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Loopholing Discrete Diffusion

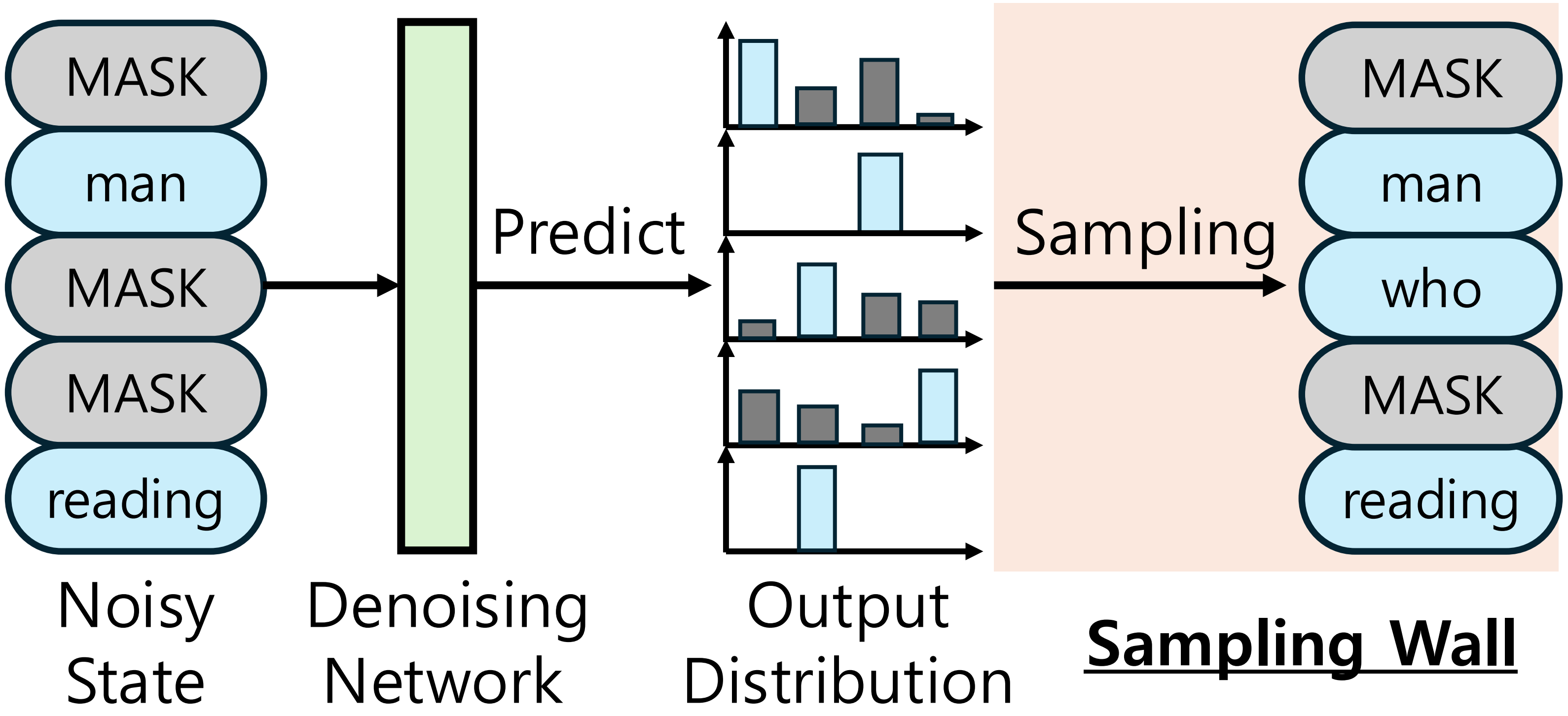
Deterministic Bypass of the Sampling Wall

Mingyu Jo[1], Jaesik Yoon[1,4], Justin Deschenaux[2], Caglar Gulcehre[2,3], Sungjin Ahn[1,5]

[1]KAIST [2]EPFL [3]Microsoft [4]SAP [5]NYU

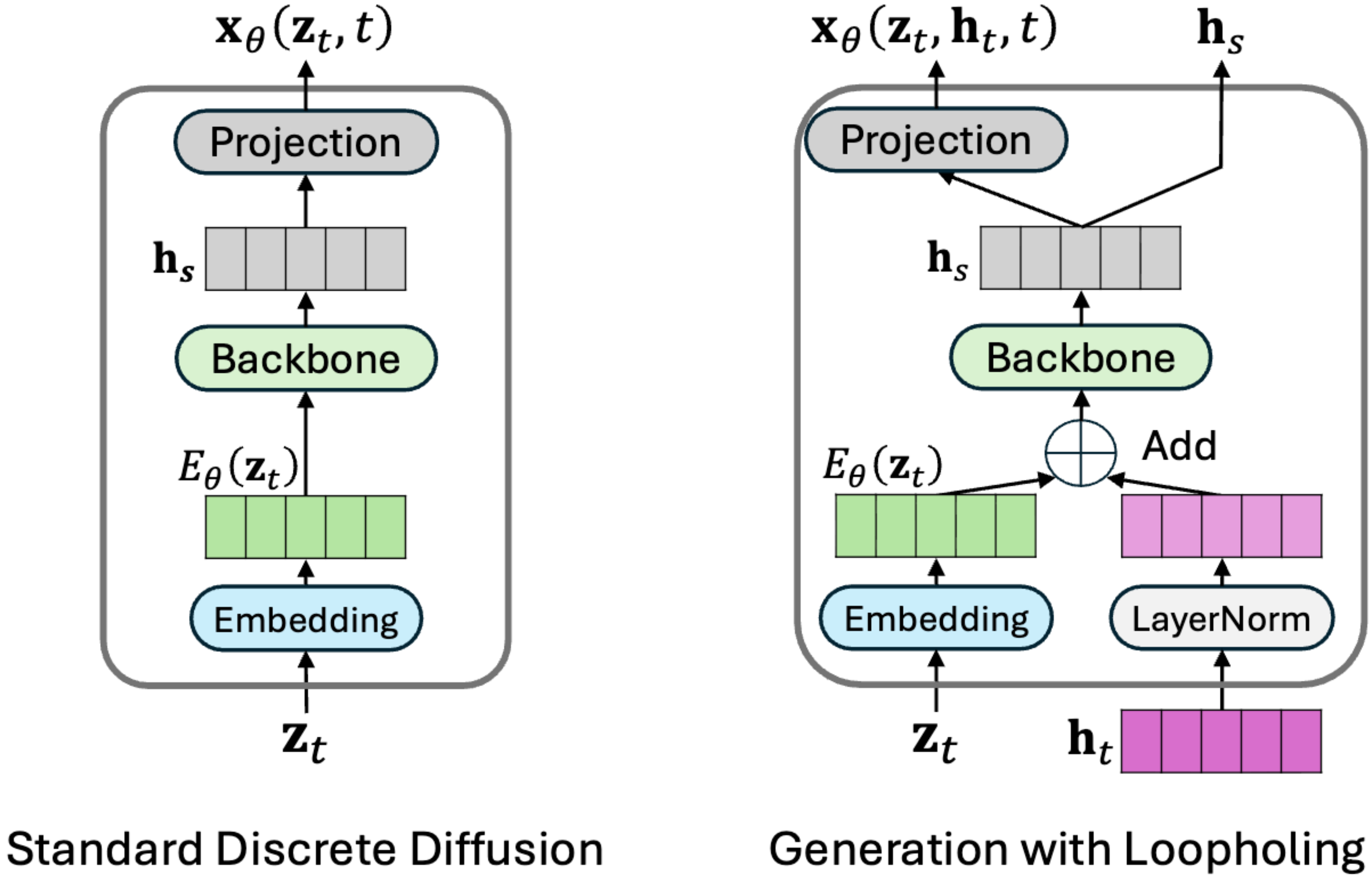
The Sampling Wall Problem

Rich distributional information collapses into one-hot vectors after sampling.



Loopholing: Deterministic Latent Pathway

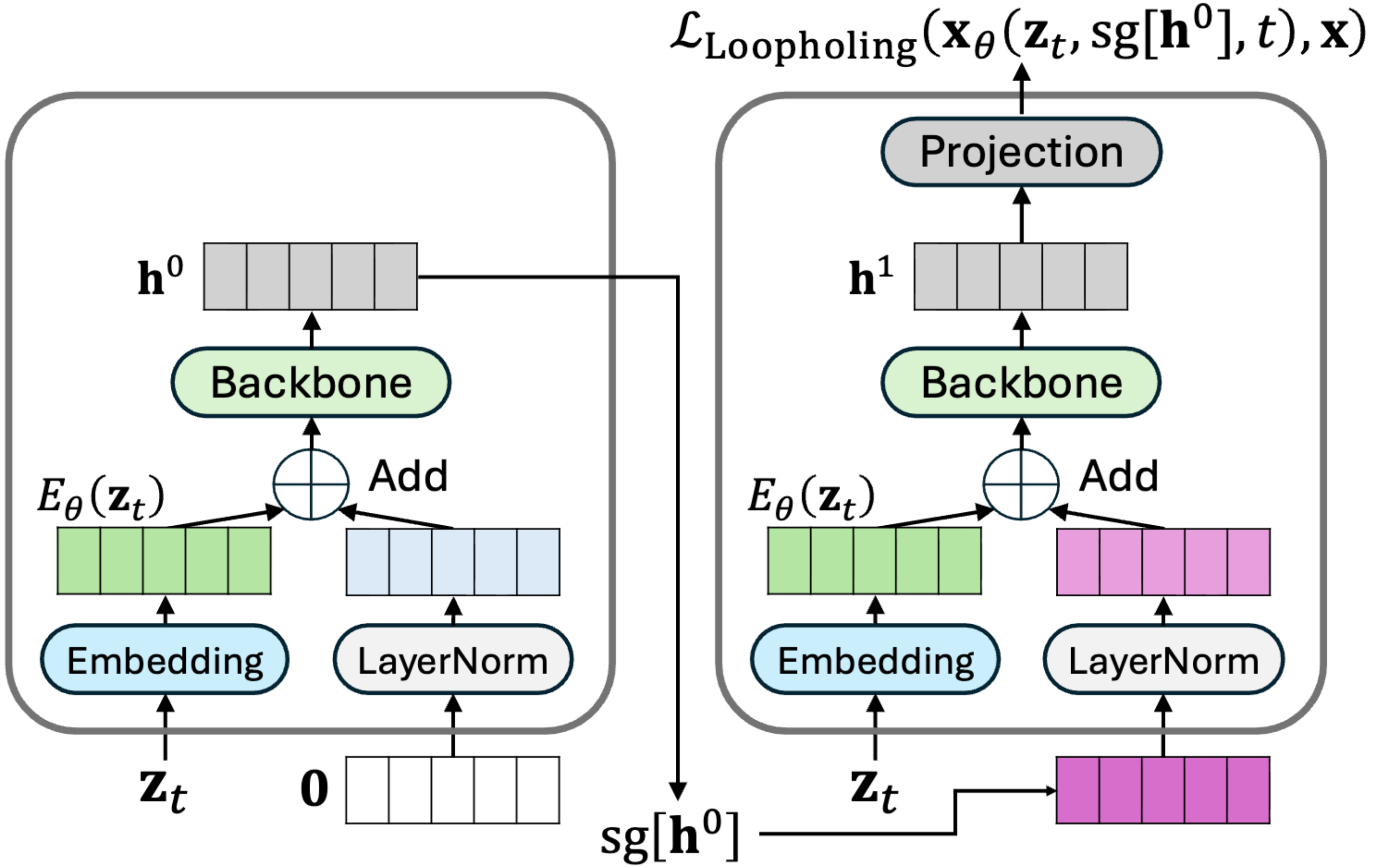
Bypass the sampling wall by directly propagating the rich latent $\mathbf{h}_s$ to the next step.



$$(\mathbf{x}_\theta(\mathbf{z}_t, \mathbf{h}_t, t), \mathbf{h}_s) = f_{\text{Loopholing}}(\mathbf{z}_t, \mathbf{h}_t, t)$$

Training with Self-Conditioning

Avoids costly trajectory unrolling. Two forward passes per training step.



Training with Self-conditioned Loopholing

$$L_{Loopholing} = \mathbb{E}_{t,\mathbf{z}_t}\left[1[\mathbf{z}_t = m]\,\frac{\alpha'_t}{1-\alpha_t}\left(\log\left\langle \mathbf{x}_\theta^1(\mathbf{z}_t, \text{sg}[\mathbf{h}^0], t), \mathbf{x}\right\rangle\right)\right]$$

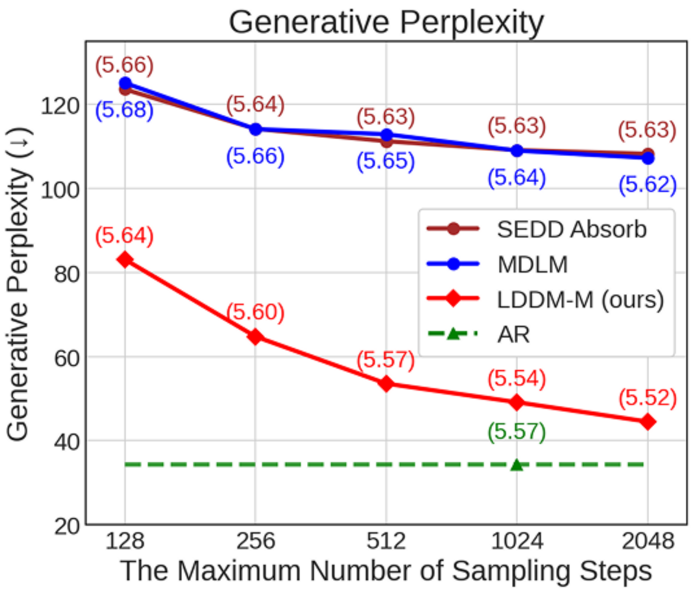
Results – Likelihood

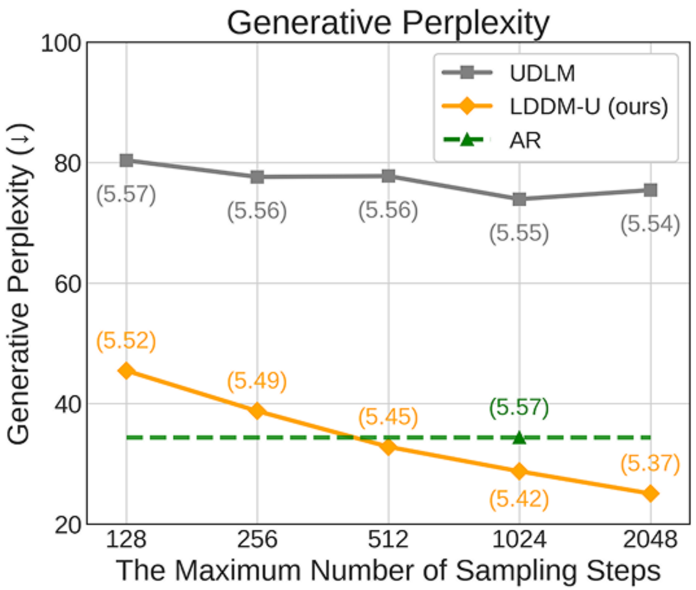
Loopholing consistently improves perplexity across both masked and uniform diffusion frameworks.

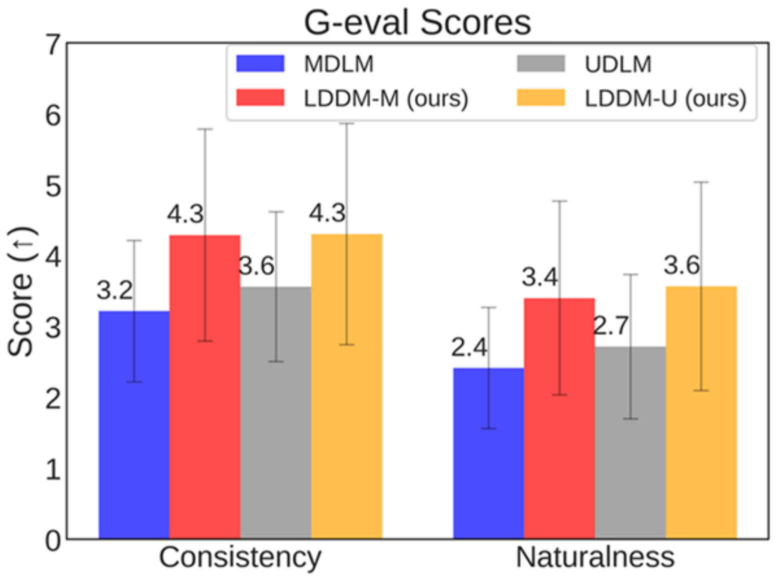
	PTB	Wikitext	LM1B	Lambada	AG News	Pubmed	Arxiv
Masked Diffusion							
SEDD Absorb†	97.87	38.34	74.71	50.15	76.54	45.25	39.75
MDLM†	86.33	36.30	**66.73**	48.36	68.62	41.94	37.52
Uniform Diffusion							
UDLM†	77.28	38.48	81.41	51.68	76.81	46.18	41.19
Ours (LDDMs)							
LDDM-M (ours)	85.80	**33.27**	69.53	**44.22**	**62.55**	**39.74**	**34.96**
LDDM-U (ours)	**71.52**	38.89	79.60	52.34	76.81	45.05	41.02

Results – Generation Quality

Up to 61% reduction in generative perplexity, closing the gap with autoregressive models.







Results – Reasoning Performance

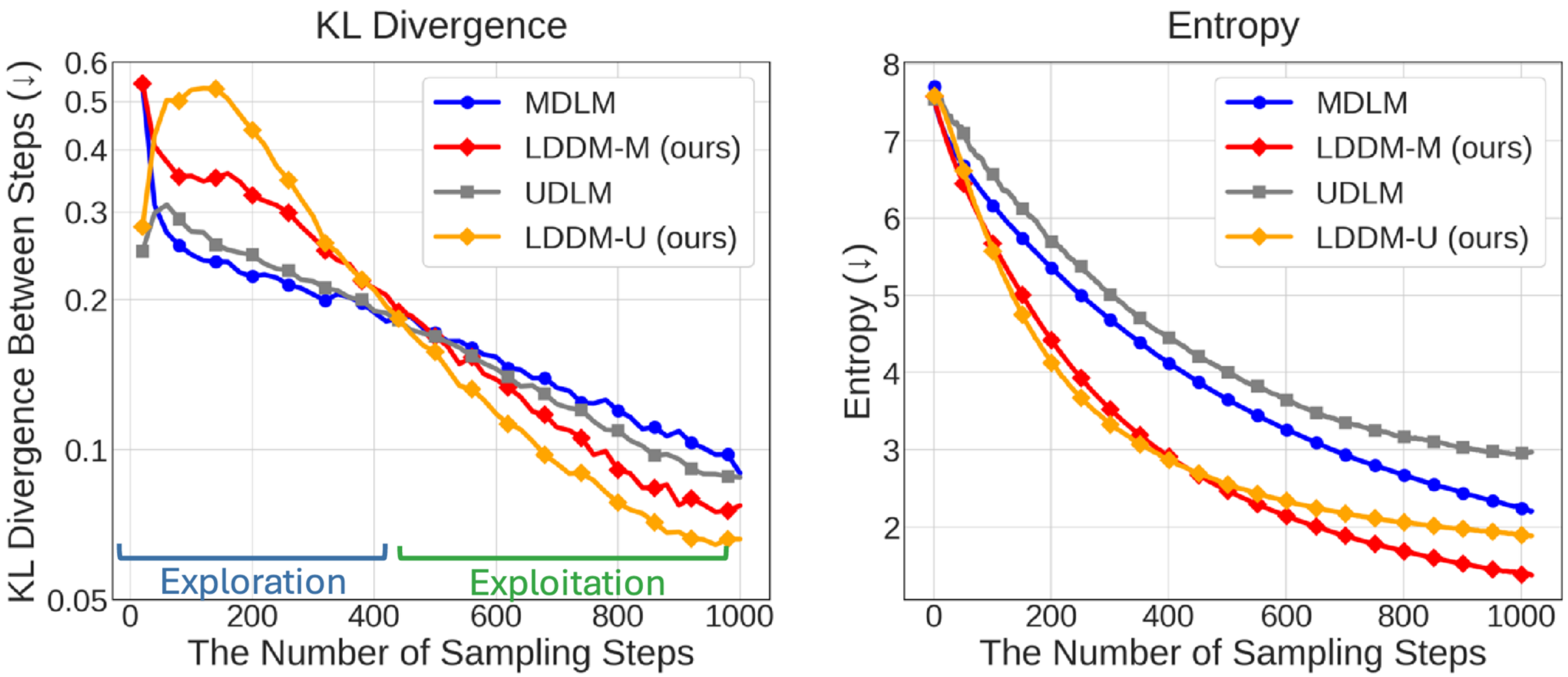
Loopholing boosts arithmetic reasoning accuracy by preserving richer solution-space representations.

Table 3: Success rates (%) on the Countdown (CD) and Game of 24 (G24) tasks.

Architecture	Params	CD 4	G 24	CD 5
MGDM[1]	6M	45	12	5.9
	85M	86.5	47	35.7
LDDM-G (Ours)	6M	**56.3**	**28**	**10.3**
	85M	**94.4**	**63**	**41.3**

Results – Stable Generation

LDDMs explore more actively early on, then refine more stably, with consistently lower entropy.



Thank you for listening

Paper

https://arxiv.org/abs/2510.19304

Project Page

https://sites.google.com/view/lddms/home

Code

https://github.com/ahn-ml/lddm