RecSys2024-LDRI-Rebuttal-Complexity Analysis

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In this document, we provide a complexity analysis of the backbones, baselines, and our methods (LDRI and LDRI-iter) as compared in our main text. In addition to the inference time compared in the main text, we also compare the FLOPs and the number of parameters.

More details are listed in Table 1.

1 COMPARISON OF COMPLEXITY

Table 1. Comparison of FLOPs per Batch, numbers of parameters and relative inference time between backbones (DeepFM, NFM and AFM), baselines (TCCM, TaFR and DCR-MoE), and our proposed LDRI, LDRI-iter. The relative inference time displays the relative running time spent on inference compared to NFM, which serves as the reference method.

Dataset	Method	FLOPs per Batch	Parameters	Inference Time (Relative)
KuaiRand-Pure	TCCM	111,516,672	0.7M	1.6532
	DeepFM DeepFM+TaFR	9,101,312 9,101,312	0.7M 0.7M	1.0092 1.1544
	DeepFM+DCR-MoE	2,783,574,016	0.7M 0.9M	1.1544
	DeepFM+LDRI (-iter) (Ours)	18563072	0.9M	1.4283 (1.4333)
	NFM	507,904	0.7M	1.0000
	NFM+TaFR	507,904	0.7M	1.0813
	NFM+DCR-MoE	2,779,576,320	0.9M	1.3248
	NFM+LDRI (-iter) (Ours)	9969664	0.9M	1.1078 (1.1046)
	AFM	21,766,144	0.7M	1.0245
	AFM+TaFR	21,766,144	0.7M	1.0936
	AFM+DCR-MoE	2,801,006,592	0.9M	1.6427
	AFM+LDRI (-iter) (Ours)	31,227,904	0.9M	1.1541 (1.1462)
KuaiRand-1K	TCCM	111,516,672	97.3M	3.4462
	DeepFM	9,101,312	100M	1.1874
	DeepFM+TaFR	91,013,12	100M	1.1964
	DeepFM+DCR-MoE	3,098,606,592	200M	2.2076
	DeepFM+LDRI (-iter) (Ours)	18,563,072	200M	1.2462 (1.2309)
	NFM	507,904	100M	1.0000
	NFM+TaFR	507,904	100M	1.1590
	NFM+DCR-MoE	3,094,608,896	200M	2.2143
	NFM+LDRI (-iter) (Ours)	9,969,664	200M	1.2127 (1.2201)
	AFM	21,766,144	100M	1.2317
	AFM+TaFR	21,766,144	100M	1.2376
	AFM+DCR-MoE	3,116,039,168	200M	2.5714
	AFM+LDRI (-iter) (Ours)	31,227,904	200M	1.2329 (1.2400)

As shown in Table 1, LDRI (-iter) is a lightweight plugin. Among the various methods, LDRI (-iter) maintains a FLOPs count that is second only to the backbones, and the number of parameters does not increase significantly. Additionally,

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LDRI (-iter) maintains a very low inference time. On the contrary, TCCM and DCR-MoE feature exceptionally high FLOPs owing to their intricate model architectures, incorporating elements like Attention mechanisms, and the intricate design of Mixture of Experts (MoE), which impose substantial computational demands.

Although TaFR does not introduce additional FLOPs and parameters, it involves a substantial amount of feature engineering and data preprocessing work. Moreover, it necessitates additional storage space for the preprocessed data, thereby increasing the model's overall storage requirements.

Overall, LDRI stands out as a highly effective recommendation model that is also lightweight, with low complexity. It strikes an optimal balance between recommendation performance and computational efficiency.