CL4CTR: A Contrastive Learning Framework for CTR Prediction

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code: https://github.com/cl4ctr/cl4ctr

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Introduction

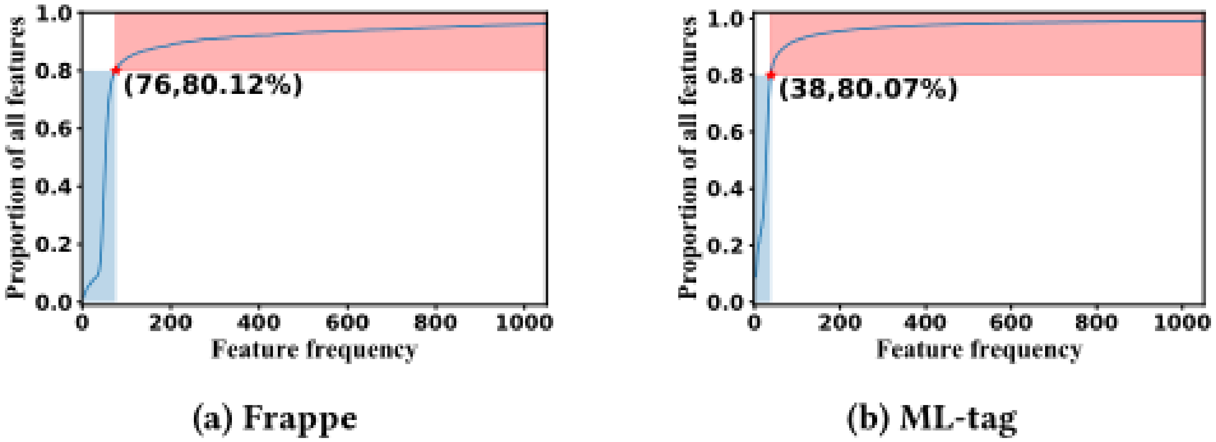


Figure 1: Cumulative distribution of feature frequencies. (38, 80.07%) indicates that features with feature frequencies less than or equal to 38 times account for 80.07% of all features.

In Figure 1, we present the feature cumulative distributions of Frappe and ML-tag datasets.

We can observe a clear "long tail" distribution of feature frequencies, e.g., bottom 80% of features appeared only 38 times or less in the ML-tag dataset.

Approach

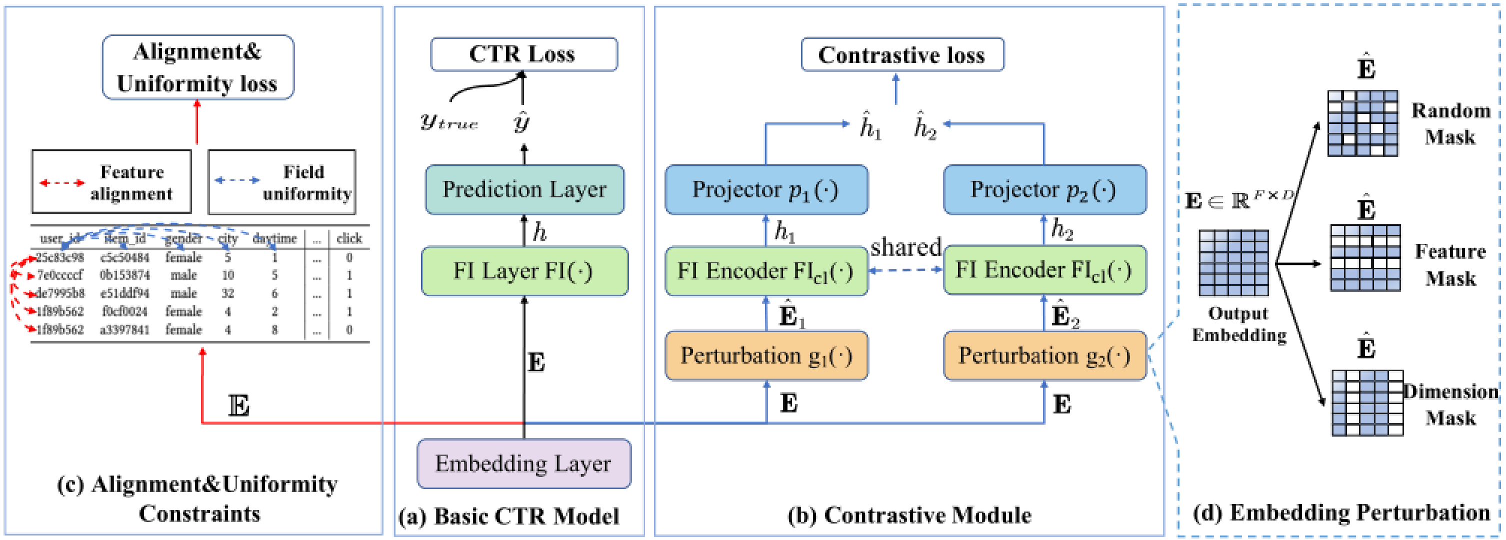


Table 1: An example of multi-field tabular data for CTR prediction. Each row represents an input instance and each column indicates a field. Moreover, each field contains multiple features, but each feature only belongs to one field.

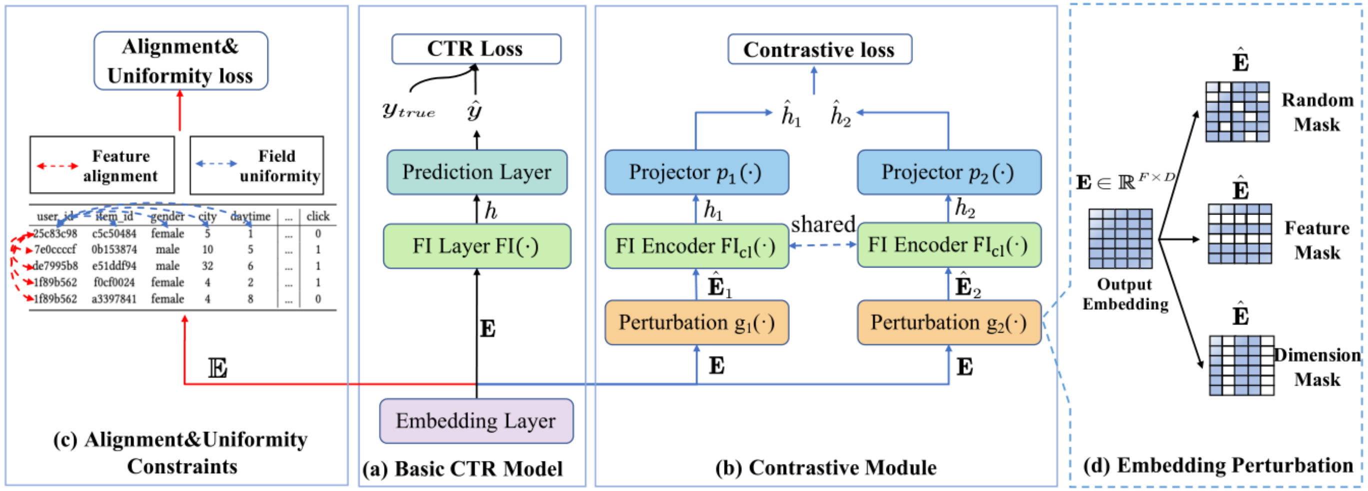
user_id	item_id	gender	city	daytime	...	click
25c83c98	c5c50484	female	5	1	...	0
7e0ccccf	0b153874	male	10	5	...	1
de7995b8	e51ddf94	male	32	6	...	1
1f89b562	f0cf0024	female	4	2	...	1
1f89b562	a3397841	female	4	8	...	0

x_i represented by a one-hot vector

$$\mathrm{E} = [\mathrm{e}^1; \mathrm{e}^2; ...; \mathrm{e}^F] \in \mathbb{R}^{F\times D}$$

ally, we use $\mathbb{E} = [\mathrm{E}_1, \mathrm{E}_2, ..., \mathrm{E}_F] \in \mathbb{R}^{M\times D}$ to represent all feature representations, where E_f is the subset representation of the f-th field $f \in \{1, 2, ..., F\}$. $|\mathrm{E}_f|$ is the number of features belonging to field f, and $M = \sum_{f=1}^{F} |\mathrm{E}_f|$.

Approach



$$\mathcal{L}_{ctr} = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log\left(\sigma\left(\hat{y}_i\right)\right) + \left(1-y_i\right)\log\left(1-\sigma\left(\hat{y}_i\right)\right)\right). \quad (1)$$

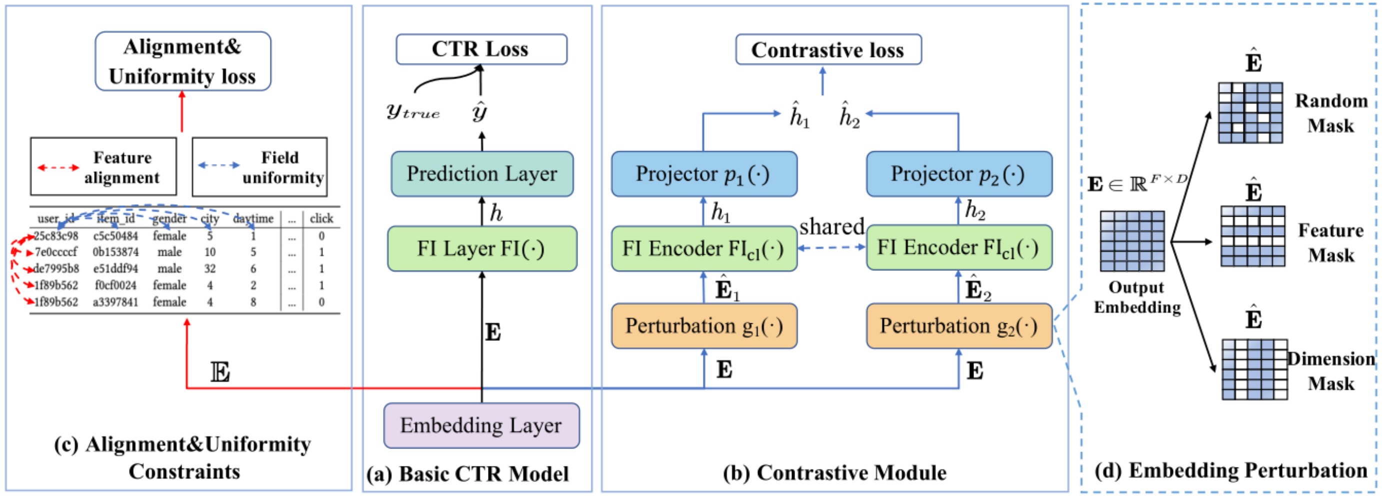
$$\hat{\mathrm{E}} = \mathrm{g}_r(\mathrm{E}) = \mathrm{E}\cdot\mathrm{I}, \mathrm{I} \sim \mathrm{Bernoulli}(p) \in \mathbb{E}^{F\times D}. \quad (2)$$

$$\hat{\mathrm{E}} = \mathrm{g}_f(\mathrm{E}) = [\hat{\mathrm{e}}^1; \hat{\mathrm{e}}^2; ...; \hat{\mathrm{e}}^F], \hat{\mathrm{e}}^f = \begin{cases} \mathrm{e}^f, & t \notin \mathcal{T} \\ [\mathrm{mask}], & t \in \mathcal{T} \end{cases}, \quad (3)$$

$$\hat{\mathrm{E}} = \mathrm{g}_d(\mathrm{E}) = [de^1; de^2; ...; de^F], d \sim \mathrm{Bernoulli}(p) \in \mathbb{R}^D, \quad (4)$$

$$h_1 = FI_{cl}(\hat{\mathrm{E}}_1), h_2 = FI_{cl}(\hat{\mathrm{E}}_2). \quad (5)$$

Approach



$$\hat{h}_1 = p_1(h_1), \hat{h}_2 = p_2(h_2). \tag{6}$$

$$\mathcal{L}_{cl} = \frac{1}{B} \sum_{i=1}^{B} \left\| \hat{h}_{i,1} - \hat{h}_{i,2} \right\|_2^2 . \tag{7}$$

$$\mathcal{L}_a = \sum_{f=1}^{F} \sum_{\mathrm{e_i},\mathrm{e_j} \in \mathrm{E}_f} \|\mathrm{e_i} - \mathrm{e_j}\|_2^2, \tag{8}$$

$$\mathcal{L}_u = \sum_{\substack{\mathrm{e_i} \in \mathrm{E}_f \\ 1<=f<=F}} \sum_{\mathrm{e_j} \in (\mathbb{E} - \mathrm{E}_f)} sim(\mathrm{e_i}, \mathrm{e_j}). \tag{9}$$

$$\mathcal{L}_{total} = \mathcal{L}_{ctr} + \alpha \cdot \mathcal{L}_{cl} + \beta \cdot (\mathcal{L}_a + \mathcal{L}_u), \tag{10}$$

Experiments

Table 2: Dataset statistics.

Datasets	Positive	#Training	#Validation	#Test	#Features	#Fields
Frappe	33%	202K	58K	29K	5K	10
ML-tag	33%	1,404K	401K	201K	90K	3
ML-1M	57.5%	800K	100K	100K	10K	5
SafeDriver	3.64%	476K	59K	59K	600	57

Experiments

Table 3: Overall accuracy comparison in the four datasets. ΔAUC and $\Delta Logloss$ indicate averaged performance boost compared with DCN-V2. *RelaImp* denotes the relative improvements compared with the strongest baseline. Bold scores are the best performance, while underlined scores are the second best. Improvements over baselines are statistically significant with p<0.01.

Model Class	Datasets / Model	Frappe AUC	Frappe Logloss	ML-tag AUC	ML-tag Logloss	ML-1M AUC	ML-1M Logloss	SafeDriver AUC	SafeDriver Logloss	ΔAUC ↑	$\Delta Logloss$ ↓
First-order	LR	0.9331	0.2894	0.9348	0.2960	0.7899	0.5417	0.6244	0.1622	-3.35%	0.0572
Second-Order	FM	0.9746	0.1856	0.9488	0.2595	0.8023	0.5332	0.6301	0.1538	-1.22%	0.0179
	FwFM	0.9756	0.1784	0.9582	0.2531	0.8046	0.5281	0.6335	0.1532	-0.74%	0.0131
	IFM	0.9771	0.1581	0.9515	0.2497	0.8080	0.5286	0.6353	0.1526	-0.70%	0.0071
	FmFM	0.9801	0.1682	0.9552	0.2493	0.8093	0.5264	0.6378	0.1518	-0.39%	0.0088
High-Order	CrossNet	0.9800	0.1658	0.9549	0.2480	0.8114	0.5218	0.6336	0.1517	-0.50%	0.0067
	IPNN	0.9809	0.1604	0.9607	0.2295	0.8110	0.5190	0.6373	0.1521	-0.19%	0.0001
	OPNN	0.9799	0.1683	0.9599	0.2421	0.8112	0.5185	0.6375	0.1519	-0.22%	0.0051
	FINT	0.9807	0.1578	0.9557	0.2430	0.8123	0.5192	0.6349	0.1522	-0.38%	0.0029
	DCAP	0.9801	0.1612	0.9560	0.2428	0.8130	0.5171	0.6390	0.1512	-0.20%	0.0030
Ensemble	WDL	0.9770	0.1783	0.9599	0.2660	0.8093	0.5226	0.6353	0.1525	-0.44%	0.0110
	DCN	0.9788	0.1621	0.9550	0.2472	0.8125	0.5175	0.6379	0.1514	-0.32%	0.0044
	DeepFM	0.9780	0.1732	0.9586	0.2551	0.8061	0.5259	0.6318	0.1529	-0.69%	0.0117
	xDeepFM	0.9799	0.1750	0.9604	0.2472	0.8082	0.5244	0.6403	0.1515	-0.19%	0.0094
	FiBiNET	0.9793	0.1707	0.9548	0.2532	0.8032	0.5313	0.6391	0.1505	-0.56%	0.0113
	AutoInt+	0.9783	0.1762	0.9535	0.2562	0.8099	0.5219	0.6310	0.1516	-0.73%	0.0114
	AFN+	0.9786	0.1637	0.9561	0.2468	0.8041	0.5304	0.6374	0.1517	-0.58%	0.0080
	TFNet	0.9798	0.1708	0.9527	0.2551	0.8099	0.5212	0.6387	0.1533	-0.41%	0.0100
	FED	0.9791	0.1606	0.9557	0.2465	0.8128	0.5184	0.6369	0.1534	-0.33%	0.0046
	DCN-V2	0.9803	0.1595	0.9610	0.2330	0.8132	0.5169	0.6406	0.1510	-	-
Ours	$CL4CTR_{FM}$	**0.9822**	**0.1324**	**0.9621**	**0.2102**	**0.8164**	**0.5136**	**0.6449**	**0.1483**	0.34%	-0.0140
	RelaImp	0.13%	16.10%	0.11%	8.41%	0.39%	0.64%	0.67%	1.46%	-	-

Experiments

Table 4: Compatibility study of CL4CTR.

Model	Frappe		ML-1M		SafeDriver	
	AUC	Logloss	AUC	Logloss	AUC	Logloss
FM	0.9746	0.1856	0.8023	0.5332	0.6244	0.1622
$CL4CTR_{FM}$	**0.9822**	**0.1324**	**0.8164**	**0.5136**	**0.6449**	**0.1483**
FwFM	0.9756	0.1784	0.8046	0.5281	0.6335	0.1532
$CL4CTR_{FwFM}$	**0.9815**	**0.1532**	**0.8118**	**0.5192**	**0.6421**	**0.1487**
DeepFM	0.9780	0.1732	0.8061	0.5259	0.6318	0.1529
$CL4CTR_{DeepFM}$	**0.9813**	**0.1677**	**0.8113**	**0.5194**	**0.6381**	**0.1504**
Autoint+	0.9783	0.1762	0.8099	0.5219	0.6310	0.1516
$CL4CTR_{Autoint+}$	**0.9802**	**0.1684**	**0.8122**	**0.5174**	**0.6402**	**0.1506**
DCN	0.9788	0.1621	0.8125	0.5170	0.6379	0.1514
$CL4CTR_{DCN}$	**0.9808**	**0.1566**	**0.8164**	**0.5125**	**0.6415**	**0.1494**
DCN-V2	0.9803	0.1595	0.8132	0.5169	0.6406	0.1510
$CL4CTR_{DCN-V2}$	**0.9812**	**0.1549**	**0.8144**	**0.5153**	**0.6411**	**0.1497**

Experiments

Table 5: Impact of data augmentation methods.

Base model	Variants	Frappe AUC	Frappe Logloss	SafeDriver AUC	SafeDriver Logloss
FM	Base	0.9746	0.1856	0.6244	0.1622
	Random	**0.9822**	**0.1324**	**0.6449**	**0.1483**
	Feature	0.9814	0.1328	0.6303	0.1539
	Dimension	0.9816	0.1334	0.6404	0.1505
FwFM	Base	0.9756	0.1784	0.6335	0.1532
	Random	0.9815	0.1532	0.6421	0.1487
	Feature	**0.9822**	**0.1513**	0.6384	0.1483
	Dimension	0.9811	0.1465	**0.6455**	**0.1508**
DeepFM	Base	0.9780	0.1817	0.6318	0.1529
	Random	**0.9813**	**0.1677**	**0.6381**	**0.1504**
	Feature	0.9798	0.1750	0.6341	0.1522
	Dimension	0.9804	0.1697	0.6353	0.1514
DCN	Base	0.9788	0.1611	0.6379	0.1514
	Random	**0.9808**	**0.1566**	**0.6415**	**0.1494**
	Feature	0.9804	0.1601	0.6409	0.1508
	Dimension	0.9803	0.1573	0.6411	0.1504

Experiments

Table 6: Impact of different FI encoder $FI_{cl}(\cdot)$.

Base model	FI Encoder	Frappe AUC	Frappe Logloss	ML-1M AUC	ML-1M Logloss
FM	Base	0.9746	0.1856	0.8023	0.5332
	DNN	0.9804	0.1404	**0.8177**	**0.5123**
	Transformer	**0.9822**	**0.1324**	0.8164	0.5136
	CrossNet2	0.9801	0.1438	0.8170	0.5143
FwFM	Base	0.9756	0.1784	0.8046	0.5281
	DNN	0.9809	**0.1504**	0.8064	0.5264
	Transformer	0.9815	0.1532	**0.8118**	**0.5192**
	CrossNet2	**0.9822**	0.1675	0.8102	0.5231
DeepFM	Base	0.9780	0.1732	0.8061	0.5259
	DNN	0.9804	0.1710	0.8101	0.5206
	Transformer	**0.9813**	**0.1704**	**0.8113**	**0.5194**
	CrossNet2	0.9791	0.1719	0.8109	0.5202
DCN-V2	Base	0.9803	0.1595	0.8132	0.5169
	DNN	0.9807	0.1573	**0.8151**	**0.5144**
	Transformer	**0.9812**	**0.1549**	0.8144	0.5153
	CrossNet2	0.9804	0.1588	0.8141	0.5155

Experiments

Table 7: Impact of SSL signals in the loss function.

Model	Loss Function	Frappe		ML-1M	
		AUC	Logloss	AUC	Logloss
FM	$\mathcal{L}_{ctr}$	0.9746	0.1856	0.8023	0.5332
	$+\mathcal{L}_{cl}$	0.9794	0.1485	0.8102	0.5230
	$+(\mathcal{L}_a+\mathcal{L}_u)$	0.9812	0.1455	0.8139	0.5175
	$+\mathcal{L}_{cl}+(\mathcal{L}_a+\mathcal{L}_u)$	**0.9822**	**0.1324**	**0.8164**	**0.5136**
FwFM	$\mathcal{L}_{ctr}$	0.9756	0.1784	0.8046	0.5281
	$+\mathcal{L}_{cl}$	0.9785	0.1553	0.8109	0.5229
	$+(\mathcal{L}_a+\mathcal{L}_u)$	0.9812	0.1536	0.8098	0.5252
	$+\mathcal{L}_{cl}+(\mathcal{L}_a+\mathcal{L}_u)$	**0.9815**	**0.1532**	**0.8118**	**0.5192**
DeepFM	$\mathcal{L}_{ctr}$	0.9780	0.1817	0.8061	0.5259
	$+\mathcal{L}_{cl}$	0.9794	0.1701	0.8094	0.5235
	$+(\mathcal{L}_a+\mathcal{L}_u)$	0.9784	0.1791	0.8103	0.5214
	$+\mathcal{L}_{cl}+(\mathcal{L}_a+\mathcal{L}_u)$	**0.9813**	**0.1677**	**0.8113**	**0.5194**
DCN	$\mathcal{L}_{ctr}$	0.9788	0.1611	0.8125	0.5170
	$+\mathcal{L}_{cl}$	0.9802	0.1585	0.8138	0.5150
	$+(\mathcal{L}_a+\mathcal{L}_u)$	0.9792	0.1600	0.8129	0.5188
	$+\mathcal{L}_{cl}+(\mathcal{L}_a+\mathcal{L}_u)$	**0.9808**	**0.1566**	**0.8164**	**0.5125**

Experiments

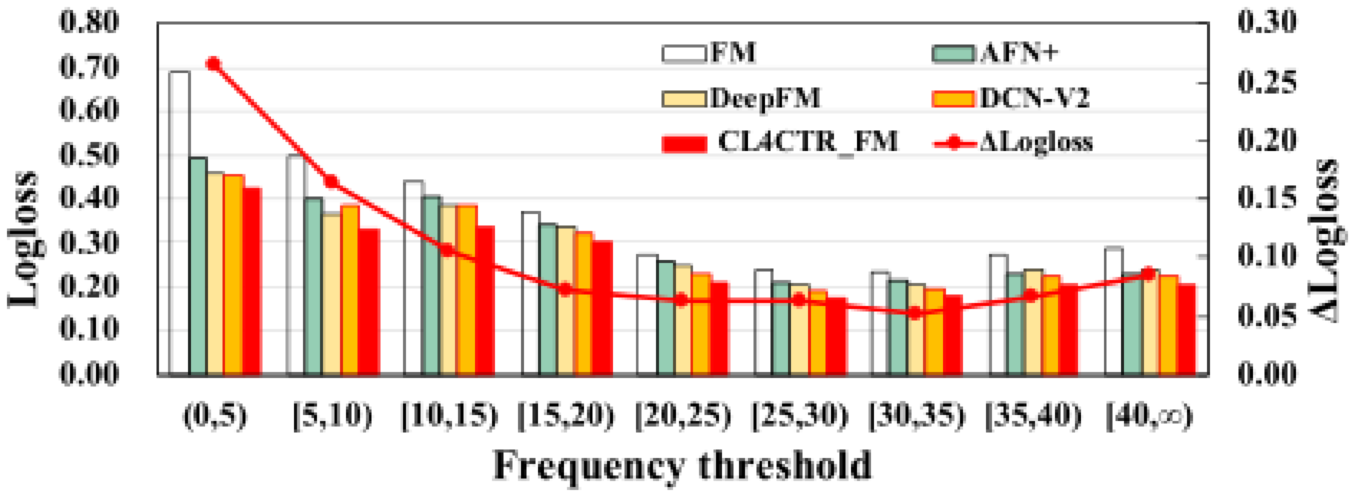
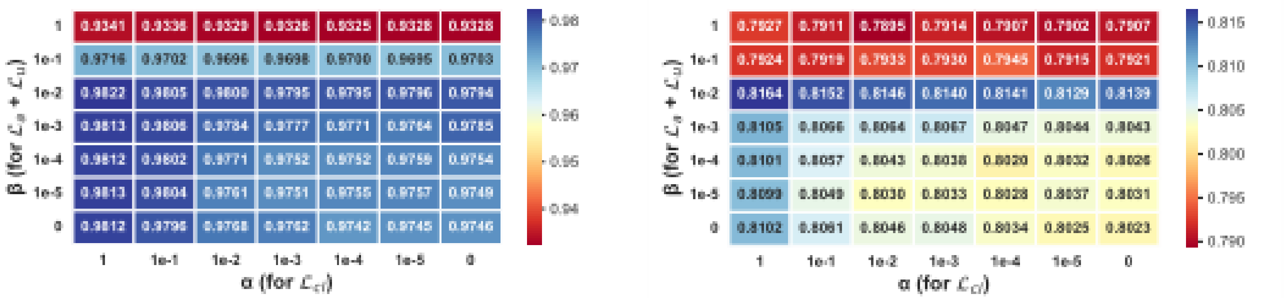


Figure 3: Improvement vs. feature frequency.

Experiments



(a) The AUC of Frappe **(b) The AUC of ML-1M**

Figure 4: Performance of $CL4CTR_{FM}$ w.r.t. different weights assigned to three SSL signals: α for $\mathcal{L}_c$, β for $\mathcal{L}_a$ and $\mathcal{L}_u$.

Experiments

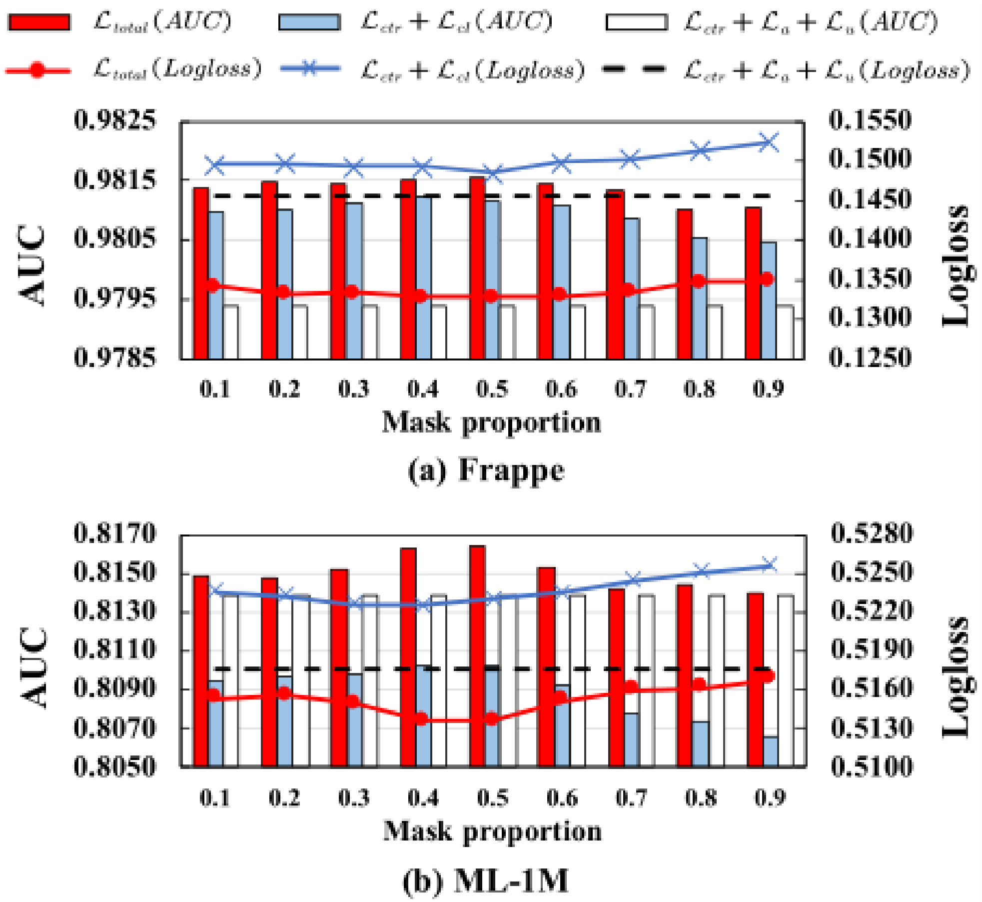


Figure 5: Impact of random mask proportion.

Experiments

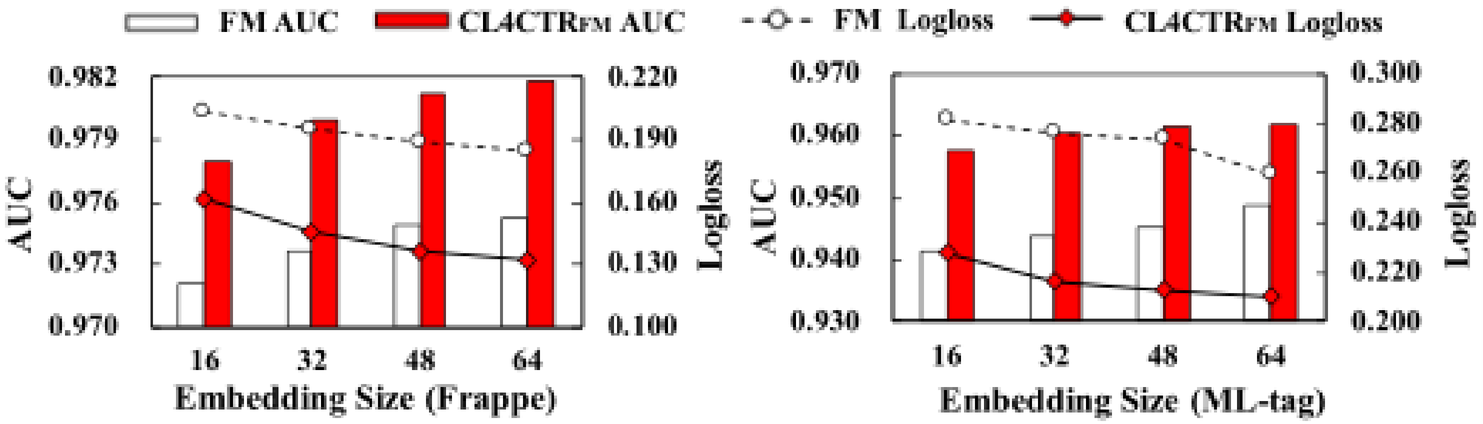


Figure 6: Impact of embedding size on FM and $CL4CTR_{FM}$.

Thank you！