

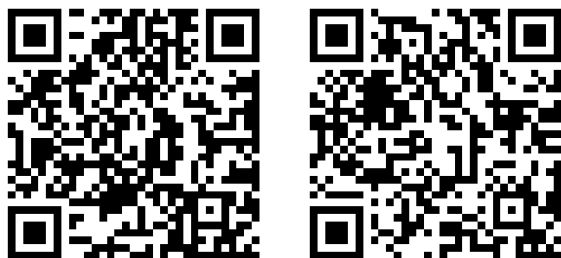
# RecDCL: Dual Contrastive Learning for Recommendation (Oral)

Dan Zhang, Yangliao Geng, Wenwen Gong, Zhongang Qi, Zhiyu Chen, Xing Tang, Ying Shan, Yuxiao Dong, and Jie Tang

Tsinghua University, Tencent



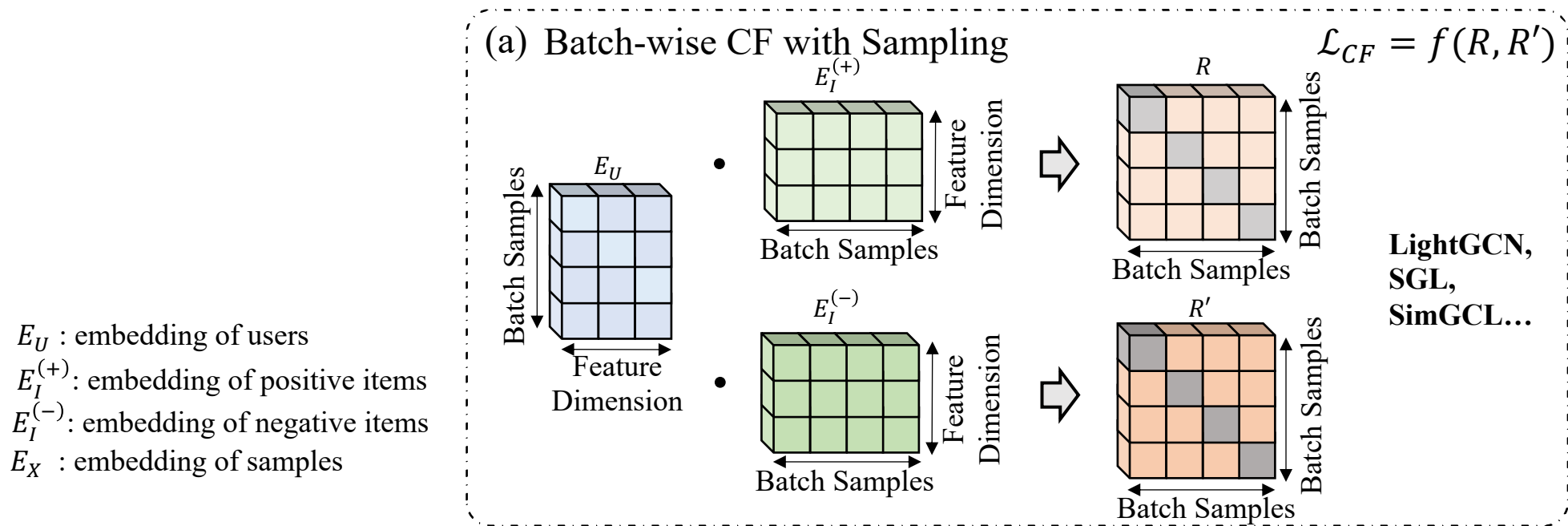
**Tencent** 腾讯



# Contrastive Learning (CL)-Based Recommendation

- Background

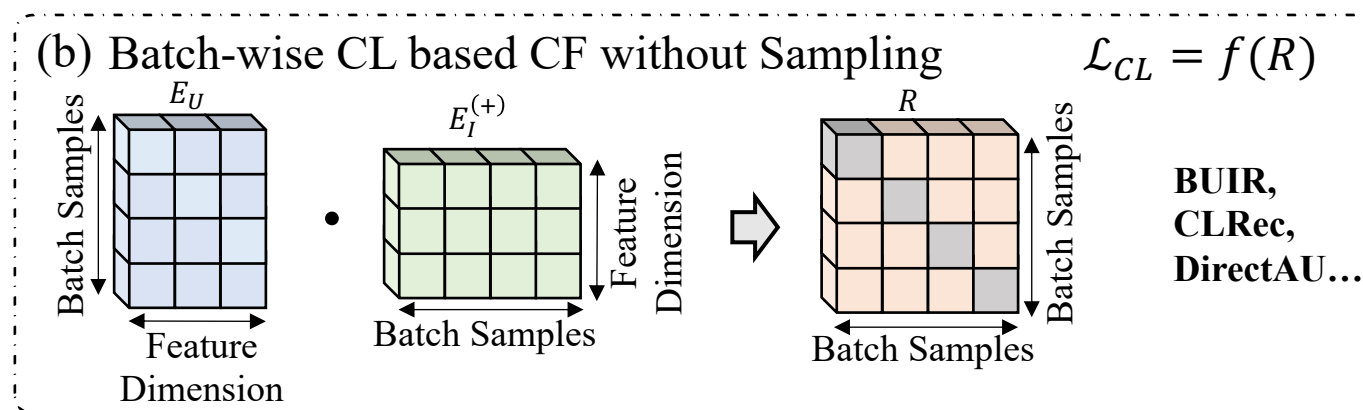
- Using data augmentation to address **scarce labeled data**
- Batch-wise objectives: maximize distance between positive pairs, minimize distance between negative pairs



# CL-Based Recommendation (RecDCL)

- Background

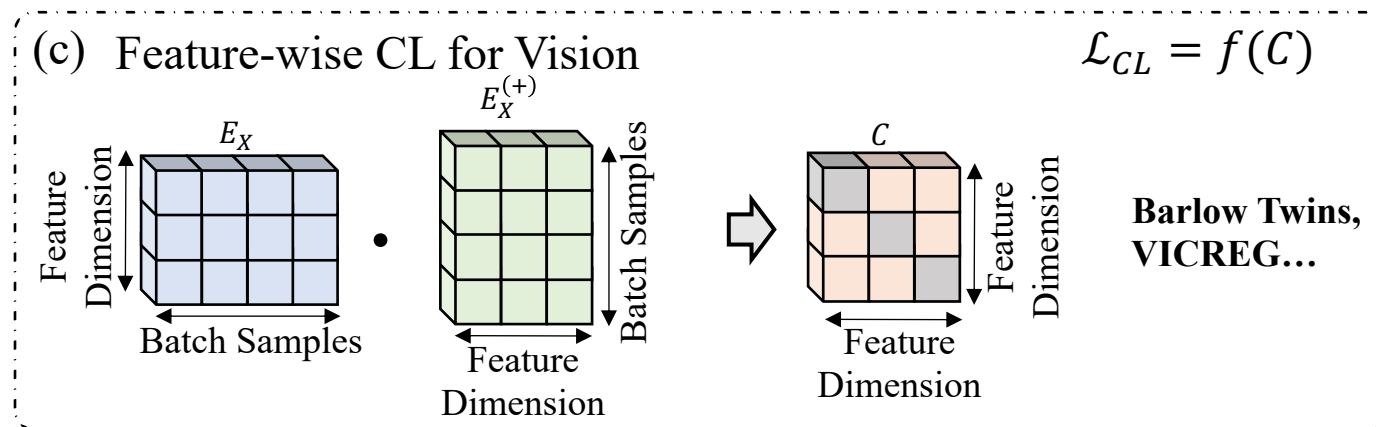
- Using data augmentation to address **scarce labeled data**
- Batch-wise objectives: maximize distance between positive pairs, minimize distance between negative pair
- Batch-wise GNNs-based Rec methods depend on negative pairs



# CL-Based Recommendation (RecDCL)

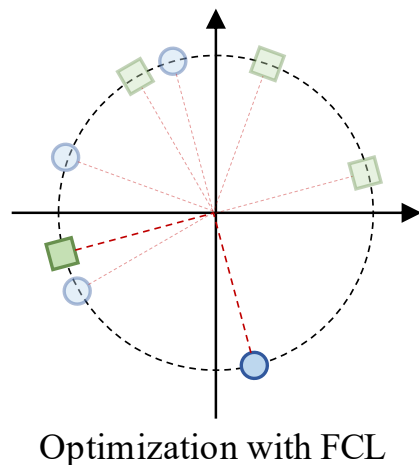
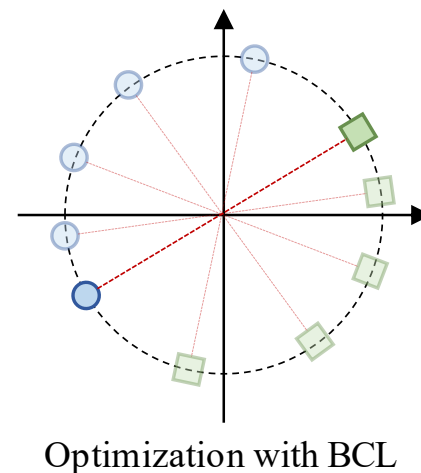
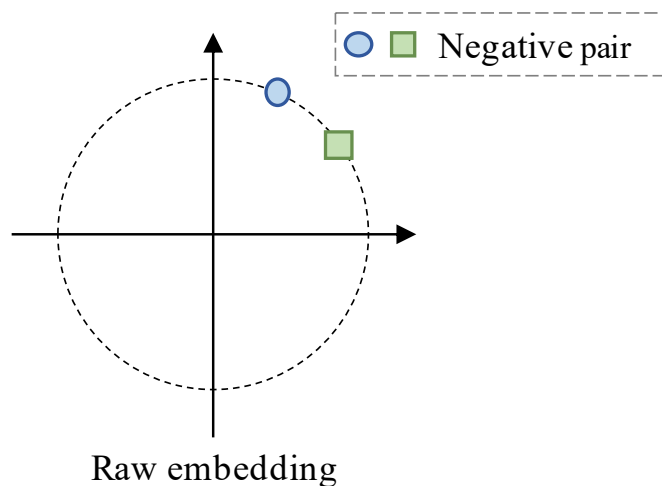
- Background

➤ Feature-wise CL (FCL) methods can avoid collapse



# CL-Based Recommendation (RecDCL)

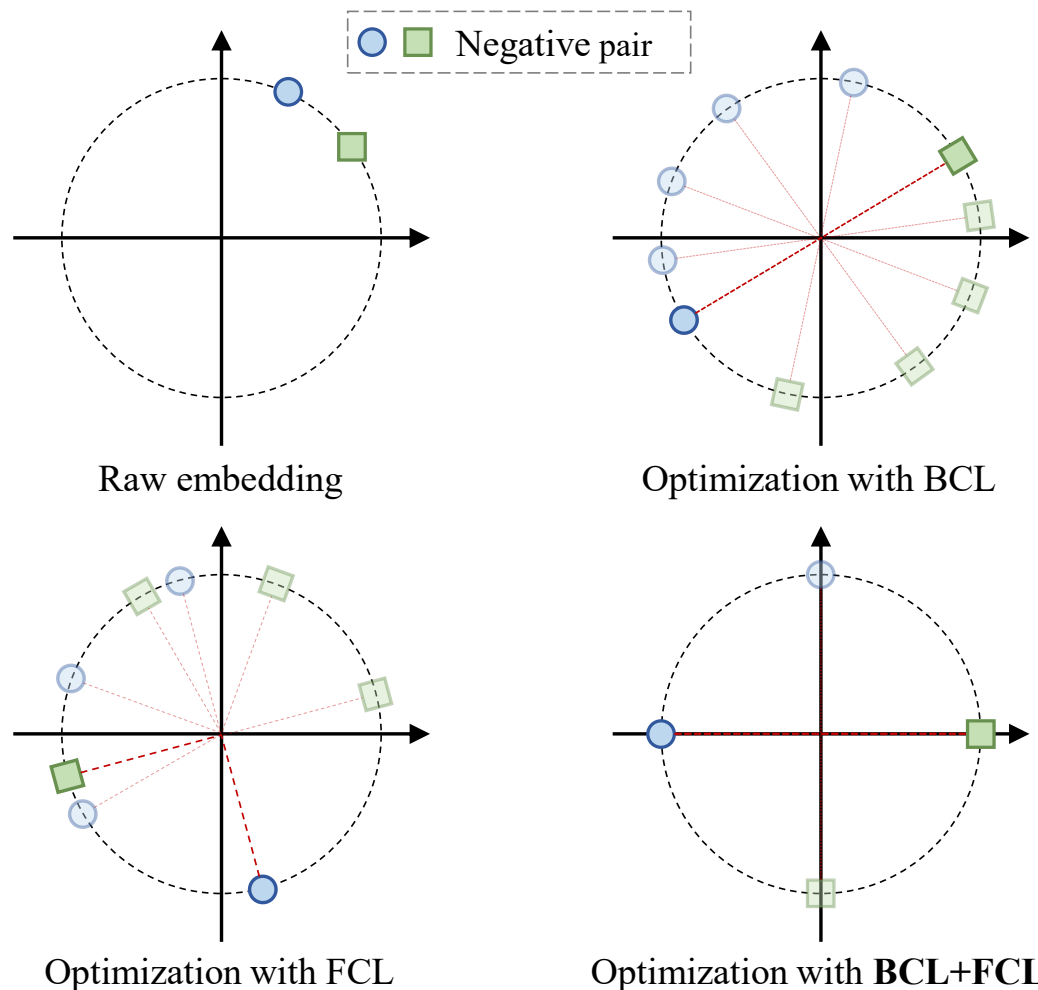
- The effects of BCL and FCL



Optimization with BCL+FCL  
?

# CL-Based Recommendation (RecDCL)

- The effects of BCL, FCL, and BCL+FCL



Paper



# CL-Based Recommendation (RecDCL)

## Batch/Feature-wise Dual Objectives

- Understanding BCL and FCL

**Table 1: Critical comparison between BCL methods, FCL methods, and RecDCL.**

Models	Embedding Information	Sample Information	Redundant Solution	Distribution
BCL	✗	✓	✓	Even
FCL	✓	✗	✗	Orthogonal
RecDCL	✓	✓	✗	Even

# CL-Based Recommendation (RecDCL)

## Batch/Feature-wise Dual Objectives

- Theoretical Insights

$$\mathcal{Z}_B^\star \triangleq \arg \min_{\mathbf{z}_1, \mathbf{z}_2 \in \mathcal{S}^{D-1}} \underbrace{\exp(\mathbf{z}_1^T \mathbf{z}_2)}_{\text{push-away in BCL}}$$

$$\mathcal{Z}_F^\star \triangleq \arg \min_{\mathbf{z}_1, \mathbf{z}_2 \in \mathcal{S}^{D-1}} \underbrace{\sum_{i=1}^D \sum_{j \neq i} (C_{ij})^2}_{\text{push-away in FCL}}$$

$$|\mathcal{Z}_B^\star| \geq \infty \quad \text{and} \quad |\mathcal{Z}_F^\star| \geq \infty;$$

$$\mathcal{Z}_B^\star \cap \mathcal{Z}_F^\star \neq \emptyset$$



More details in Appendix A.1 in our paper!

- $\mathbf{z}_1, \mathbf{z}_2$ : representations of a negative pair
- $\mathcal{Z}_B^\star, \mathcal{Z}_F^\star$ : solution sets of push-away objectives in BCL and FCL



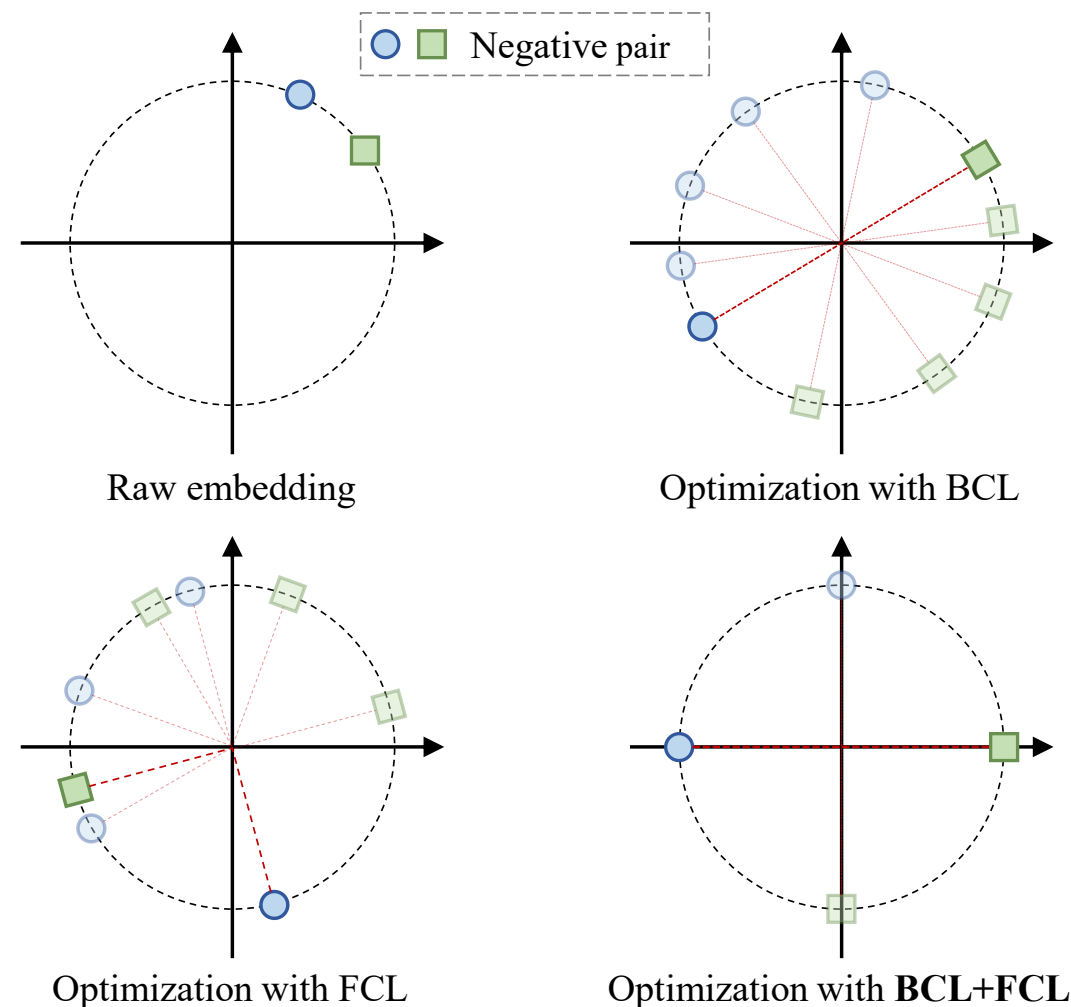
# CL-Based Recommendation (RecDCL)

## Batch/Feature-wise Dual Objectives

- ◆ We theoretically analyze the relation between BCL and FCL, and find that combining BCL and FCL helps eliminate redundant solutions but never misses an optimal solution.



More details in Appendix A.2 in our paper!



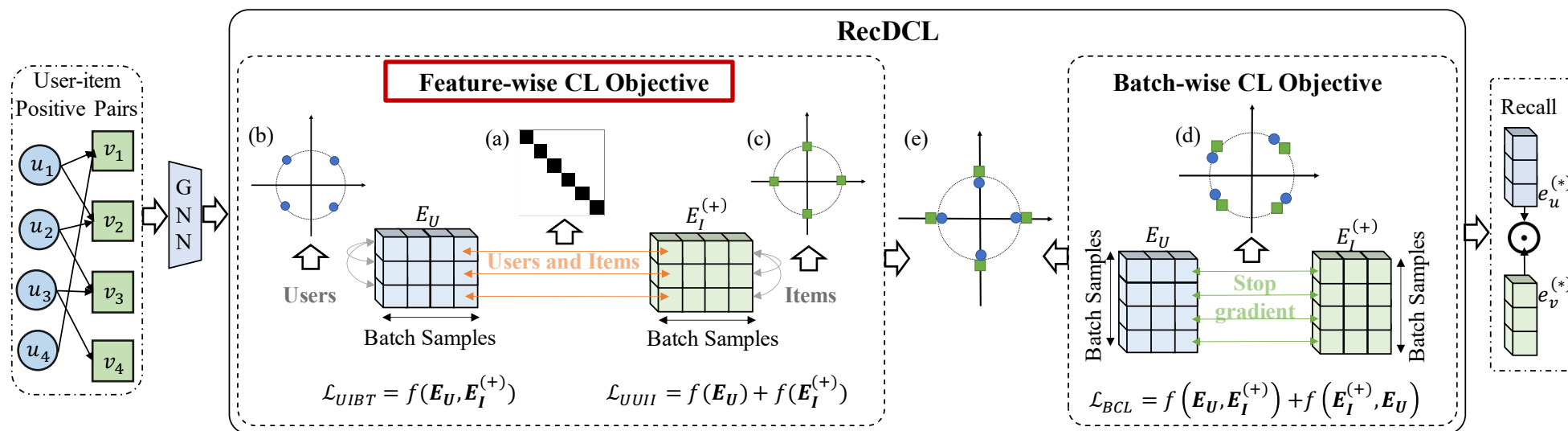
# CL-Based Recommendation (RecDCL)

## Batch/Feature-wise Dual Objectives

- ◆ We theoretically analyze the relation between BCL and FCL, and find that combining BCL and FCL helps eliminate redundant solutions but never misses an optimal solution.
- ◆ We propose a dual contrastive learning recommendation framework --- RecDCL.

# CL-Based Recommendation (RecDCL)

## Batch/Feature-wise Dual Objectives



- RecDCL

➤ FCL: Eliminate redundancy between users and items

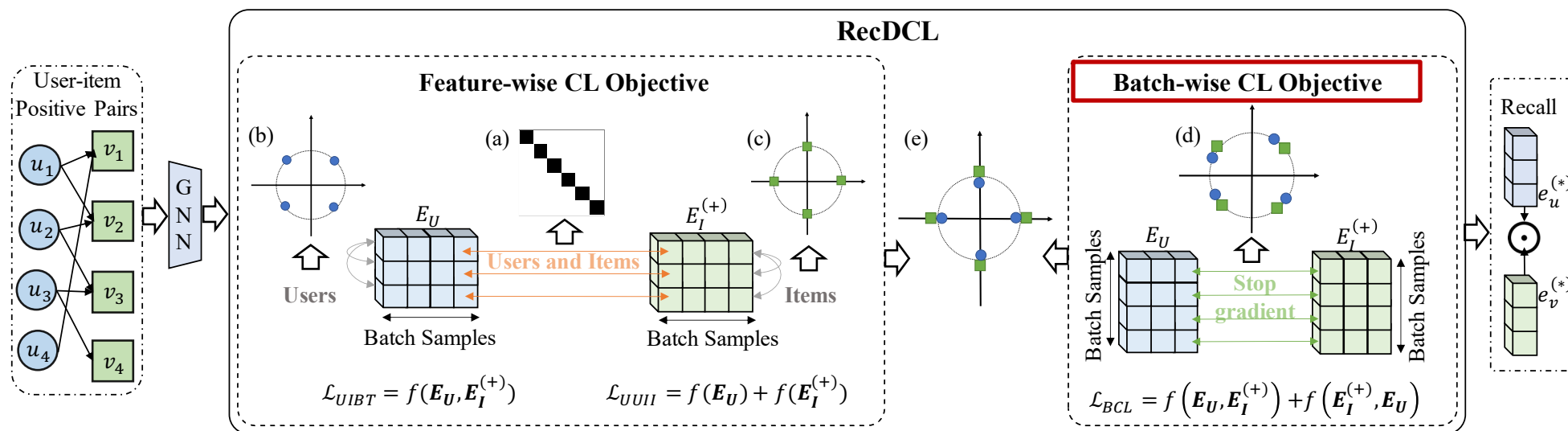
Eliminate redundancy within users and items.

$$\mathcal{L}_{UIBT} = \underbrace{\frac{1}{F} \sum_m (1 - C_{mm})^2}_{\text{invariance}} + \underbrace{\frac{\gamma}{F} \sum_m \sum_{m \neq n} C_{mn}^2}_{\text{redundancy reduction}}.$$

$$\mathcal{L}_{UIII} = \frac{1}{2} \log \sum_{m \neq n} (a(E_U^m)^\top E_U^n + c)^e + \frac{1}{2} \log \sum_{m \neq n} (a(E_I^m)^\top E_I^n + c)^e,$$

# CL-Based Recommendation (RecDCL)

## Batch/Feature-wise Dual Objectives



- RecDCL

➤ FCL: Eliminate redundancy between users and items

Eliminate redundancy within users and items.

➤ BCL: contrastive representation on output  $\mathcal{L}_{BCL} = \frac{1}{2}S(h(E_U), sg(\hat{E}_I)) + \frac{1}{2}S(sg(\hat{E}_U), h(E_I)),$

$$\mathcal{L}_{UIBT} = \underbrace{\frac{1}{F} \sum_m (1 - C_{mm})^2}_{\text{invariance}} + \underbrace{\frac{\gamma}{F} \sum_m \sum_{m \neq n} C_{mn}^2}_{\text{redundancy reduction}}.$$

$$\mathcal{L}_{UUII} = \frac{1}{2} \log \sum_{m \neq n} (a(E_U^m)^\top E_U^n + c)^e + \frac{1}{2} \log \sum_{m \neq n} (a(E_I^m)^\top E_I^n + c)^e,$$

# CL-Based Recommendation (RecDCL)

## Batch/Feature-wise Dual Objectives

- RecDCL outperforms STOA GNNs-based and SSL-based methods on four public datasets

- Recall@20

5.34% ↑

Models	Dataset	Beauty		Food		Game		Yelp	
	Metrics	R@20	N@20	R@20	N@20	R@20	N@20	R@20	N@20
Base	Pop	3.25	1.31	5.74	3.40	2.82	1.06	1.58	0.96
MF-based	BPR-MF	14.12	6.62	27.02	21.04	18.16	8.33	6.92	4.29
	NeuMF	7.66	3.46	15.28	8.79	10.36	4.28	6.01	3.63
VAE-based	Mult-VAE	11.37	5.46	24.89	20.77	15.50	7.18	9.51	5.84
	RecVAE	12.76	6.37	26.69	22.29	17.65	8.38	10.70	6.69
GNNs-based	NGCF	13.27	6.28	26.84	20.96	18.04	8.31	7.29	4.45
	LightGCN	13.48	6.25	24.56	16.77	19.20	8.91	8.43	5.23
SSL-based	BUIR	14.60	7.29	28.26	22.19	15.04	6.73	8.08	4.97
	CLRec	15.17	<u>7.56</u>	27.64	20.65	20.12	9.60	10.95	6.89
	DirectAU	<u>15.43</u>	7.49	<u>28.57</u>	<u>22.41</u>	<u>20.14</u>	<u>9.55</u>	<u>10.97</u>	<u>6.92</u>
	<b>DCL</b>	<b>15.59</b>	7.54	<b>28.63</b>	<b>22.52</b>	<b>20.20</b>	<b>9.58</b>	<b>10.99</b>	<b>6.96</b>
	%Improv.	1.04%	0.67%	0.21%	0.49%	0.30%	0.31%	0.18%	0.58%
	<b>RecDCL</b>	<b>15.78</b>	<b>7.89</b>	<b>28.95</b>	<b>23.27</b>	<b>20.44</b>	<b>9.87</b>	<b>11.59</b>	<b>7.28</b>
	%Improv.	2.27%	5.34%	1.33%	3.84%	1.49%	3.35%	5.65%	5.20%
	<i>p</i> -value	0.004115	0.000478	0.002255	0.000017	0.264695	0.029848	0.001402	0.006503

<sup>1</sup> Note that we tune embedding size from 32 to 2048 and report the best results for all baselines and our method RecDCL. Generally, the embedding size is set by default to 64.

<sup>2</sup> Indeed, RecDCL is the very first work to explore the effectiveness of FCL for recommendations. We have looked and found that there are no appropriate baselines for FCL. To comprehensively compare, we conduct the experiments in ablation studies, that is UIBT for FCL.

# CL-Based Recommendation (RecDCL)

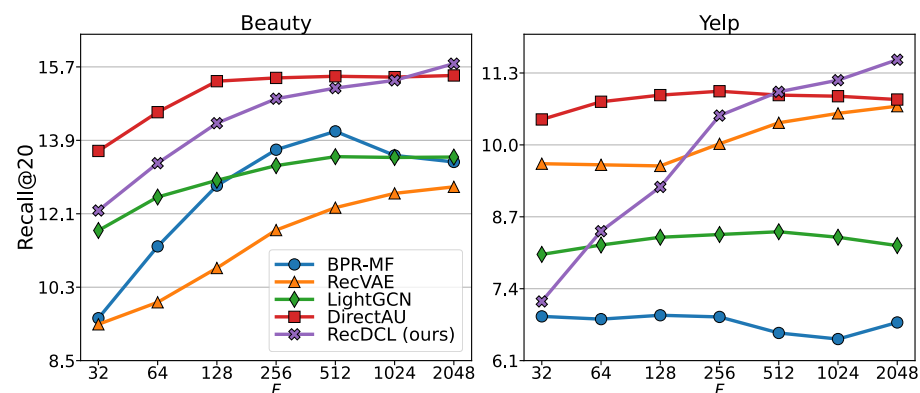
## Batch/Feature-wise Dual Objectives

- We show the effectiveness of RecDCL on private industry dataset

**NDCG@20 7.53% ↑**

Method	BPR-MF	LightGCN	DirectAU	RecDCL	%Improv.
Recall@20	<u>35.27</u>	33.48	31.34	<b>36.47</b>	3.40%
NDCG@20	<u>16.61</u>	15.08	14.07	<b>17.86</b>	7.53%

- Ablation study

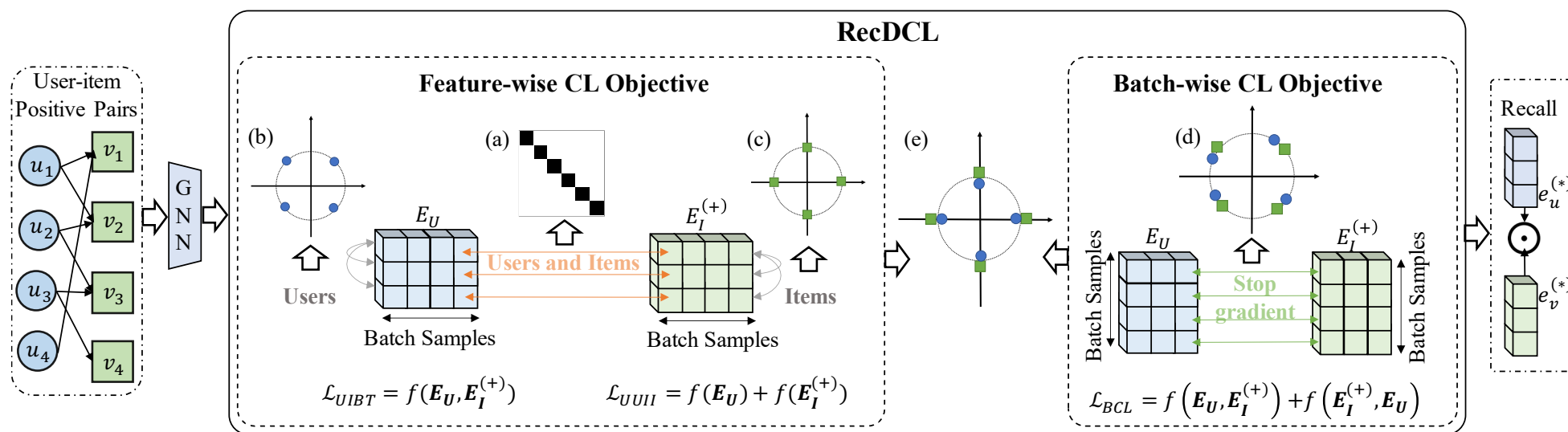


The effect of different embedding sizes.

Method	Beauty		Yelp	
	Recall@20	NDCG@20	Recall@20	NDCG@20
LightGCN	13.48	6.25	8.43	5.28
w/ UIBT	14.78	7.47	9.92	6.18
w/ POLY	1.01	0.50	0.06	0.03
w/ AUG	14.90	7.51	10.08	6.36
w/ UIBT & POLY	14.88	7.43	<u>11.00</u>	<u>6.85</u>
w/ UIBT & AUG	<u>15.64</u>	<u>7.63</u>	10.73	6.78
w/ POLY & AUG	15.16	7.59	7.65	4.66
RecDCL	<b>15.78</b>	<b>7.89</b>	<b>11.59</b>	<b>7.28</b>
%Improv.	17.06%	26.24%	37.49%	37.88%

# Thanks!

## RecDCL: Dual Contrastive Learning for Recommendation



Dan Zhang, Yangliao Geng, Wenwen Gong, Zhongang Qi, Zhiyu Chen, Xing Tang, Ying Shan, Yuxiao Dong, Jie Tang. RecDCL: Dual Contrastive Learning for Recommendation. In Proceedings of TheWebConf (WWW'24).

Code & Data <https://github.com/THUDM/RecDCL>

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