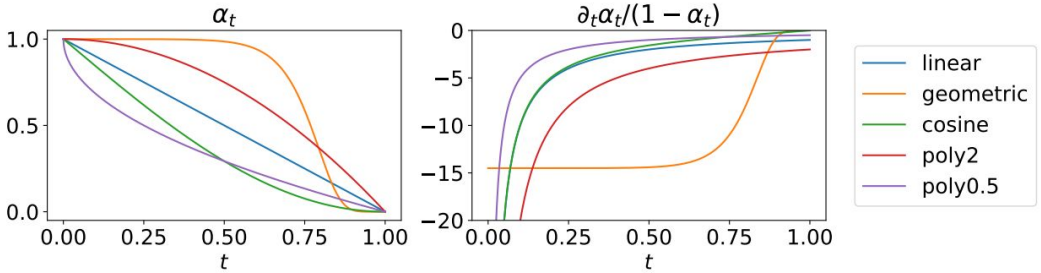

Figure 1: Masking schedules in the literature: (Left) α_t; (Right) weight of the cross-entropy loss w.r.t. t; Equations for these schedules are given in Tab. 4 in Appendix.

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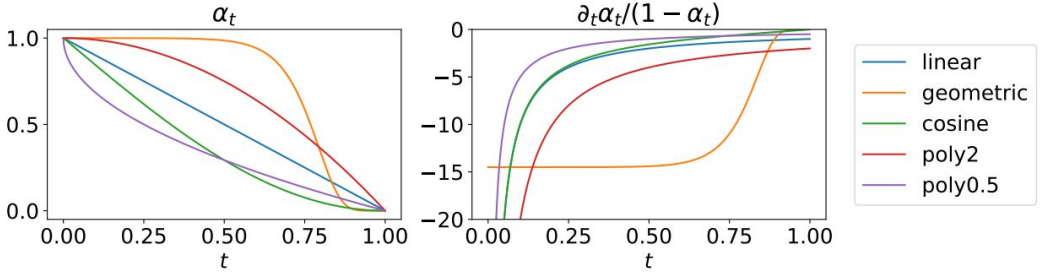

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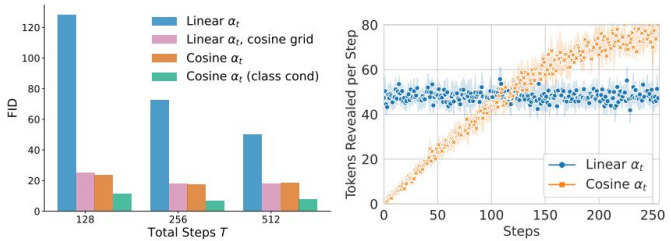

Figure 2: Left: FID evaluation for 50k samples randomly generated from MD4 on pixel-level modeling of ImageNet 64×64 (numbers in Tab. 6). Right: Number of tokens revealed per generation step ($T = 256$). Each image consists of $64 \times 64 \times 3 = 12288$ tokens.

Strategy 1: Greedy/Top probability sampling

Train for the Worst, Plan for the Best:
Understanding Token Ordering in Masked Diffusions

Jaeyeon Kim [*1] Kulin Shah [*2] Vasilis Kontonis [2] Sham Kakade [1] Sitan Chen [1]

To unmask $K \in \mathbb{N}$ tokens in a step from time t to time s (often $K = \text{round}(N\frac{\alpha_t}{\alpha_s})$) :

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- Select the top K indices to decode/sample in decreasing order of $c_{(i)}$.

Strategy 2: Top Probability Margin

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Similar to Top Probability (Strategy 1), except use probability margin for confidence score:

$$c_{(i)} = p_\theta(x_i^t)^{(v_1)} - p_\theta(x_i^t)^{(v_2)}$$

Where

$$v_1 = \arg\max_{v \in \mathcal{V}} p_\theta(x_i^t)^{(v)} \qquad v_2 = \arg\max_{v \in \mathcal{V} \setminus \{v_1\}} p_\theta(x_i^t)^{(v)}$$

I.e. the difference between the two highest probabilities for a given token index.

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Select top K of indices according to $c_{(i)}$

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Helps to avoid prematurely unmasking at an index where two token values both have high probability.

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Helps to avoid prematurely unmasking at an index where two token values both have high probability.

Table 2. Comparison of accuracy for solving the Sudoku puzzle.

Method	# Param	Accuracy
ARM (w/o ordering)	42M	9.73%
ARM (with ordering)		87.18%
MDM (vanilla)	6M	6.88%
MDM (Top probability)		18.51%
MDM (Top prob. margin)		89.49%

Table 3. Comparison of accuracy for solving the Zebra puzzle.

Method	# Param	Accuracy
ARM (w/o ordering)	42M	80.31 %
ARM (with ordering)		91.17 %
MDM (vanilla)	19M	76.9 %
MDM (Top probability)		98.5 %
MDM (Top prob. margin)		98.3 %

Table 4. Performance of different inference strategies for LLaDa 8B model on coding and math tasks.

Method	HumanEval-Single	HumanEval-Multi	HumanEval-Split	Math	MMLU	ROCStories
Vanilla	31.8%	16.5%	14.2%	28.5%	33.2%	21.23%
Top probability	32.9%	20.8%	18.4%	31.3%	**36.5%**	21.10%
Top prob. margin	**33.5%**	**25.4%**	**22.3%**	**34.3%**	35.4%	**21.41%**

Strategy 3: Confidence-Aware Parallel Decoding

Unmask tokens that have a highest-token probability above a global threshold.

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Like top probability, let $c_i = \max_{v \in \mathcal{V}} p_\theta(x_i^t)^{(v)}$ and let $c_{(i)}$ be the i-th largest value of c_i .

NVIDIA 2025-7-4

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Unmask tokens that have a highest-token probability above a global threshold.

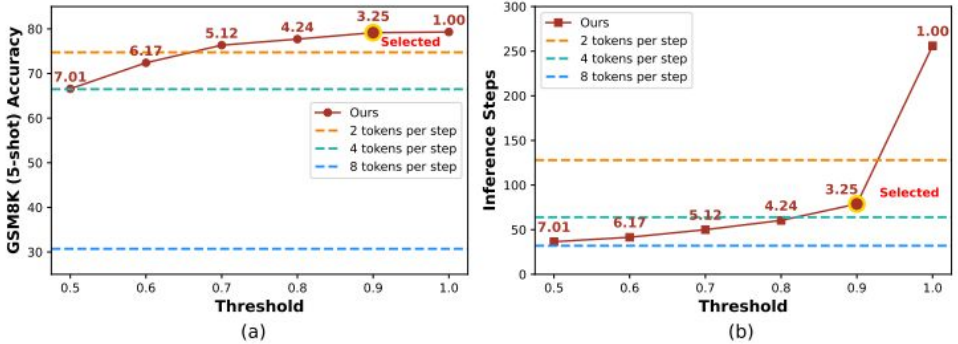
Like top probability, let $c_i = \max_{v \in \mathcal{V}} p_\theta(x_i^t)^{(v)}$ and let $c_{(i)}$ be the i-th largest value of c_i.

Unmask all tokens $1, \ldots, n$ where

$$(n+1)(1 - c_{(n)}) < f$$

for some global threshold f

(they test $f \in [0.5, 1]$).



(red numbers are # tokens decoded per step)

Strategy 4: PC Samplers (Position-Aware Calibration)

PC-Sampler: Position-Aware Calibration of Decoding Bias in Masked Diffusion Models

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Weight the confidence score as $s_t^i = w^i c_t^i$, for timestep t and (currently masked) index i.

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- Note that large λ encourages autoregressive-like decoding
- Small λ encourages more flexible orderings for decoding

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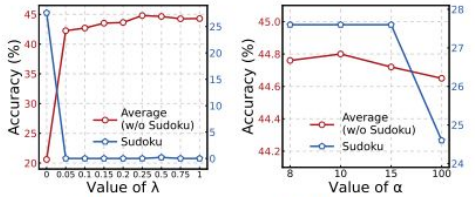
[2]Department of Computer Science and Technology, Institute for AI, Tsinghua University, Beijing, China
[3]Alibaba Group, Hangzhou, China

Weight the confidence score as $s_t^i = w^i c_t^i$, for timestep t and (currently masked) index i.

Write $w^i = e^{-\lambda i}$ and $c_i^t = \min(-\max_{v \in \mathcal{V}} p_\theta(x_i^t)^{(v)} \log p_{\mathcal{D}'}(v), c_{\text{MAX}})$ for $\lambda \geq 0$ and where $p_{\mathcal{D}'}(v)$ is the prob. of seeing token v in some large corpus $\mathcal{D}'$

- Note that large λ encourages autoregressive-like decoding
- Small λ encourages more flexible orderings for decoding
- They hand-select some $\lambda \in [0, 1]$ depending on the task



(a) Ablation on λ. (b) Ablation on α.

Figure 4: Ablation studies on the two key hyperparameters in our approach: (a) the positional decay coefficient λ and (b) the clipping threshold α. To analyze task-dependent effects, we split the evaluation into two groups: the blue line shows the average performance across all datasets except Sudoku, while the orange line shows the performance specifically on Sudoku.

$(\alpha := c_{\text{MAX}})$

Strategy 4: PC Samplers (Position-Aware Calibration)

PC-Sampler: Position-Aware Calibration of Decoding Bias in Masked Diffusion Models

Pengcheng Huang[1*], Shuhao Liu[1*], Zhenghao Liu[1], Yukun Yan[2], Shuo Wang[2], Zulong Chen[3], Tong Xiao[1]

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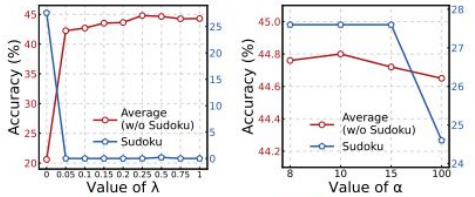
- Note that large λ encourages autoregressive-like decoding
- Small λ encourages more flexible orderings for decoding
- They hand-select some $\lambda \in [0, 1]$ depending on the task
- imo this is a wasted opportunity to learn the λ values in a more interesting way...



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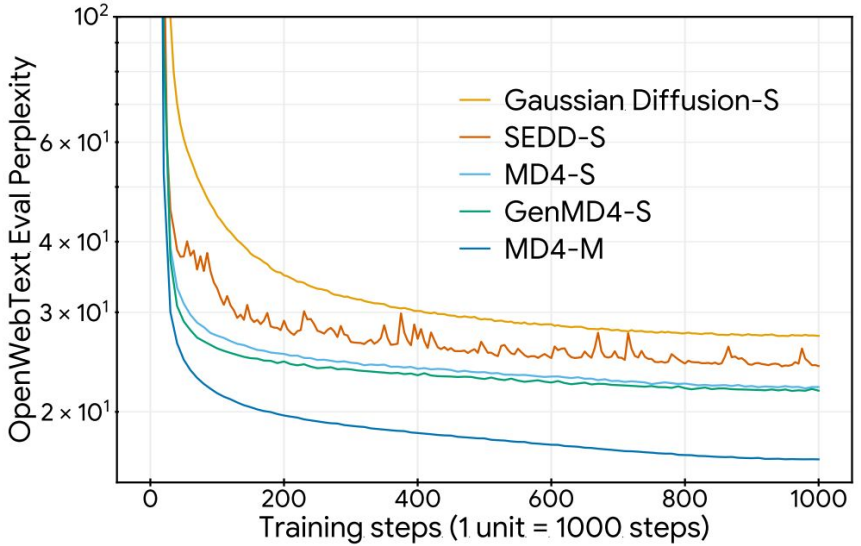
Strategy 4.1: GenMD4

Simplified and Generalized Masked Diffusion for Discrete Data

Jiaxin Shi*, Kehang Han*, Zhe Wang, Arnaud Doucet, Michalis K. Titsias
Google DeepMind

For each token position i, use a denoising schedule/probability $\alpha_{t,i} = 1 - t^{w_i}$ where we learn w_i per index via gradient descent.



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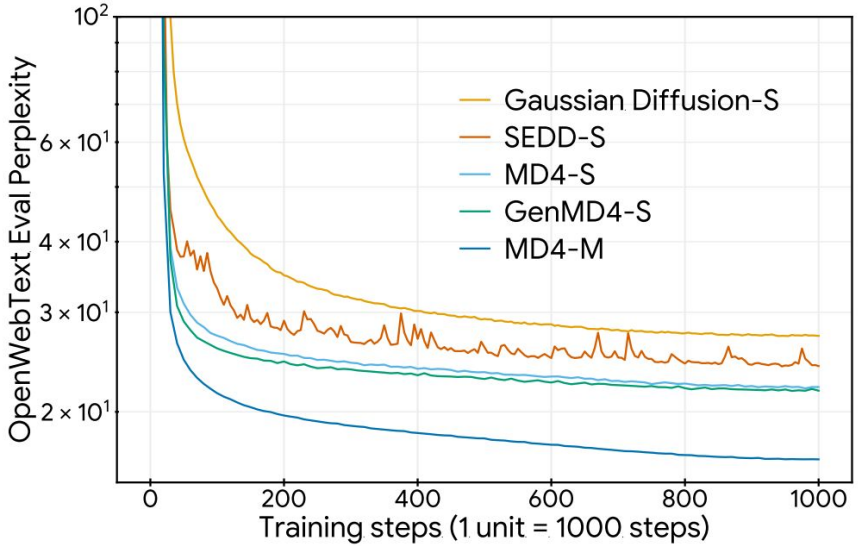

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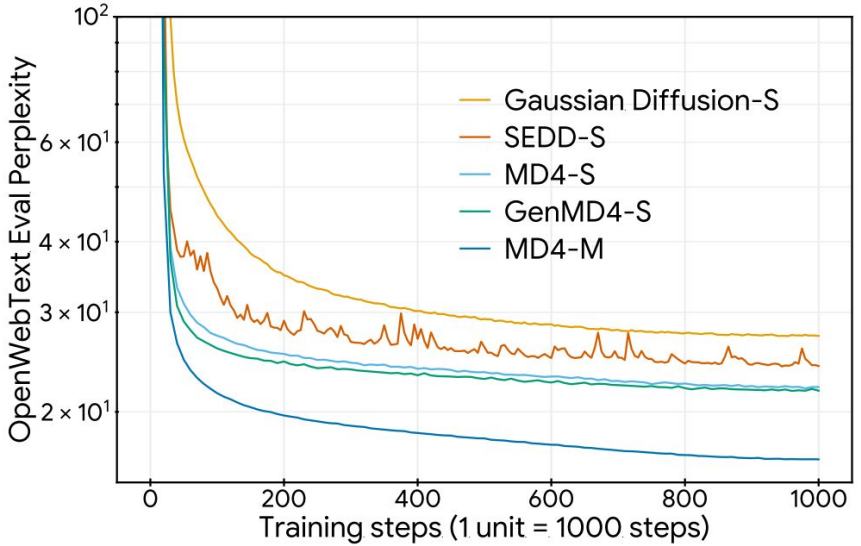

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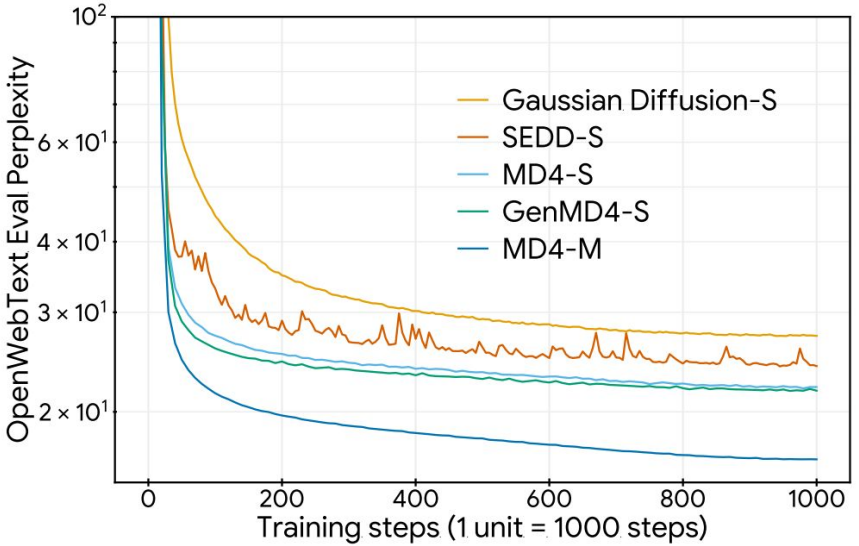
- Difficult to optimise
  - Use reinforce leave-one-out
- “Easily overfits”
- Doesn’t seem like a feasible solution long-term



Strategy 4.2: Hyperschedules

Unifying Autoregressive and Diffusion-Based Sequence Generation

Nima Fathi, Torsten Scholak & Pierre-André Noël
ServiceNow Research
nima.fathi@mila.quebec, {torsten.scholak,pierre-andre.noel}@servicenow.com

Unifying autoregression and diffusion: basically just set (by hand) some patterns for $\alpha_t =: \tau_t$ depending on the token index to encourage decoding to behave more or less autoregressively (depending on the task).

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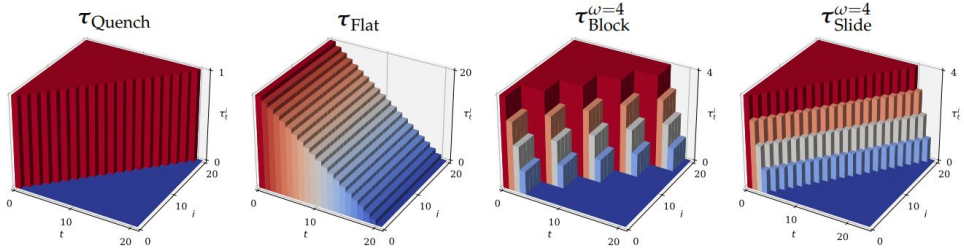

(a) Quenched (AR). (b) Flat annealing. (c) Block annealing. (d) Slide annealing.

Figure 2: We introduce τ-*hyperschedules*, subjecting different token positions i with different noise levels (red high; blue low) at different generation step t. (a) Standard AR models (*e.g.*, GPT) determine tokens one by one, "quenching" each of them to full determination in a single step. They may thus be construed as an extreme case of a diffusion model. (b) Standard diffusion models (*e.g.*, SEDD) gradually anneal all tokens independently of their position. (c) Block-wise application of flat annealing, here for blocks of width $\omega = 4$. (d) Annealing with a sliding window ("smoothed" AR), here using window width $\omega = 4$. These last two examples share important features of both AR and diffusion models.

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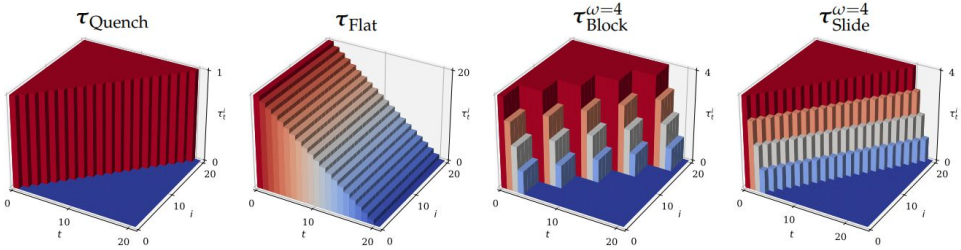

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		Parameters	PPL (↓)
Autoregressive	OmniNet$_T$ (Tay et al., 2021)	100M	21.5
	Transformer (65B tokens) (Sahoo et al., 2024)‡	110M	22.3
Diffusion	SEDD (65B tokens) (Lou et al., 2024)	110M	32.8
	MDLM (65B tokens) (Sahoo et al., 2024)	110M	31.8
	BD3-LMs $L' = 4$ (65B tokens) (Arriola et al., 2025)	110M	28.2
Diffusion (Ours)	γ-Hybrid $[\gamma{=}0.02, \tau_{\text{Flat}}, \text{ALIGNED}]$ (56B tokens)	110M	**27.8**
	γ-Hybrid $[\gamma{=}0.02, \tau_{\text{Flat}}, \text{SHIFTED}]$ (56B tokens)	110 M	28.3
	γ-Hybrid $[\gamma{=}0.02, \tau^{\omega=d/64}_{\text{Block}}, \text{ALIGNED}]$ (65B)	110M	**27.1**
	γ-Hybrid $[\gamma{=}0.02, \tau^{\omega=d/4}_{\text{Block}}, \text{ALIGNED}]$ (65B)	110M	**27.0**
	γ-Hybrid $[\gamma{=}0.02, \tau^{\omega=d/64}_{\text{Block}}, \text{SHIFTED}]$ (65B)	110M	**27.5**
	γ-Hybrid $[\gamma{=}0.02, \tau^{\omega=d/4}_{\text{Block}}, \text{SHIFTED}]$ (65B)	110M	**26.6**

Table 2: Test perplexities (PPL; ↓) on LM1B. Perplexity values for diffusion models are upper-bound estimations. †Reported in He et al. (2022). ‡Reported in Sahoo et al. (2024). Best diffusion value is bolded.

Strategy 5: Entropy Bound Samplers

Accelerated Sampling from Masked Diffusion Models via Entropy Bounded Unmasking

Heli Ben-Hamu, Itai Gat, Daniel Severo, Niklas Nolte, Brian Karrer

FAIR at Meta

Unmask the largest subset of token indices $r \subseteq [N]$ such that

$$\sum_{i \in r} H(p_\theta(x_i^t)) - \max_{i \in [N]} H(p_\theta(x_i^t)) \leq \gamma$$

for some $\gamma \geq 0$.

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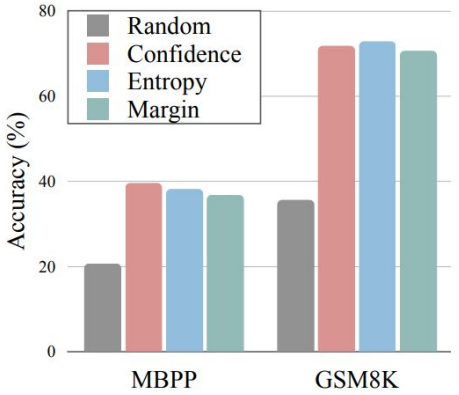
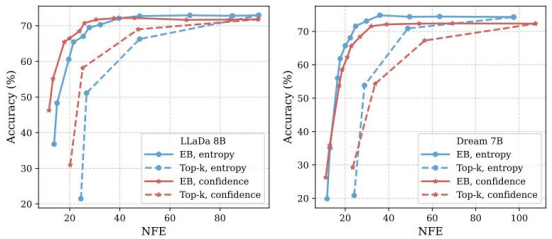


Figure 2 Performance of greedy sampling with various unmasking criteria from LLaDa 8B Base model.



(c) GSM8K

Strategy 6: Learning an auxiliary index-selection model

As in the previous strategy, consider the problem as finding a subset of token indices $r \subseteq [N]$ for each denoising step (in discrete time) $r_1, \ldots, r_T$ s.t. $\cup_t r_t = [N]$ and $r_t \cap r'_t = \emptyset$ for all $t \neq t'$ (i.e. $r_1, \ldots, r_T$ form a partition of $[N]$).

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Let's treat r_t as a random variable with approximate posterior $Q_\phi(r_{t+1}|x^t, x_{\text{data}})$ and generative distribution $P_\theta(r_{t+1}|x^t)$, then optimise with VI.

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Hopefully this will give us:

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Hopefully this will give us:

- Sensible simultaneous decoding (of tokens which don't contradict each other)
  - Maybe better overall performance
- Decoding in many fewer steps, T, than other methods
  - Hopefully a better performance-speed trade-off

Final thoughts

- I may have been too pessimistic about the future of discrete diffusion LLMs in my earlier presentation

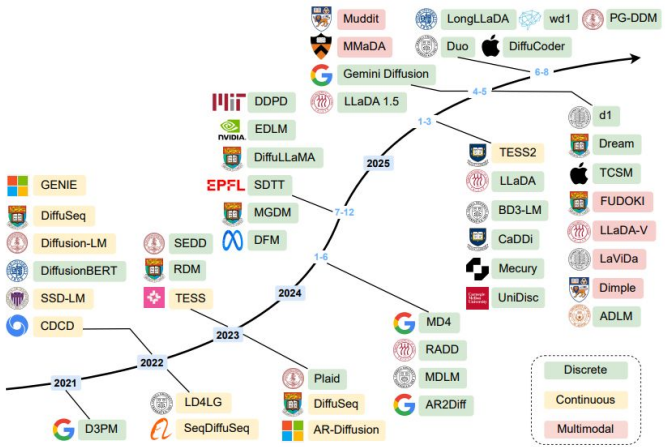

Fig. 1. Timeline of Diffusion Language Models. This figure highlights key milestones in the development of DLMs, categorized into three groups: continuous DLMs, discrete DLMs, and recent multimodal DLMs. We observe that while early research predominantly focused on continuous DLMs, discrete DLMs have gained increasing popularity in more recent years.

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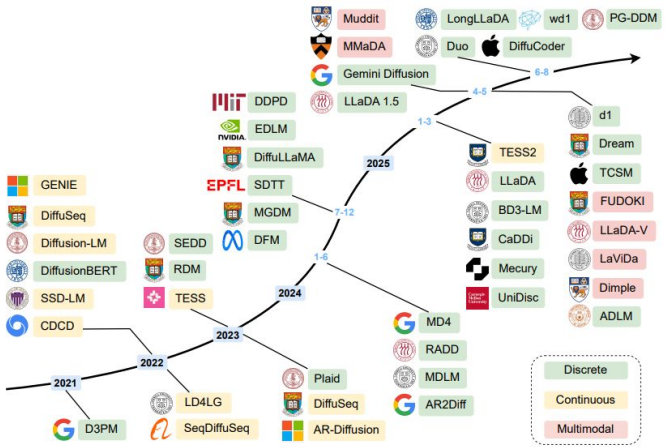

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Final thoughts

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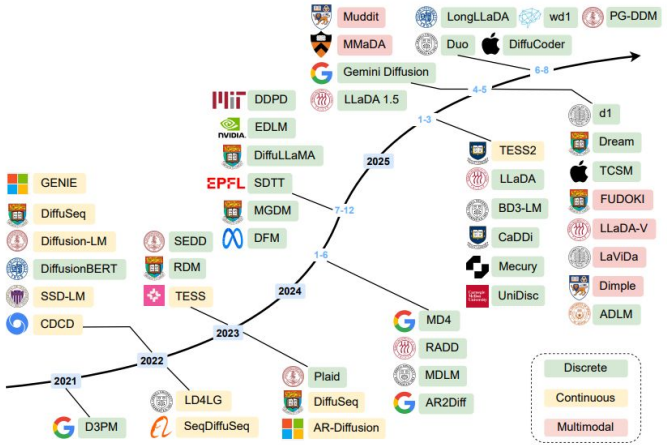
- I'm still not certain if they'll 'beat' ARMs (but it's not impossible)
- But I do still think they're fun



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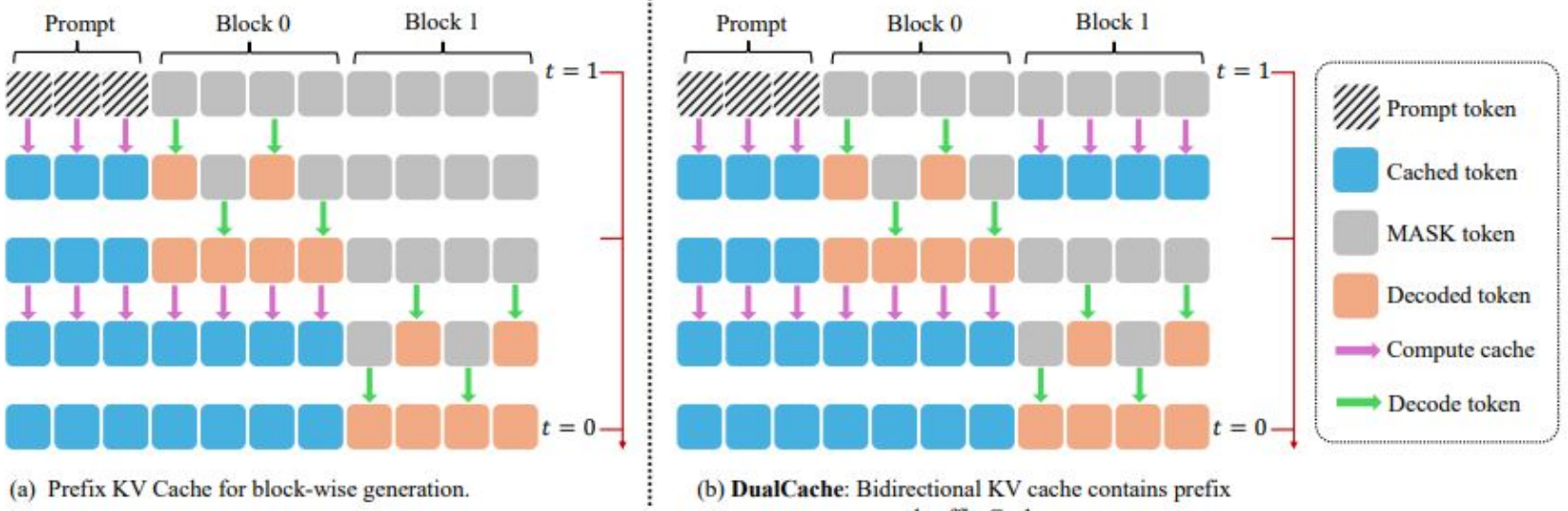
Bonus: Blockwise KV-Caching

Fast-dLLM: Training-free Acceleration of Diffusion LLM by Enabling KV Cache and Parallel Decoding

Chengyue Wu[1,2*] Hao Zhang[2*] Shuchen Xue[4] Zhijian Liu[2] Shizhe Diao[2] Ligeng Zhu[2]
Ping Luo[1] Song Han[2,3] Enze Xie[2]



(a) Prefix KV Cache for block-wise generation.

(b) **DualCache**: Bidirectional KV cache contains prefix and suffix Cache.

Figure 2 | **Illustration of our Key-Value Cache for Block-Wise Decoding.** (a) During prefix-only caching, the KV cache is computed once for the prompt and reused across multiple decoding steps within each block. The cache is updated after completing a block to maintain consistency, with negligible overhead. (b) DualCache extends this approach by caching both prefix and masked suffix tokens, further accelerating decoding. The high similarity of KV activations across steps allows effective reuse with minimal approximation error.

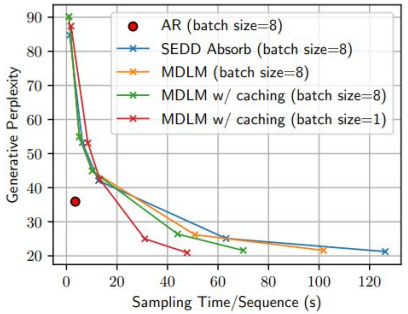
Strategy 2: Greedy + Gumbel Noise

MASKED DIFFUSION MODELS ARE SECRETLY TIME-AGNOSTIC MASKED MODELS AND EXPLOIT INACCURATE CATEGORICAL SAMPLING

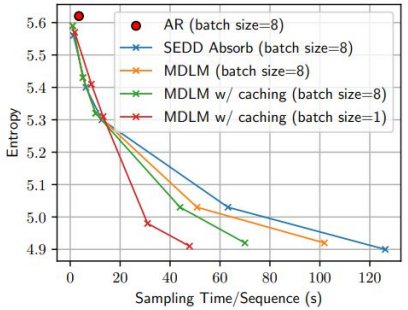
Kaiwen Zheng[1]*, **Yongxin Chen**[2], **Hanzi Mao**[2], **Ming-Yu Liu**[2], **Jun Zhu**[1]†, **Qinsheng Zhang**[2]
[1]Department of Computer Science & Technology, Institute for AI, Tsinghua University
[2]NVIDIA

Like previous but adds noise (from a truncated Gumbel distribution) to the categorical probabilities to improve numerical stability.

Authors noticed that MDMs get very low generative perplexity (as scored by some other LM, e.g. GPT2…), but often with crappy generations *if float precision isn't high enough*



(a) Generative Perplexity



(b) Entropy

There is the following definition:
The "right lane" on the lane lane lane. From the lane lane lane from lane lane to lane lane on a lane in lane lane on a front lane.
From lane lane lane the lane lane lane on the right lane from lane front lane lane to top lane.
From the right lane from a lane lane lane with the lane on the lane lane lane. The "that lane lane" on the rear lane.

Figure 6: Segment of generated text by SEDD Absorb (Lou et al., 2023) at 50k sampling steps.