# Jump Your Steps: Optimizing Sampling Schedule of Discrete Diffusion Models

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## Discrete Diffusion Models (DDMs)

- Recently, DDMs show promising results on in various fields:
  - Image
  - Language
  - Gene, Protein

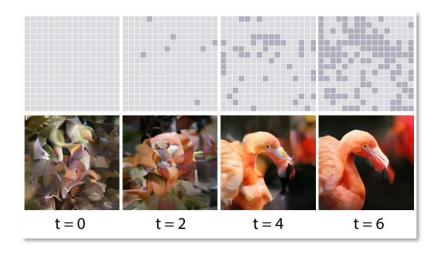
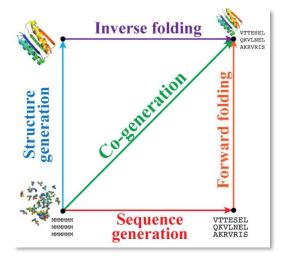


Image Generation (MaskGiT)



Language Generation (LLaDA)



Gene / Protein Generation (DFM)

## Challenges with DDMs

#### Slow sampling:

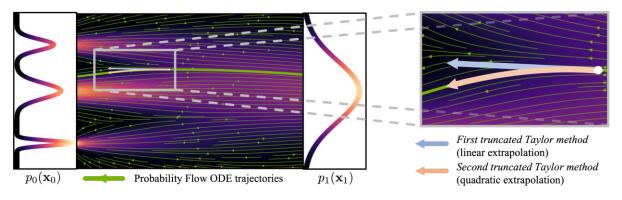
• DMs require multiple NFEs for generation.

#### Continuous DMs

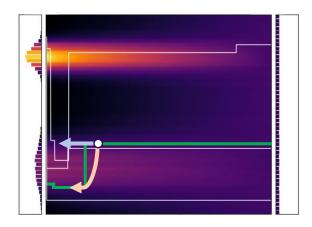
- Solution: high-order ODE / SDE solver.
- There are many previous work for fast and reliable differential equation solver.

#### Discrete DMs

- Solution: high-order Jump process solver?
- There are little work for efficient Markov jump process solver.



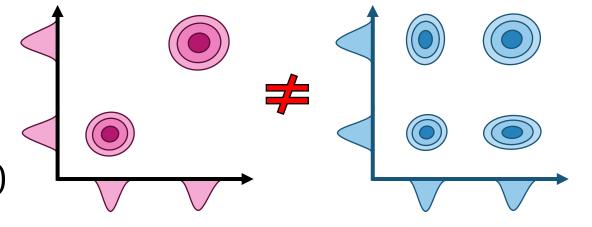
**GENIE: Higher-Order Denoising Diffusion Solvers** 



High-order Markov Jump process solvers are difficult to develop.

## Challenges with DDMs

- Faster sampling for DDMs: Parallel sampling
  - Sampling multiple tokens within single step
    - *k*-Gillespie: Sample k tokens simultaneously.
    - $\tau$ -leaping: Sample all tokens simultaneously within a given time frame.
- Compounding Decoding Error (CDE)
  - Generally, parallel sampling leads to error.
    - Parallel sampling:  $p(x_1)p(x_2)$
    - Sequential sampling:  $p(x_1)p(x_2|x_1)$
  - CDE :=  $D_{KL}(p(x_1, x_2)||p(x_1)p(x_2))$



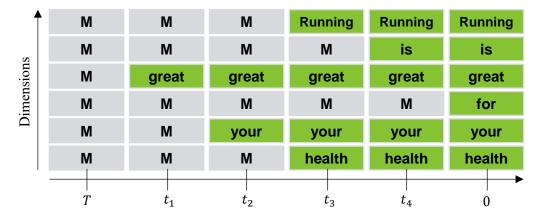
Joint distribution (Sequential sampling,  $p(x_1, x_2)$ )

Product of marginal distribution (Parallel sampling,  $p(x_1)p(x_2)$ )

## Main Idea: Motivating Example

CDE depends on timesteps

Discrete sequence trajectory:  $(X_t)_{t \in [0,T]}$ 

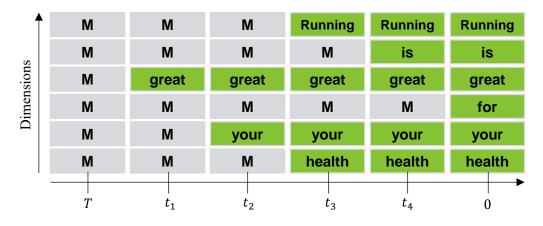


Ground-truth sampling trajectory

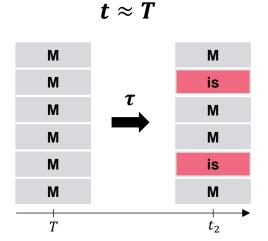
## Main Idea: Motivating Example

#### CDE depends on timesteps

Discrete sequence trajectory:  $(X_t)_{t \in [0,T]}$ 

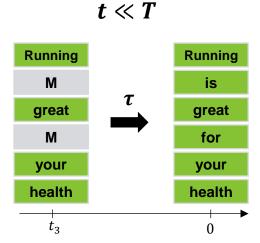


Ground-truth sampling trajectory



High CDE

Parallel sampling hurts performance.



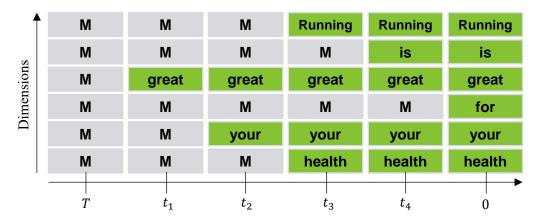
Low CDE

Minimal impact from parallel generation.

## Main Idea: Jump Your steps

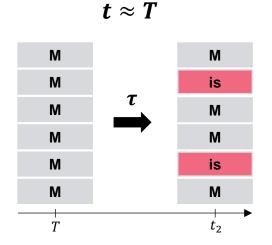
#### CDE depends on timesteps

Discrete sequence trajectory:  $(X_t)_{t \in [0,T]}$ 



Ground-truth sampling trajectory

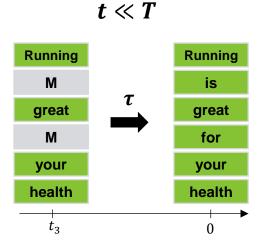
Optimizing Sampling Schedule of DDMs



#### High CDE

Parallel sampling hurts performance.

Use **small step size** when decoding error is large



#### Low CDE

Minimal impact from parallel generation.



Use **large step size** when decoding error is small

## Theory

Theorem 3.1 Eq. (10)  $\mathcal{D}_{\mathrm{KL}}(\mathbb{P}_{0} \| \mathbb{Q}_{0}^{t_{0} \star t_{1} \star \cdots \star 0}) \leq \sum_{i=0}^{N-1} \mathcal{D}_{\mathrm{KL}}(\mathbb{P}_{t_{i+1}} \| \mathbb{Q}_{t_{i+1}}^{t_{i} \star t_{i+1}}) \leq \mathcal{D}_{\mathrm{KL}}(\mathbb{P}_{\mathrm{paths}} \| \mathbb{Q}_{\mathrm{paths}}^{t_{0} \star t_{1} \star \cdots \star 0})$   $\downarrow \text{Eqs. (3, 5)} \qquad \qquad \downarrow \text{Theorem 3.2}$   $\sum_{i=0}^{N-1} \mathcal{E}_{\mathrm{CDE}}(t_{i} \to t_{i+1}) \qquad \text{KLUB}(\mathbb{P}_{0} \| \mathbb{Q}_{0}^{t_{0} \star t_{1} \star \cdots \star 0})$ 

**Motivation: Minimize CDE** 

Q: Why should we minimize CDE?

**A:** It improves the sampling quality.

## Theory

Theorem 3.1 Eq. (10)
$$\mathcal{D}_{\mathrm{KL}}(\mathbb{P}_{0}\|\mathbb{Q}_{0}^{t_{0} \to t_{1} \to \cdots \to 0}) \leq \sum_{i=0}^{N-1} \mathcal{D}_{\mathrm{KL}}(\mathbb{P}_{t_{i+1}}\|\mathbb{Q}_{t_{i+1}}^{t_{i} \to t_{i+1}}) \leq \mathcal{D}_{\mathrm{KL}}(\mathbb{P}_{\mathrm{paths}}\|\mathbb{Q}_{\mathrm{paths}}^{t_{0} \to t_{1} \to \cdots \to 0})$$

$$\downarrow \text{Eqs. (3, 5)} \qquad \qquad \downarrow \text{Theorem 3.2}$$

$$\sum_{i=0}^{N-1} \mathcal{E}_{\mathrm{CDE}}(t_{i} \to t_{i+1}) \qquad \qquad \text{KLUB}(\mathbb{P}_{0}\|\mathbb{Q}_{0}^{t_{0} \to t_{1} \to \cdots \to 0})$$

**Motivation: Minimize CDE** 

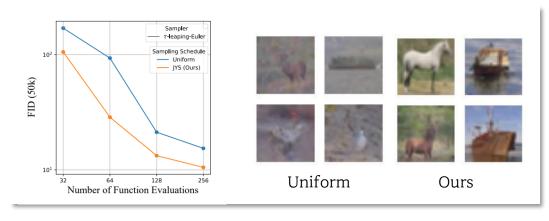
Q: How could we minimize CDE? A: Using trackable upper-bound.

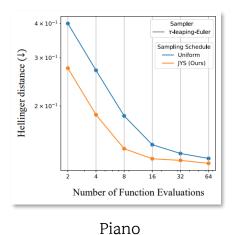
**Trackable Upper-bound** 

### Results

#### Improved Sampling quality:

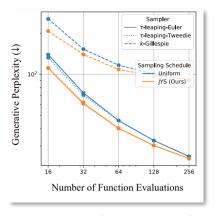
• JYS sampling scheduler achieves performance improvement regardless of data domain or model.



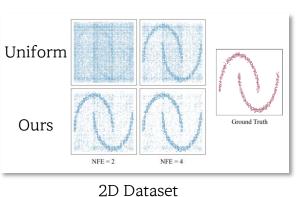


τ-leaping-Euler
τ-leaping-Tweedie

--- k-Gillespie
Sampling Schedule



CIFAR10



10° JYS (Ours)

CountDown

Number of Function Evaluations

Language (GPT-2 scale)

Thank you