Continuous-time Discrete-space Diffusion Model for Recommendation

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Key Points

- **CDRec**: A novel framework that introduces **discrete-space diffusion** for efficient recommendation in **continuous-time steps**.
- **Popularity-aware Noise Schedule**: Simulates real-world interaction dynamics to generate more *informative diffusion trajectories* and improve training/sampling efficiency.
- **Consistency-driven Diffusion Parameterization**: A *consistency function* with a contrastive learning objective to inject collaborative signals and guide the diffusion process.
- **Empirical Results**: Experiments on three real-world datasets show CDRec outperforms state-of-the-art baselines, with ablations validating each component.

1. Introduction

1.1 Motivation

- *Diffusion Aligns with Recommendation:* Model the *distribution* of potential user-item interactions from inherently *incomplete and noisy* historical data.

1.2 Limitations of Diffusion Recommenders

Continuous-space diffusion models vs. discrete CF data

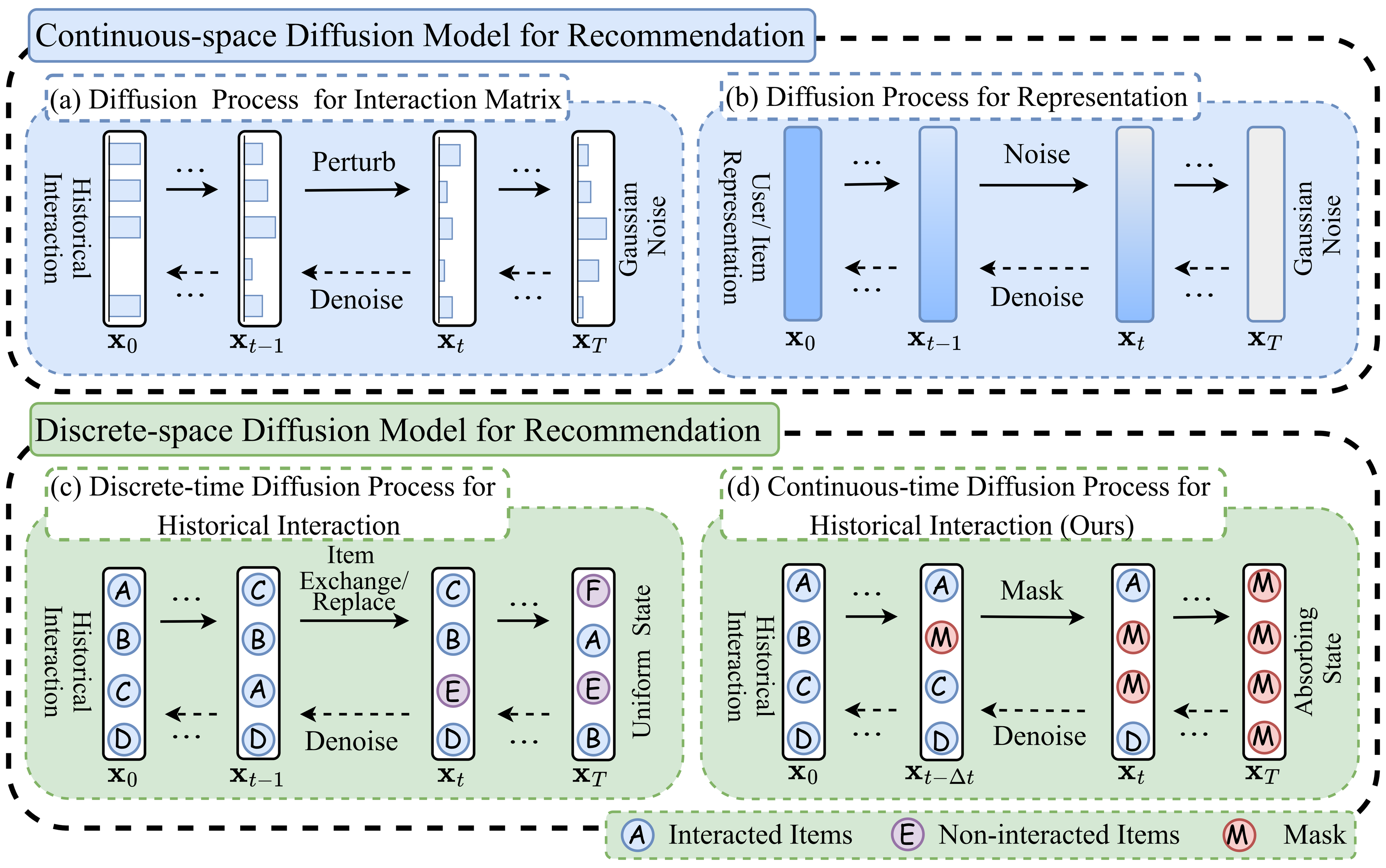
- Isotropic Gaussian noise on **interaction matrices** breaks *item dependencies* and *collaborative graph structure* in interaction matrices.
- Gaussian corruption of **representations** degrades *semantic consistency* and yields *uninformative diffusion trajectories*, hindering training and sampling.

1.3 Diffusion Models in Discrete State-spaces

Employs **discrete state transitions** (e.g., swapping, replacement) to progressively transform data toward a stationary distribution.

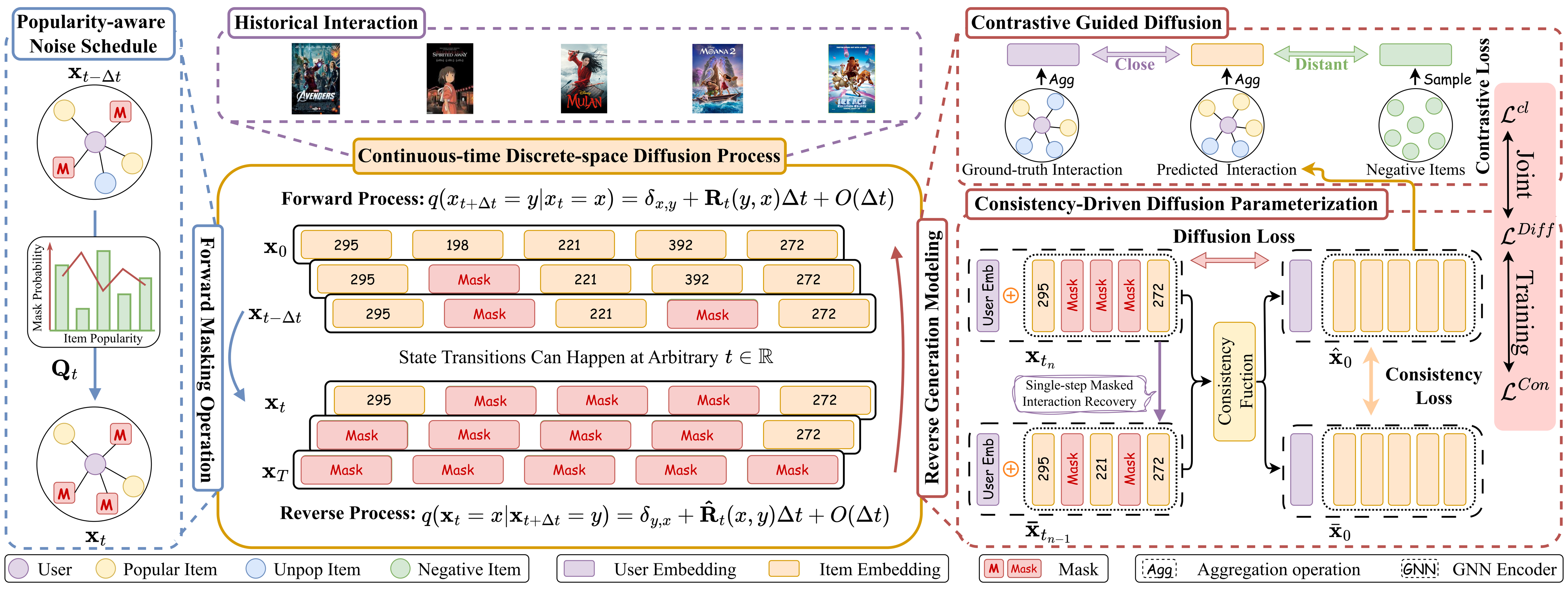
- Main Challenges.

(i) Uniform perturbations destroy user preference signals and lack semantic meaning
(ii) Undeveloped theoretical tools for discrete reverse processes require custom solutions for efficient training and generation.
(iii) Effectively integrate collaborative signals for personalized recommendation



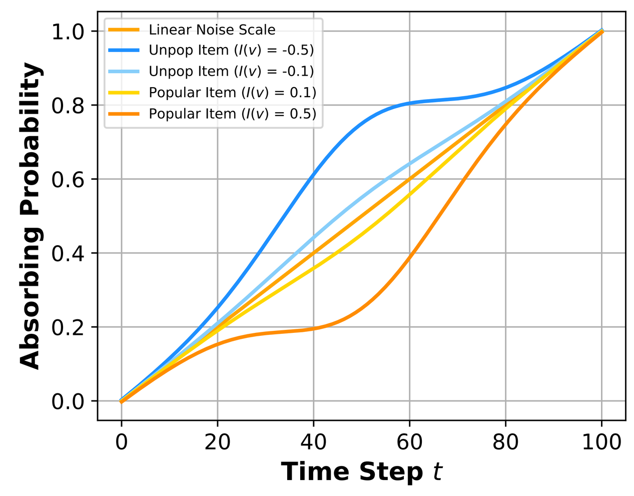
2. Proposed Method

2.1 CDRec Framework



2.2 Key Advancement

- Forward: Popularity-aware noise schedule with lower absorption for popular items, enabling easy-to-hard generation.
- Reverse: Consistency-based parameterization over masked histories to capture user behavior and support single-/multi-step generation.

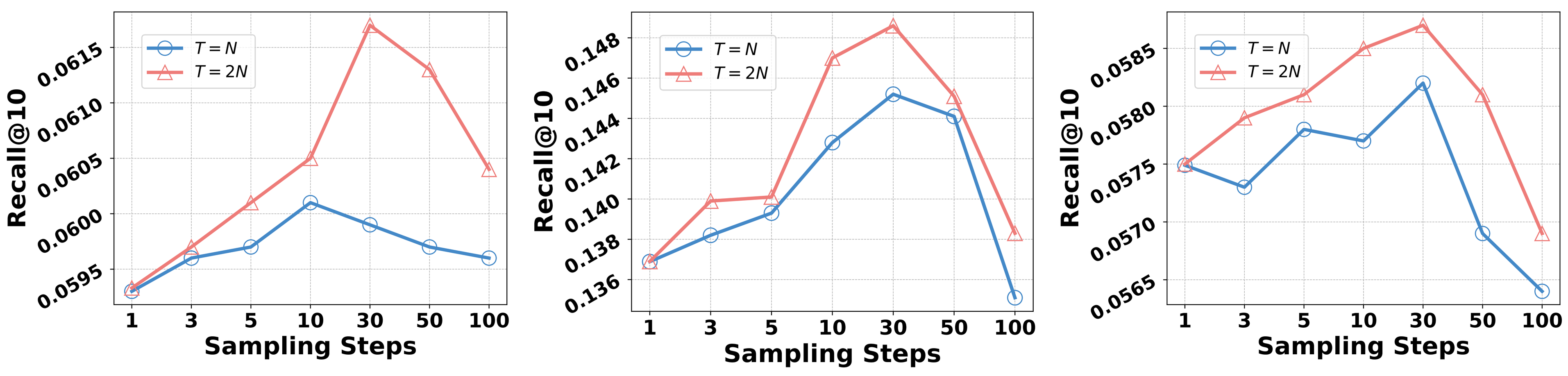


3. Experiments

3.1 Overall Performance

Dataset	Ciao				MovieLens-1M				Dianping			
Method	R@10	R@5	N@10	N@5	R@10	R@5	N@10	N@5	R@10	R@5	N@10	N@5
NGCF	0.0483	0.0266	0.0396	0.0321	0.1201	0.0724	0.1212	0.1136	0.0531	0.0316	0.0381	0.0317
LightGCN	0.0525	0.0312	0.0441	0.0370	0.1297	0.0783	0.1231	0.1193	0.0543	0.0333	0.0421	0.0339
SGL	0.0553	0.0364	0.0493	0.0438	0.1319	0.0852	0.1277	0.1207	0.0546	0.0339	0.0433	0.0365
Muti-VAE	0.0517	0.0361	0.0409	0.0341	0.1337	0.0863	0.1193	0.1152	0.0547	0.0341	0.0415	0.0345
VGCL	0.0568	0.0346	0.0477	0.0422	0.1339	0.0846	0.1315	0.1273	0.0551	0.0336	0.0431	0.0353
DiffRec	0.0436	0.0289	0.0397	0.0361	0.1351	0.0839	0.1379	0.1309	0.0556	0.0345	0.0439	0.0367
L-DiffRec	0.0458	0.0293	0.0417	0.0371	0.1326	0.0799	0.1351	0.1169	0.0539	0.0327	0.0435	0.0371
BSPM	0.0590	0.0363	0.0518	0.0447	0.1399	0.0871	0.01347	0.1301	0.0557	0.0329	0.0441	0.0359
GiffCF	0.0584	0.0372	0.0473	0.0396	0.1426	0.0857	0.1395	0.1293	0.0505	0.0339	0.0412	0.0361
CDRec	**0.0617**	**0.0390**	**0.0539**	**0.0473**	**0.1486**	**0.0931**	**0.1469**	**0.1384**	**0.0586**	**0.0355**	**0.0471**	**0.0394**
%Improve	4.58%	4.84%	4.06%	5.81%	4.21%	6.88%	5.30%	5.72%	5.21%	2.90%	6.80%	6.19%

3.2 Parameter Sensitivity of Diffusion Steps



3.3 Case Study

Frequency	2127	2260	293	1508	1284	450	771	63	2252	2071
$t = 0$	1210	2028	3507	3578	2791	1129	648	3821	593	527
$t = 10$	1210	2028	M	3578	2791	1129	648	3821	593	527
$t = 20$	1210	2028	M	3578	2791	1129	M	M	593	527
$t = 30$	1210	2028	M	M	2791	M	M	M	593	527
$t = 40$	1210	2028	M	M	2791	M	M	M	593	M
$t = 50$	M	2028	M	M	M	M	M	M	593	M
$t = 60$	M	M	M	M	M	M	M	M	M	M

Action Comedy Drama M Mask