Exhibit Hall C,D,E Wed. 3 Dec. 4:30 P.M.

ReDi: Rectified Discrete Flow

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Discrete Flow-based Models (DFMs)

Discrete Flow-based models learn $p_{\theta}(X_1|X_0)$, where X_1 is data and X_0 is initial state.



Masked Generative Models^[1]

Uniform Diffusion Sampling step: 0/8 many water during of to water put without thought between necessary million now go important from general potential this try family over try so building from so your just general own a someone to always could example state to out been go I which up after state make how other I oil we possible without shall have while hot beautiful they faigfywirkx start man could you in thought when take friend always should had of first me different than is see necessary be example Absorbing Diffusion Sampling step: 00/30

Diffusion Language Models^[2]

DFMs are based on the **factorized modeling** to treat high-dimensional data.

$$p(X_{t+h}|X_t) = \prod_{i=1}^N p(X_{t+h}^{(i)}|X_t) + o(h)$$
Joint Modeling Factorized Modeling $ightarrow \mathtt{D^N \, logits}$ $ightarrow \mathtt{D \, x \, N \, logits}$

The necessity of **factorized modeling** introduces **factorization error** that hinders few-step generation of DFMs.

$$p(X_1|X_0) \;
eq \; \prod_{i=1}^N p(X_1^{(i)}|X_0)$$

Joint Modeling

Factorized Modeling

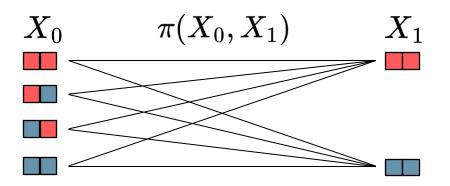
We adopt **conditional Total Correlation(TC)** to characterize the factorization error.

$$TC_{\pi}(X_1|X_0) = \mathbb{E}_{x_0}[D_{KL}(p(X_1|X_0=x_0)||\prod_{i=1}^N p(X_1^{(i)}|X_0=x_0))]$$

We observe that the conditional TC depends on the coupling $\pi(X_0,X_1)$.

$$egin{aligned} TC_{\pi}(X_1|X_0) &= \mathbb{E}_{x_0}[D_{KL}(p(X_1|X_0=x_0)||\prod_{i=1}^N p(X_1^{(i)}|X_0=x_0))] \ &= rac{\pi(X_0=x_0,X_1)}{p(X_0=x_0)} \end{aligned}$$

We observe that the conditional TC depends on the coupling $\pi(X_0, X_1)$.



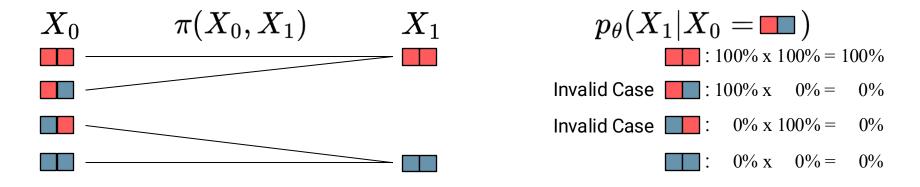
$$p_{\theta}(X_1|X_0=\blacksquare)$$

Invalid Case $= 50\% \times 50\% = 25\%$

Invalid Case $150\% \times 50\% = 25\%$

 $50\% \times 50\% = 25\%$

We observe that the conditional TC depends on the coupling $\pi(X_0,X_1)$.



ReDi: Rectified Discrete Flow

We propose to **rectify the coupling** to reduce the conditional Total Correlation.

$$\pi_{k+1}(X_0,X_1) = p(X_0)p_{ heta}(X_1|X_0)$$
 Data Generation

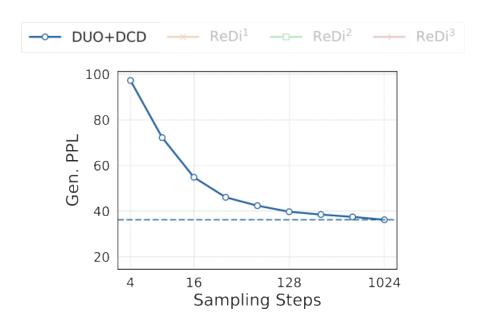
ReDi: Rectified Discrete Flow

Theoretical Result: each rectification iteration reduces conditional Total Correlation.

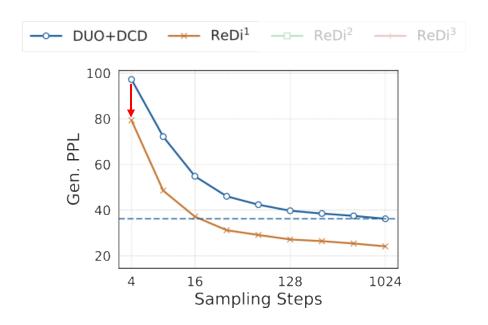
$$TC_{k+1}(X_1|X_0) \leq TC_k(X_1|X_0)$$



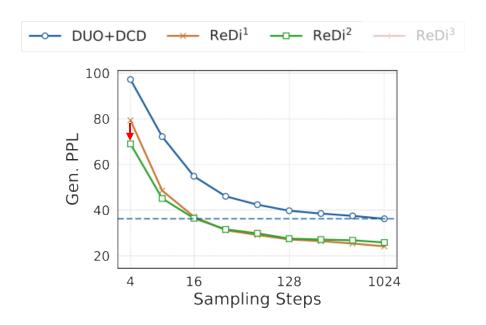
ReDi enhances few-step performance of the teacher models on OpenWebText.



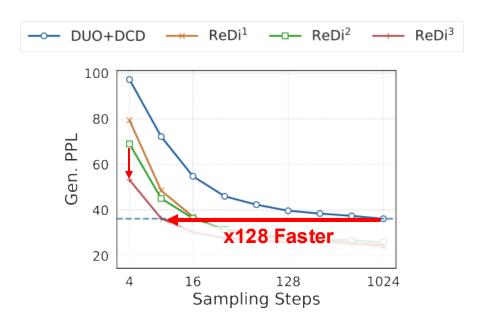
ReDi enhances few-step performance of the teacher models on OpenWebText.



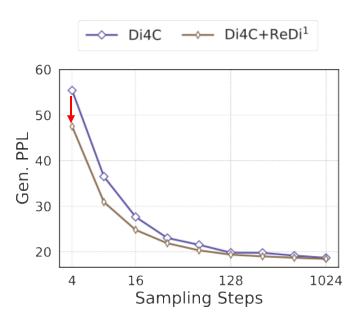
ReDi enhances few-step performance of the teacher models on OpenWebText.



ReDi accelerates the teacher model by up to 128x.



ReDi can be combined with other distillation method.



ReDi on Image Generation

ReDi enables **1-step generation** on class-conditional ImageNet.

Step	Model	FID (↓)	IS (†)
1	MaskGIT [3]	95.16	12
	$SDTT^{\dagger}$ [10]	90.40	14
	Di4C [17]	90.32	13
	${\sf ReDi}^1$	37.43	49
	${\sf ReDi}^2$	21.80	90
	ReDi ³ -distill	11.68	182

1-step Generation Results MaskGIT SDTT Di₄C ReDi¹ ReDi² ReDi³-distill

Conclusion

- Factorization error hinders few-step generation.
- Factorization error can be characterized with **conditional Total Correlation** which **depends on the coupling.**
- We proposed ReDi, rectifying the coupling to reduce the factorization error.

For more details, please join our poster session.

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