LIGHTGCL: SIMPLE YET EFFECTIVE GRAPH CONTRASTIVE LEARNING FOR RECOMMENDATION

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CONTEXTO

GNNs

Graph Neural Networks

problema → escasez de datos

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GNNs

Graph Neural Networks

problema

escasez de datos

solución

APRENDIZAJE CONTRASTIVO

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Técnica que busca crear representaciones útiles de los datos comparando pares: por un lado, aquellos que son similares y por otro, los que son diferentes (Olamendy, 2024).

presenta limitaciones :(

→ pérdida de información estructural

→ mala generalización

→ *over-smoothing*

ESTADO DEL ARTE Y MARCO TEÓRICO

MARCO TEÓRICO

- **Augmentación de datos (Data Augmentation)**: proceso de generar artificialmente nuevos datos a partir de datos existentes (Amazon Web Services, Inc.).

- **Redes Neuronales de Grafos (Graph Neural Networks, GNN)**: nodos representan datos y las aristas sus relaciones. GNN aprovecha estas conexiones para aprender de estructuras complejas y sus interacciones (De Innovación Industrial Ia, C. 2021).

- **Descomposición en valores singulares (Singular Value Decomposition, SVD)**: se utiliza para reducir la dimensionalidad de una matriz (Kumar, 2022).

- **Robustez (robustness)**: Capacidad de un modelo para manejar ruidos en los datos o adaptarse a diferentes escenarios sin pérdida significativa de desempeño (Hvilshøj, 2024).

TRABAJOS RELACIONADOS

Aprendizaje Contrastivo en Grafos para Recomendación

- Métodos como SGL (Wu et al., 2021) y SimGCL(Yu et al., 2022)

  Realizan augmentaciones de datos y embeddings mediante operaciones aleatorias de eliminación de nodos y aristas.
  Limitación: esta aleatoriedad puede eliminar información clave.

- Recomendadores basados en CL, HCCF (Xia et al., 2022b) y NCL(Lin et al., 2022)

  Diseñan estrategias heurísticas para construir vistas contrastivas de embeddings.
  Limitación: Dependen de heurísticas predefinidas, lo que limita su adaptabilidad a diferentes tareas de recomendación.

TRABAJOS RELACIONADOS

Aprendizaje Auto-supervisado en Grafos

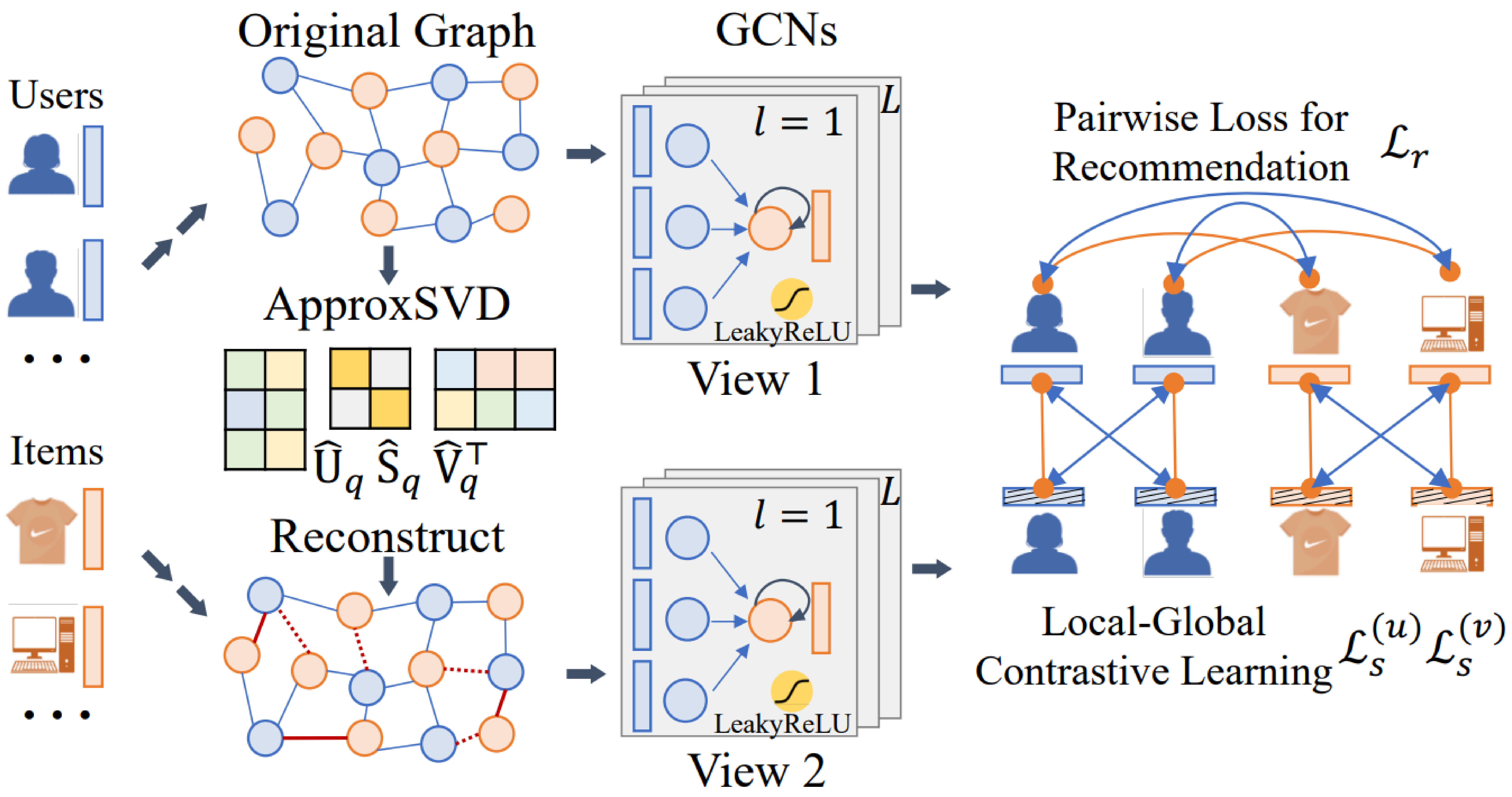
El aprendizaje auto-supervisado (SSL) mejora la representación de nodos en grafos no etiquetados.

Métodos como AutoSSL(Jin et al., 2022) combinan tareas pretextuales para augmentación (aumento de datos), SimGRACE(Xia et al., 2022a) y AutoGCL(Yin et al., 2022) generan vistas contrastivas con perturbaciones y entrenamiento end-to-end, mientras que GCA(Zhu et al., 2021b) y GraphCL(You et al., 2020) aplican augmentaciones adaptativas en topología, atributos y nodos/aristas.

CONTRIBUCIONES

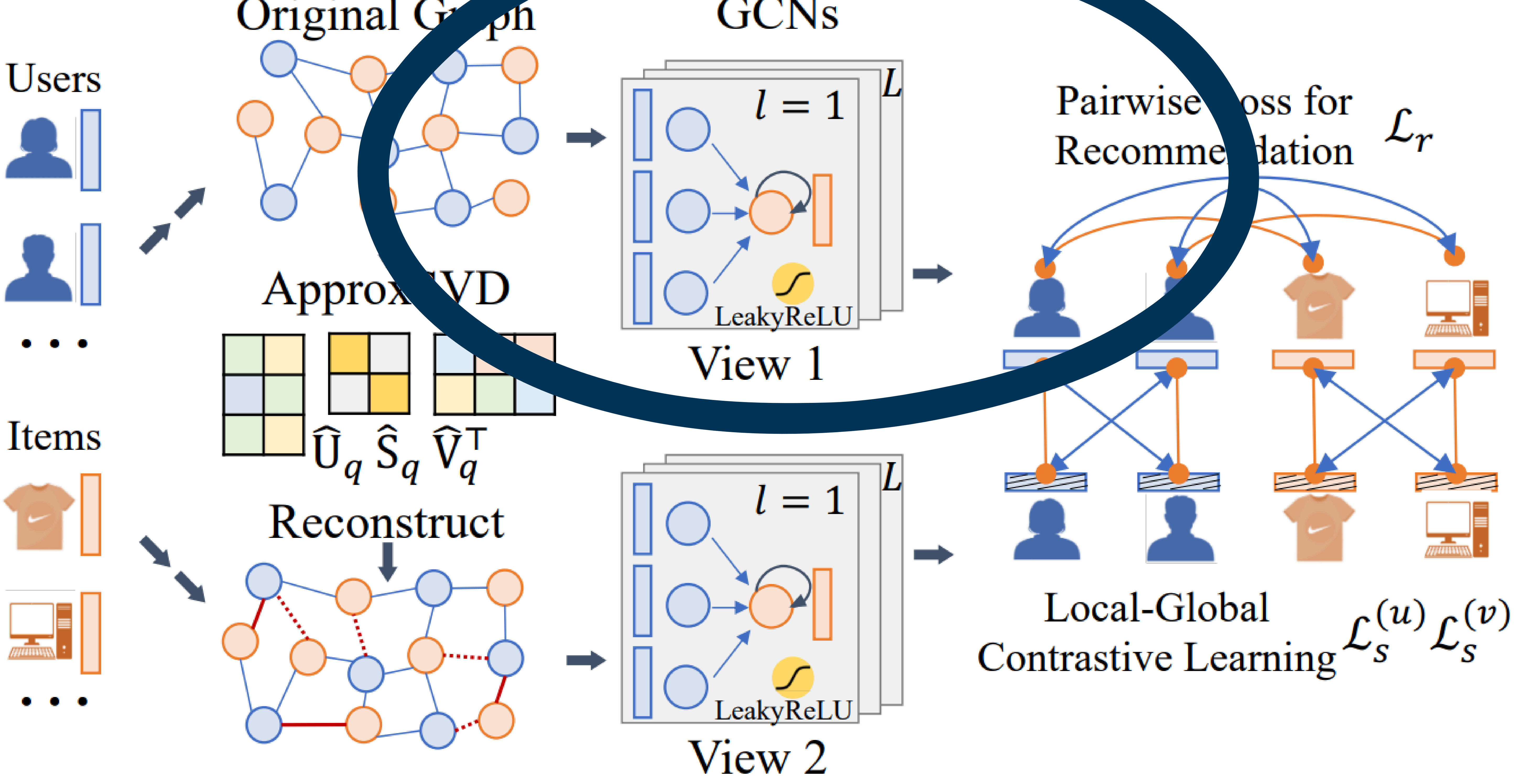
- Marco ligero y robusto de aprendizaje contrastivo en grafos.
- Se propone LightGCL, un paradigma eficiente para la augmentación de grafos.
- Mejora la eficiencia de entrenamiento frente a otros métodos basados en GCL.
- Experimentos en múltiples datasets reales demuestran su superioridad en desempeño, robustez y capacidad de generalización.

METODOLOGÍA



Original Graph
GCNs
Users
Items
ApproxSVD
$\hat{U}_q$ $\hat{S}_q$ $\hat{V}_q^\top$
Reconstruct
$l = 1$
L
LeakyReLU
View 1
View 2
Pairwise Loss for Recommendation
$\mathcal{L}_r$
Local-Global Contrastive Learning
$\mathcal{L}_s^{(u)}$ $\mathcal{L}_s^{(v)}$

LOCAL



Users
Items
Original
GCNs
$l = 1$
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LeakyReLU
View 1
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Approx
$\hat{U}_q$ $\hat{S}_q$ $\hat{V}_q^{\top}$
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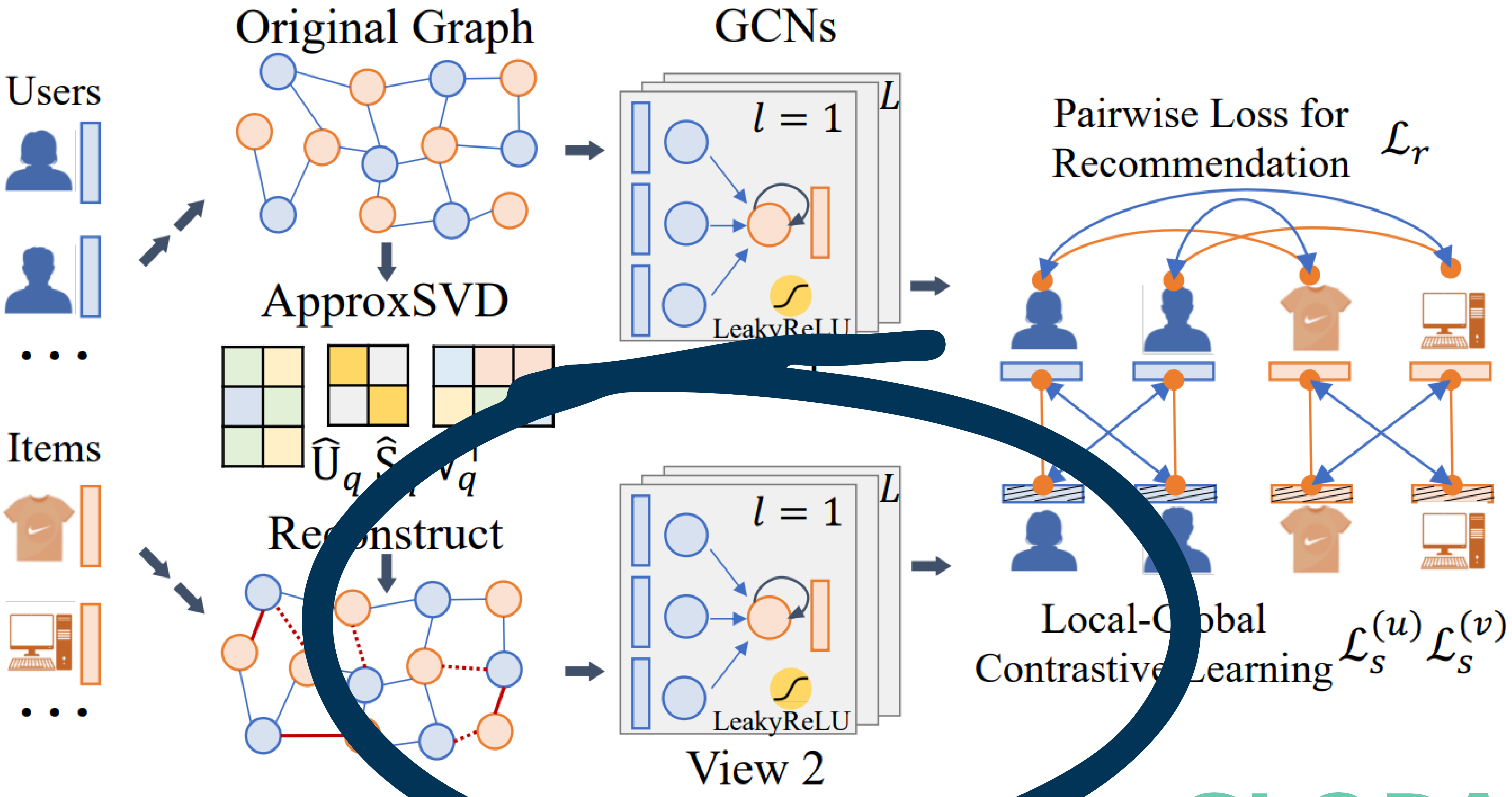
Users
Items
Original Graph
ApproxSVD
$\hat{U}_q$ $\hat{S}_q$ $\hat{V}_q^T$
Reconstruct
GCNs
$l = 1$
L
LeakyReLU
View 2
Pairwise Loss for Recommendation
$\mathcal{L}_r$
Local-Global Contrastive Learning
$\mathcal{L}_s^{(u)}$ $\mathcal{L}_s^{(v)}$

GLOBAL

GCN

usuario $\longrightarrow$ $e_i^{(u)}$

item $\longrightarrow$ $e_j^{(v)}$

$$\boldsymbol{E}^{(u)} \in \mathbb{R}^{I \times d}$$

$$\boldsymbol{E}^{(v)} \in \mathbb{R}^{J \times d}$$

$$z_{i,l}^{(u)} = \sigma(p(\tilde{A}_{i,:}) \cdot E_{l-1}^{(v)}), \quad z_{j,l}^{(v)} = \sigma(p(\tilde{A}_{:,j}) \cdot E_{l-1}^{(u)})$$

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$$z_{i,l}^{(u)} = \sigma(p(\tilde{A}_{i,:}) \cdot E_{l-1}^{(v)}), \quad z_{j,l}^{(v)} = \sigma(p(\tilde{A}_{:,j}) \cdot E_{l-1}^{(u)})$$

$$e_i^{(u)} = \sum_{l=0}^{L} z_{i,u}^{(l)}, \quad e_j^{(v)} = \sum_{l=0}^{L} z_{j,v}^{(l)}, \quad \hat{y}_{i,j} = e_i^{(u)\top} e_j^{(v)}$$

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SVD

$$\tilde{A} = \boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^{\top}$$

$$\hat{\boldsymbol{A}} = \boldsymbol{U}_q \boldsymbol{S}_q \boldsymbol{V}_q^\top$$

$$g_{i,u}^{(l)} = \sigma\left(\hat{A}_{i,:} \cdot E_v^{(l-1)}\right), \quad g_{j,v}^{(l)} = \sigma\left(\hat{A}_{:,j} \cdot E_u^{(l-1)}\right)$$

$$\hat{A}_{SVD} = U_q S_q V_q$$

Hanko et al. (2011)

$$P = U_q S_q, \quad Q = V_q S_q$$

$$\hat{A}_{SVD} E_{l-1}^{(v)} = P(Q^\top E_{l-1}^{(v)})$$

APRENDIZAJE CONTRASTIVO

$$L = L_r + \lambda_1 \cdot \left(L_s^{(u)} + L_s^{(v)} \right) + \lambda_2 \cdot \|\Theta\|_2^2$$

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$$L_s^{(u)} = \sum_{i=1}^{I} \sum_{l=1}^{L} - \log \frac{\exp\left(s\left(z_{i,l}^{(u)}, g_{i,l}^{(u)} \right) / \tau \right)}{\sum_{i'} \exp\left(s\left(z_{i,l}^{(u)}, g_{i',l}^{(u)} \right) / \tau \right)}$$

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$$L_s^{(u)} = \sum_{i=1}^{I} \sum_{l=1}^{L} -\log \frac{\exp\left(\boldsymbol{s}\left(z_{i,l}^{(u)}, g_{i,l}^{(u)}\right)/\tau\right)}{\sum_{i'} \exp\left(\boldsymbol{s}\left(z_{i,l}^{(u)}, g_{i',l}^{(u)}\right)/\tau\right)}$$

$$L_s^{(u)} = \sum_{i=1}^{I} \sum_{l=1}^{L} -\log \frac{\exp\left(s\left(z_{i,l}^{(u)}, g_{i,l}^{(u)}\right)/\tau\right)}{\sum_{i'} \exp\left(s\left(z_{i,l}^{(u)}, g_{i',l}^{(u)}\right)/\tau\right)},$$

$$L_r = \sum_{i=0}^{I} \sum_{s=1}^{S} \max\left(0, 1 - \hat{y}_{i,p_s} + \hat{y}_{i,n_s}\right)$$

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EVALUACIÓN, RESULTADOS Y COMPARACIÓN

EVALUACIÓN

01 **Desempeño en comparación con SOTA**

02 **Eficiencia del GCL ligero**

03 **Desempeño ante dispersión y sesgo**

04 **Efecto de CL local-global**

05 **Efecto de los hiper-parametros**

DATOS Y PROTOCOLOS

01

Yelp:

- 29,601 users
- 24,734 items
- 1,517,326 interactions

02

Gowalla:

- 50,821 users
- 57,440 items
- 1,172,425 interactions

03

ML-10M:

- 69,878 users
- 10,195 items
- 9,988,816 interactions

04

Amazon-Book:

- 78,578 users
- 77,801 items
- 2,240,15 interactions

05

Tmall:

- 47,939 users
- 41,390 items
- 2,357,450 interactions

DATOS Y PROTOCOLOS

SEPARACION DE DATOS

dividieron datos en conjuntos de entrenamiento, validación y prueba con una proporción de 7:2:1.

METRICAS

- Recall@N
- Normalized Discounted Cumulative Gain (NDCG)@N

donde N = {20, 40}

METODOS BASE A COMPARAR

- NCF.
- GCCF, LightGCN.
- DGCF.
- HyRec.
- GraphCL, GRACE, GCA, MHCN, SAIL, AutoGCL, SimGRACE, SGL, HCCF, SHT, SimGCL.

CONFIGURACION DE HIPER-PARAMETROS

- Tamaño de embedding: 32.
- Tamaño de lote: 256.
- Numero de capas de convolución: 2.
- λ1 y λ2 se ajustan en $\{10^{-5}, 10^{-6}, 10^{-7}\}$ y $\{10^{-4}, 10^{-5}\}$
- τ se ajusta en $\{0{,}3, 0{,}5, 1, 3, 10\}$
- Dropout: $\{0, 0{,}25\}$
- q = 5

VALIDACIÓN DE RENDIMIENTO

Table 1: Performance comparison with baselines on five datasets.

Data	Metric	DGCF	HyRec	LightGCN	MHCN	SGL	SimGRACE	GCA	HCCF	SHT	SimGCL	LightGCL	*p-val.*	*impr.*
Yelp	R@20	0.0466	0.0472	0.0482	0.0503	0.0526	0.0603	0.0621	0.0626	0.0651	0.0718	**0.0793**	7e-9	10%
	N@20	0.0395	0.0395	0.0409	0.0424	0.0444	0.0435	0.0530	0.0527	0.0546	0.0615	**0.0668**	8e-9	8%
	R@40	0.0774	0.0791	0.0803	0.0826	0.0869	0.0989	0.1021	0.1040	0.1091	0.1166	**0.1292**	2e-9	10%
	N@40	0.0511	0.0522	0.0527	0.0544	0.0571	0.0656	0.0677	0.0681	0.0709	0.0778	**0.0852**	2e-9	9%
Gowalla	R@20	0.0944	0.0901	0.0985	0.0955	0.1030	0.0869	0.0896	0.1070	0.1232	0.1357	**0.1578**	1e-6	16%
	N@20	0.0522	0.0498	0.0593	0.0574	0.0623	0.0528	0.0537	0.0644	0.0731	0.0818	**0.0935**	2e-6	14%
	R@40	0.1401	0.1356	0.1431	0.1393	0.1500	0.1276	0.1322	0.1535	0.1804	0.1956	**0.2245**	3e-6	14%
	N@40	0.0671	0.0660	0.0710	0.0689	0.0746	0.0637	0.0651	0.0767	0.0881	0.0975	**0.1108**	3e-6	13%
ML-10M	R@20	0.1763	0.1801	0.1789	0.1497	0.1833	0.2254	0.2145	0.2219	0.2173	0.2265	**0.2613**	1e-9	15%
	N@20	0.2101	0.2178	0.2128	0.1814	0.2205	0.2686	0.2613	0.2629	0.2573	0.2613	**0.3106**	3e-9	18%
	R@40	0.2681	0.2685	0.2650	0.2250	0.2768	0.3295	0.3231	0.3265	0.3211	0.3345	**0.3799**	7e-10	13%
	N@40	0.2340	0.2340	0.2322	0.1962	0.2426	0.2939	0.2871	0.2880	0.3318	0.2880	**0.3387**	1e-9	17%
Amazon	R@20	0.0211	0.0302	0.0319	0.0296	0.0327	0.0381	0.0309	0.0322	0.0441	0.0474	**0.0585**	2e-7	23%
	N@20	0.0154	0.0225	0.0236	0.0219	0.0249	0.0291	0.0238	0.0247	0.0328	0.0360	**0.0436**	2e-6	21%
	R@40	0.0351	0.0432	0.0499	0.0489	0.0531	0.0621	0.0498	0.0525	0.0719	0.0750	**0.0933**	1e-7	24%
	N@40	0.0201	0.0246	0.0290	0.0284	0.0312	0.0371	0.0301	0.0314	0.0420	0.0451	**0.0551**	9e-7	22%
Tmall	R@20	0.0235	0.0233	0.0225	0.0203	0.0268	0.0222	0.0373	0.0314	0.0387	0.0473	**0.0528**	3e-5	11%
	N@20	0.0163	0.0160	0.0154	0.0139	0.0183	0.0152	0.0252	0.0213	0.0262	0.0328	**0.0361**	1e-4	10%
	R@40	0.0394	0.0350	0.0378	0.0340	0.0446	0.0367	0.0616	0.0519	0.0645	0.0766	**0.0852**	1e-5	11%
	N@40	0.0218	0.0199	0.0208	0.0188	0.0246	0.0203	0.0337	0.0284	0.0352	0.0429	**0.0473**	7e-5	10%

VALIDACIÓN DE RENDIMIENTO

Data	Metric	NCF	GCCF	GraphCL	SAIL	GRACE	AutoGCL	LightGCL
Yelp	R@20	0.0252	0.0462	0.0462	0.0471	0.0550	0.0593	**0.0793**
	N@20	0.0202	0.0398	0.0401	0.0405	0.0470	0.0494	**0.0668**
	R@40	0.0487	0.0760	0.0764	0.0773	0.0917	0.1009	**0.1292**
	N@40	0.0289	0.0508	0.0511	0.0516	0.0605	0.0650	**0.0852**
Gowalla	R@20	0.0171	0.0951	0.0997	0.0999	0.0744	0.0832	**0.1578**
	N@20	0.0106	0.0535	0.0603	0.0602	0.0452	0.0484	**0.0935**
	R@40	0.0216	0.1392	0.1473	0.1472	0.1071	0.1291	**0.2245**
	N@40	0.0118	0.0684	0.0727	0.0725	0.0539	0.0605	**0.1108**
ML-10M	R@20	0.1097	0.1742	0.1659	0.1728	0.2107	0.2325	**0.2613**
	N@20	0.1297	0.2109	0.2038	0.2118	0.2476	0.2755	**0.3106**
	R@40	0.1634	0.2606	0.2560	0.2639	0.3075	0.3415	**0.3799**
	N@40	0.1427	0.2331	0.2250	0.2332	0.2711	0.3023	**0.3387**
Amazon	R@20	0.0142	0.0317	0.0360	0.0357	0.0360	0.0325	**0.0585**
	N@20	0.0085	0.0243	0.0266	0.0264	0.0271	0.0241	**0.0436**
	R@40	0.0223	0.0483	0.0585	0.0581	0.0583	0.0553	**0.0933**
	N@40	0.0133	0.0285	0.0340	0.0338	0.0345	0.0318	**0.0551**
Tmall	R@20	0.0082	0.0209	0.0251	0.0254	0.0303	0.0312	**0.0528**
	N@20	0.0059	0.0141	0.0175	0.0177	0.0210	0.0204	**0.0361**
	R@40	0.0140	0.0356	0.0416	0.0424	0.0505	0.0524	**0.0852**
	N@40	0.0079	0.0196	0.0233	0.0236	0.0281	0.0278	**0.0473**

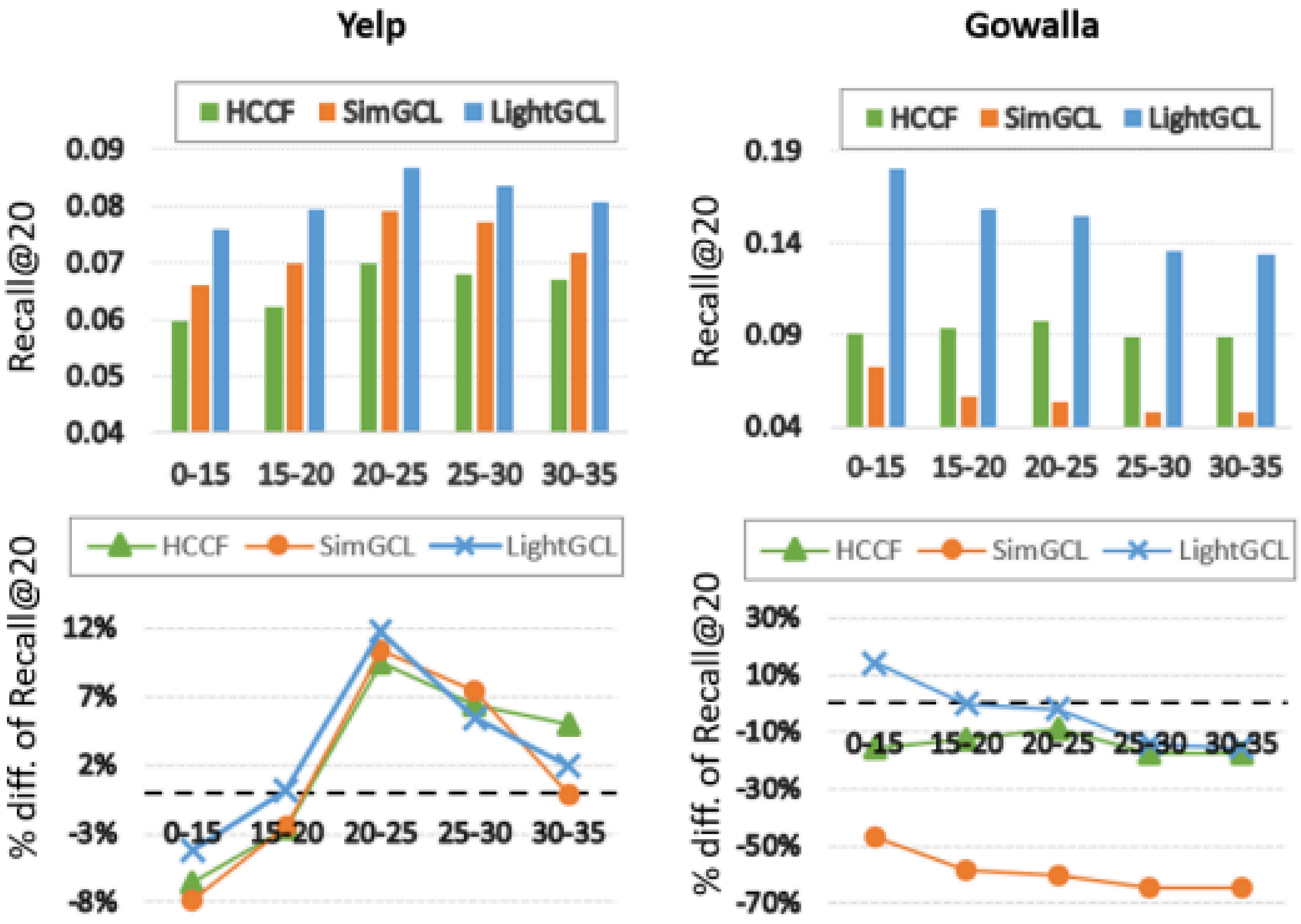
ESTUDIO DE EFICIENCIA

Table 2: Comparisons of computational complexity against baselines.

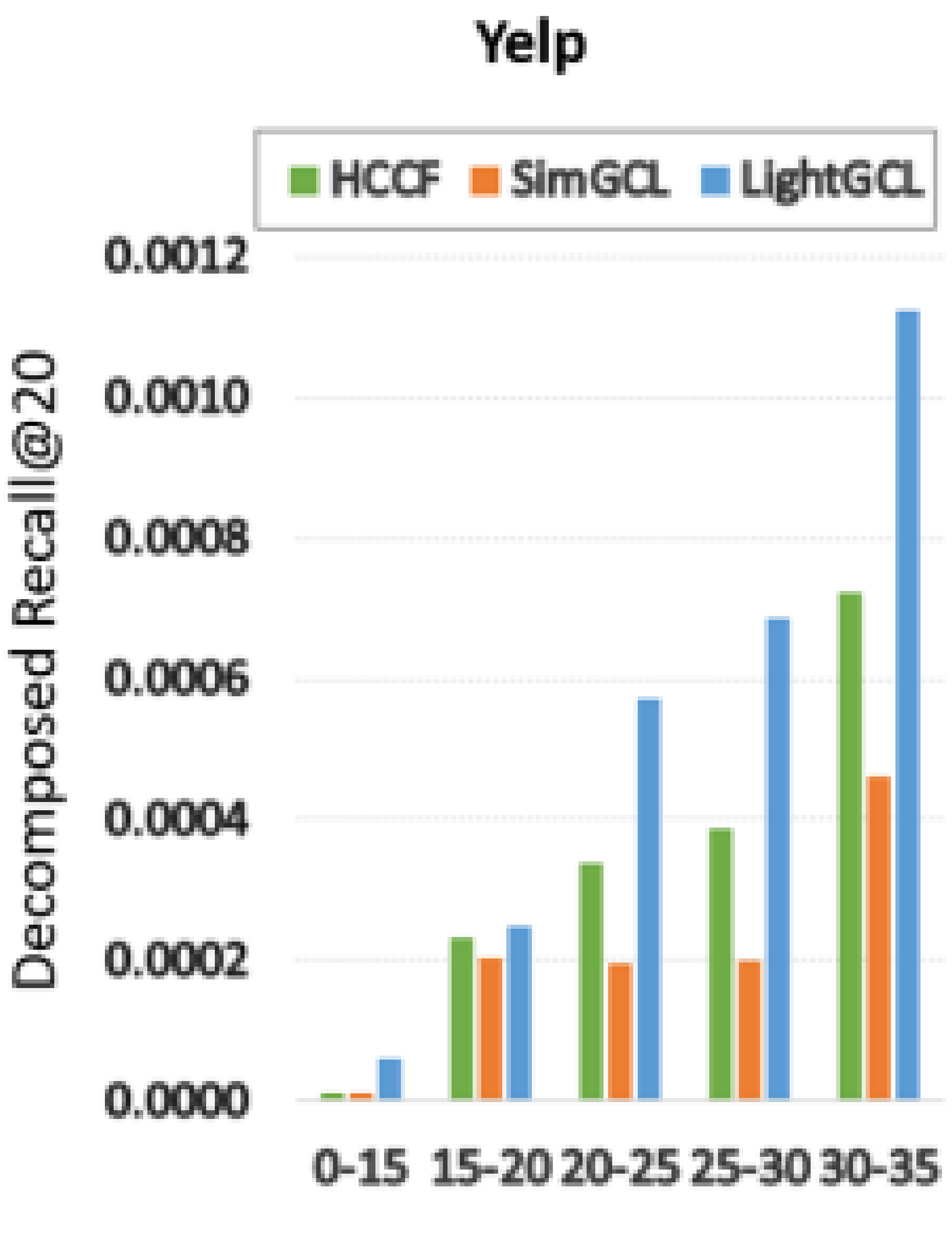
Stage	Computation	LightGCN	SGL	SimGCL	LightGCL
Pre-processing	Normalization	$O(E)$	$O(E)$	$O(E)$	$O(E)$
	SVD	–	–	–	$O(qE)$
Training	Augmentation	–	$O(2\rho E)$	–	–
	Graph Convolution	$O(2ELd)$	$O(2ELd + 4\rho ELd)$	$O(6ELd)$	$O[2ELd + 2q(I + J)Ld]$
	BPR Loss	$O(2Bd)$	$O(2Bd)$	$O(2Bd)$	$O(2Bd)$
	InfoNCE Loss	–	$O(Bd + BMd)$	$O(Bd + BMd)$	$O[(Bd + BMd)L]$

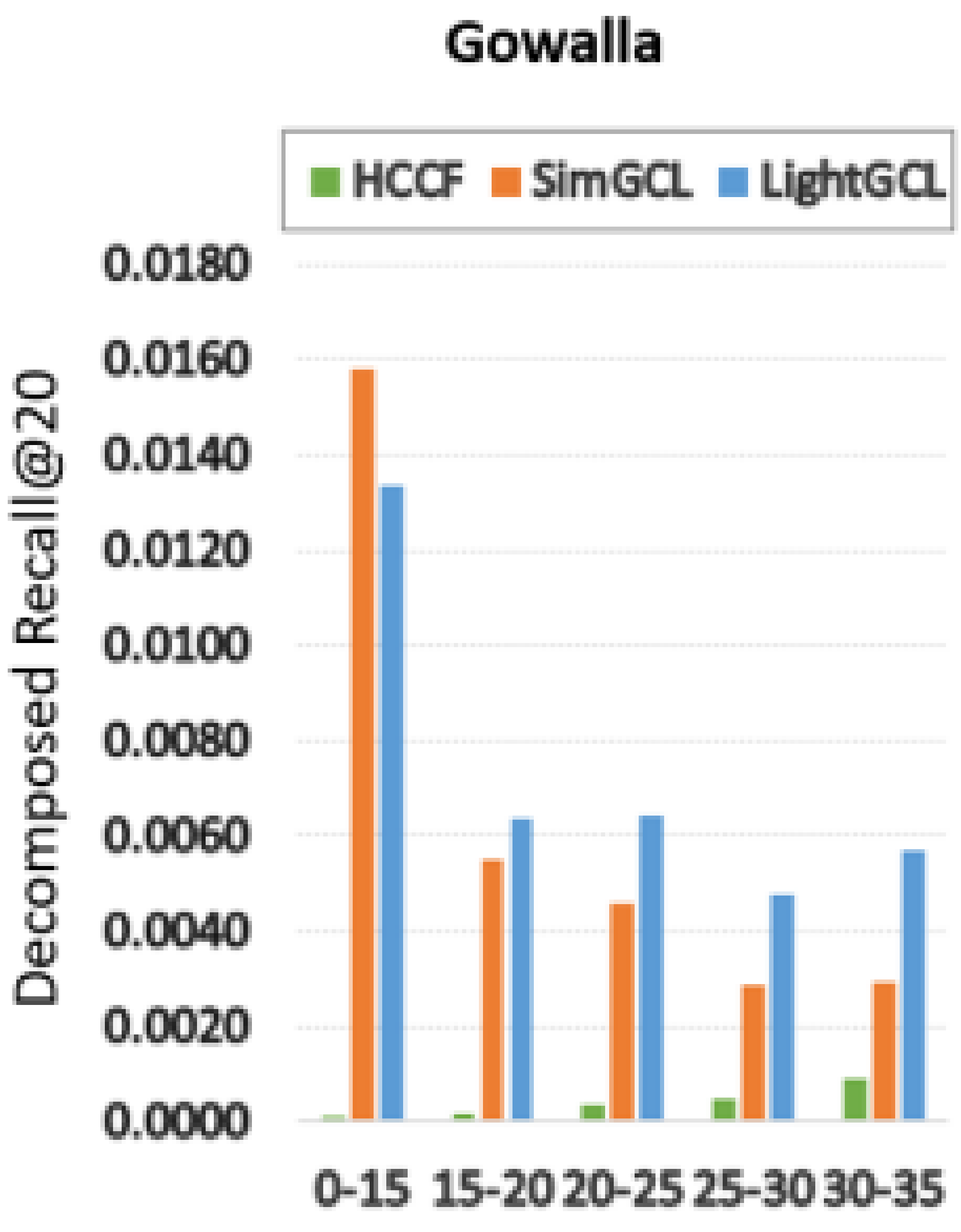
En la tabla, E, L y d representan el número de aristas, el número de capas y el tamaño de las embeddings respectivamente; ρ∈(0,1] es la tasa de retención de aristas; q es el rango requerido; I y J representan el número de usuarios e ítems; B y M son el tamaño del lote (batch) y el número de nodos en un lote (batch), respectivamente.

RESISTENCIA ANTE DISPERSION DE DATOS Y SESGO DE POPULARIDAD



RESISTENCIA ANTE DISPERSION DE DATOS Y SESGO DE POPULARIDAD





RESISTENCIA ANTE DISPERSION DE DATOS Y SESGO DE POPULARIDAD

$$Recall^{(g)} = \frac{|(\mathbb{V}^u_{rec})^{(g)} \cap \mathbb{V}^u_{test}|}{|\mathbb{V}^u_{test}|}$$

$\mathbb{V}^u_{test}$ Se refiere al conjunto de ítems de prueba para el usuario u

$(\mathbb{V}^u_{rec})^{(g)}$ Es el conjunto de los Top-K ítems recomendados para u que pertenecen al grupo g

BALANCEO ENTRE SOBRE SUAVIZADO Y SOBRE UNIFORMIDAD

Table 3: Mean Average Distance (MAD) of the embeddings learned by different methods.

Dataset	MHCN	LightGCN	LightGCL	SGL	SimGCL
Yelp	0.8806	0.9469	0.9657	0.9962	0.9956
Gowalla	0.9247	0.9568	0.9721	0.9859	0.9897

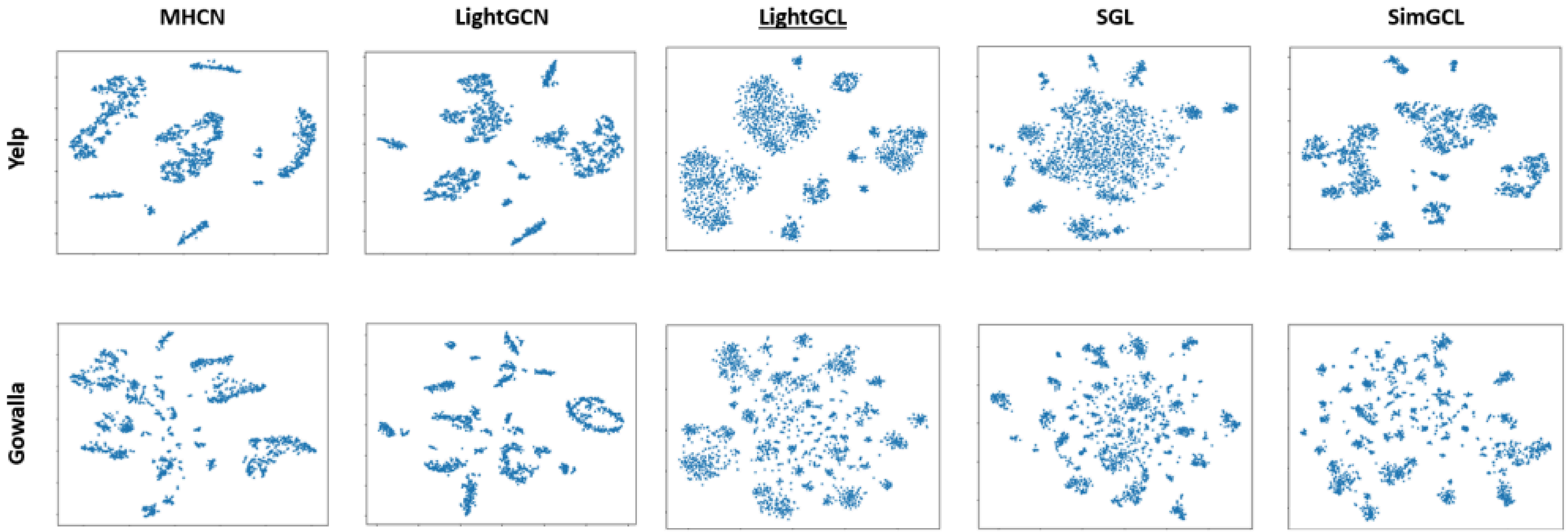


Figure 4: Embedding distributions on *Yelp* and *Gowalla* visualized with t-SNE.

ESTUDIO DE ABLACIÓN

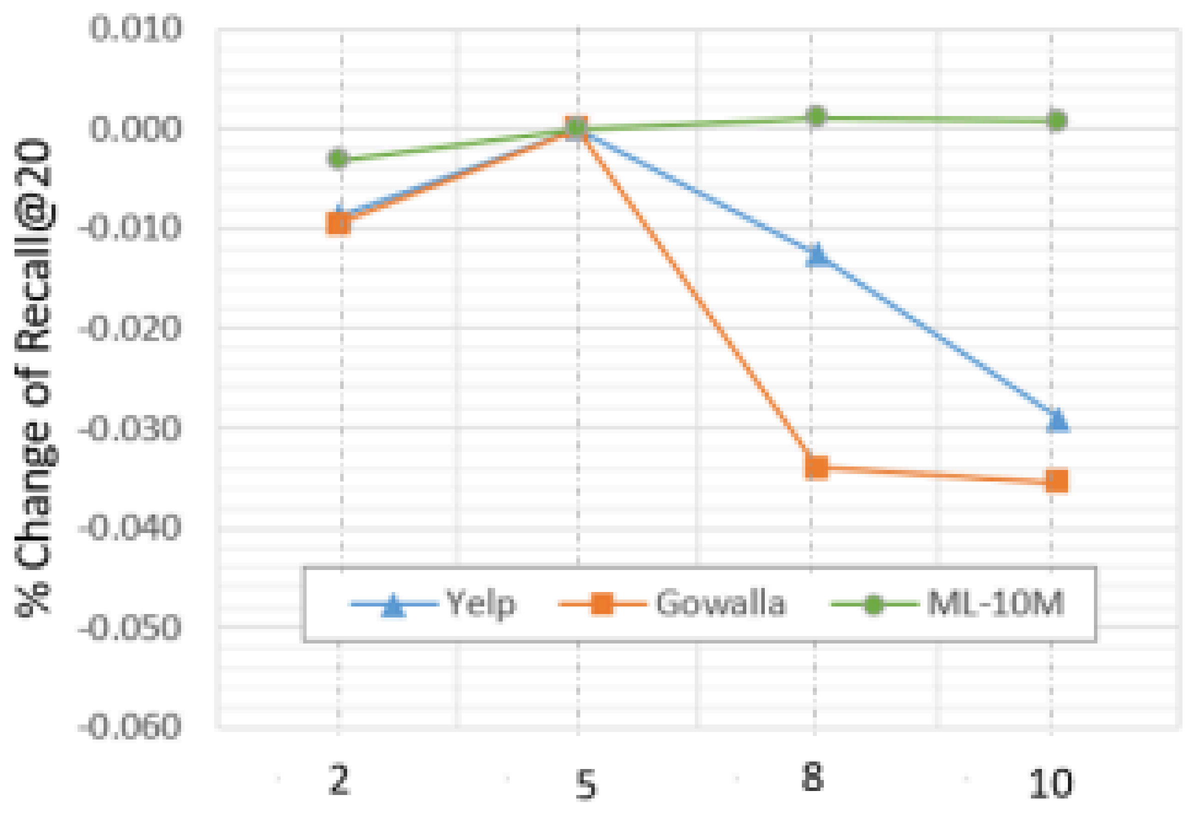


Table 4: Ablation study on LightGCL.

Variant	Yelp		Gowalla	
	Recall@20	NDCG@20	Recall@20	NDCG@20
CL-MF	0.0781	0.0659	0.1561	0.0929
CL-SVD++	0.0788	0.0666	0.1568	0.0932
LightGCL	**0.0793**	**0.0668**	**0.1578**	**0.0935**

ANÁLISIS DE HIPER-PARAMETROS

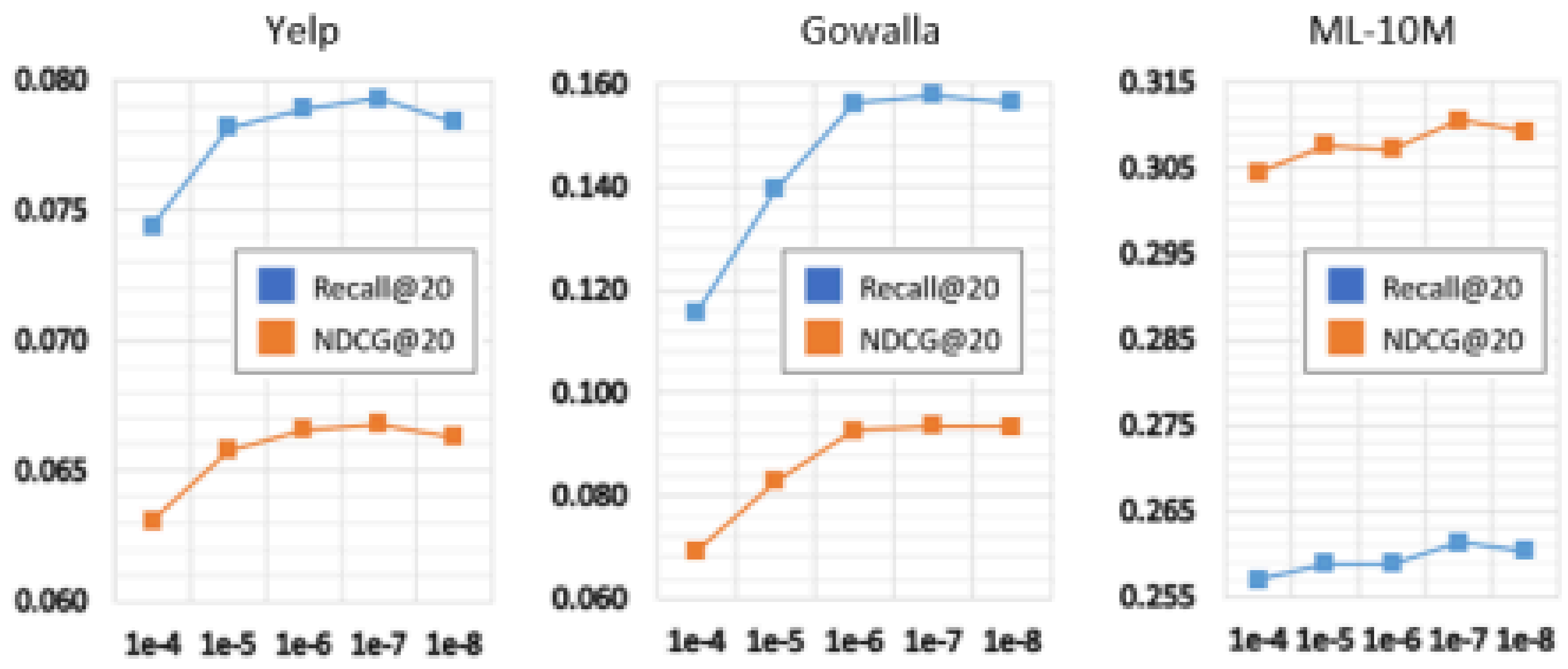


Figure 6: Impact of λ_1.

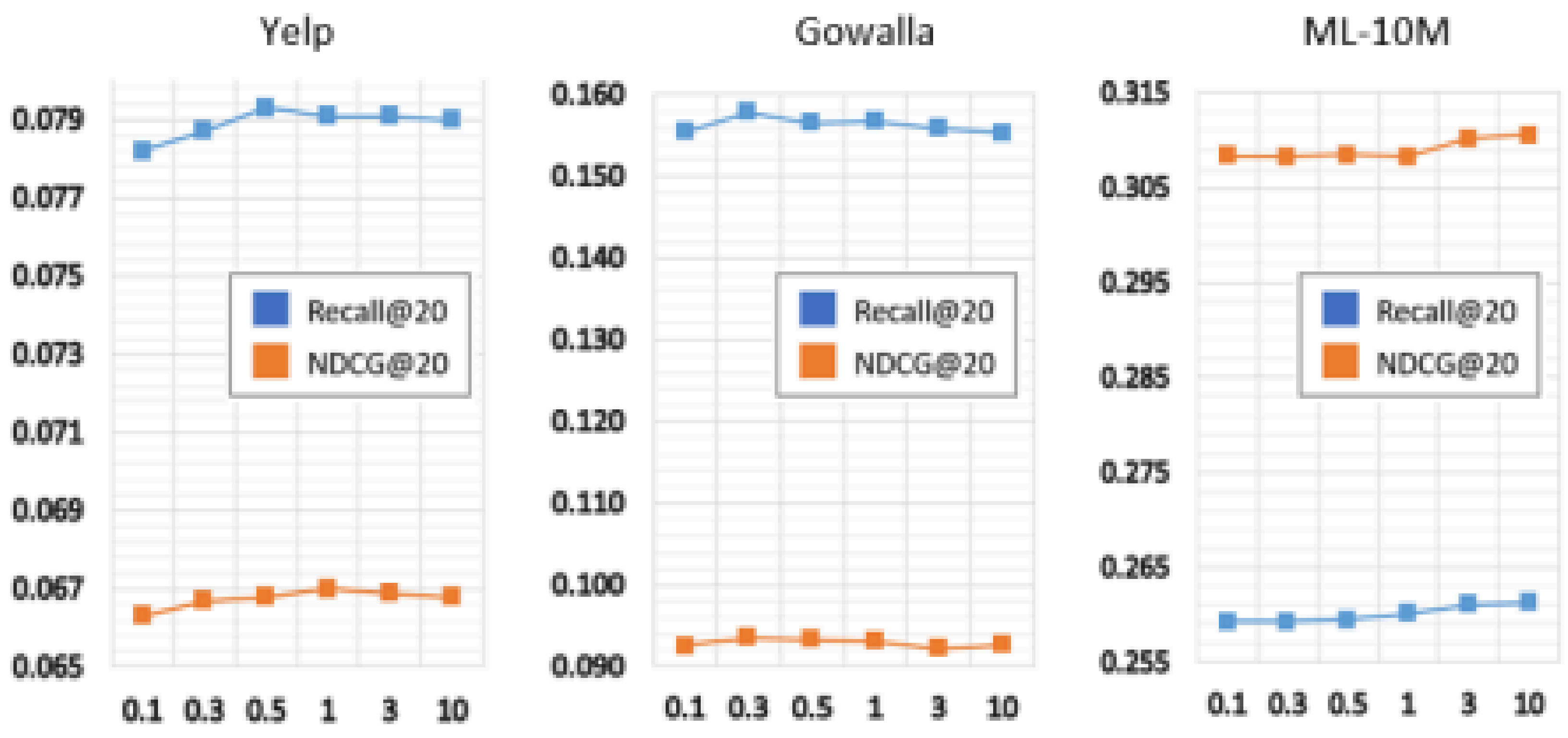
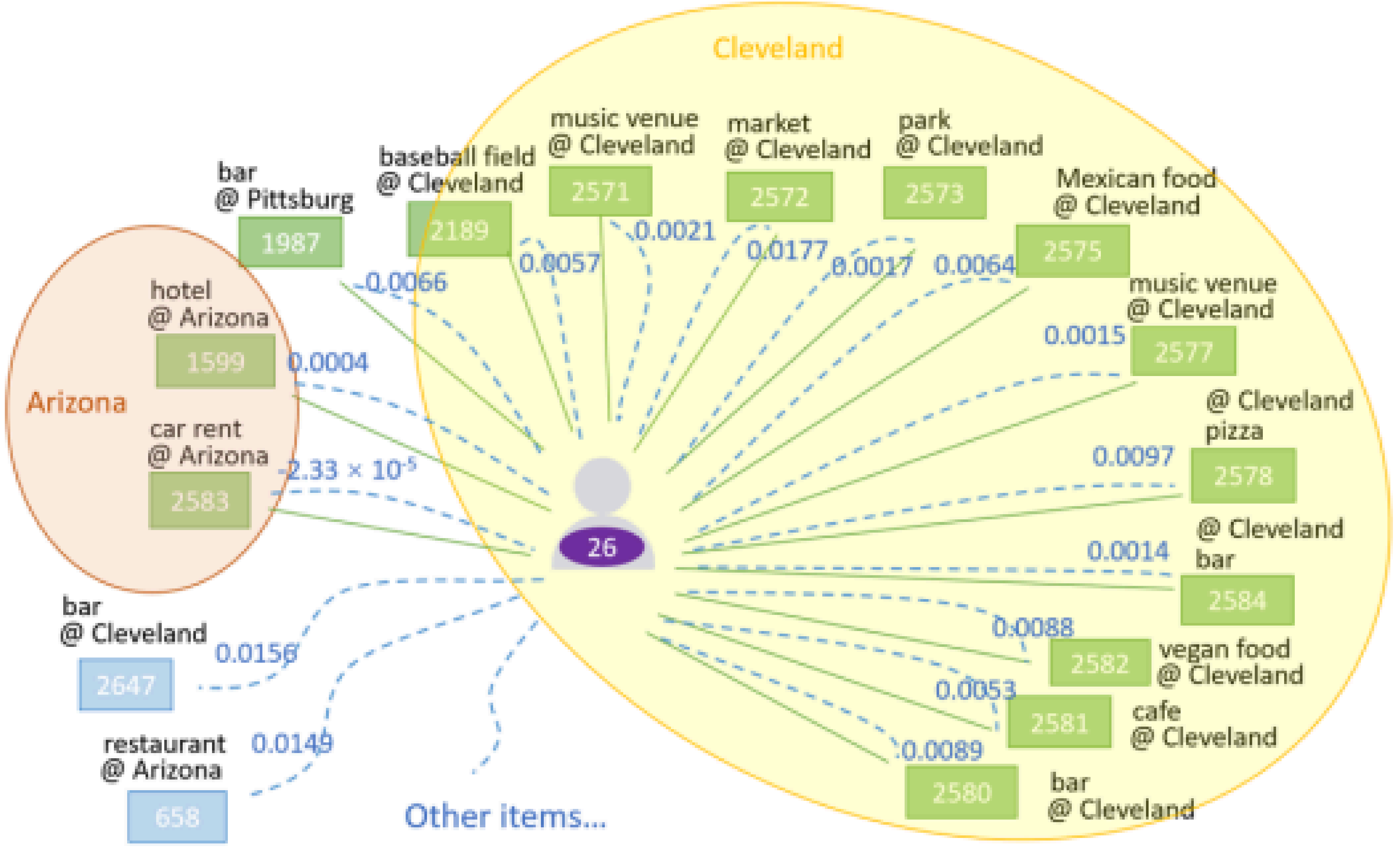


Figure 7: Impact of τ

ESTUDIO DE CASO



- item interacted in the original graph
- item not interacted in the original graph
- link in original graph
- w link in SVD-reconstructed graph with weight w

Items in the test set

id	location	category
1480	Arizona	Airport hotel
2321	Pittsburg	museum
2567	Cleveland	cinema
2569	Cleveland	shopping
2574	Cleveland	burger
2576	Cleveland	pizza
2579	Cleveland	shopping

PROBANDO EL FRAMEWORK

Final test:
Recall@20: 0.09898756675173945
Ndcg@20: 0.08527894124268165
Recall@40: 0.15828450446817116
Ndcg@40: 0.10689700000994956

0.0793
0.0668
0.1292
0.0852

PROBANDO EL FRAMEWORK

```
!python main.py --data gowalla --lambda2 0
```

```
/content/LightGCL/main.py:32: DeprecationWarning: Please import `coo_matrix` from the `scipy.spa
  train = pickle.load(f)
/content/LightGCL/main.py:35: DeprecationWarning: Please import `coo_matrix` from the `scipy.spa
  test = pickle.load(f)
Data loaded.
user_num: 50821 item_num: 57440 lambda_1: 0.2 lambda_2: 0.0 temp: 0.2 q: 5
/content/LightGCL/utils.py:34: UserWarning: torch.sparse.SparseTensor(indices, values, shape, *,
  return torch.sparse.FloatTensor(indices, values, shape)
Adj matrix normalized.
Performing SVD...
SVD done.
Test data processed.
100% 287/287 [01:29<00:00,  3.20it/s]
Epoch: 0 Loss: 3.7773968359319174 Loss_r: 0.36744839721440437 Loss_s: 3.409948441209693
 19% 38/199 [00:07<00:30,  5.27it/s]
```

Final test:

Recall@20: 0.20952968092246668

Ndcg@20: 0.12186391072660664

Recall@40: 0.29651290848434 56

Ndcg@40: 0.14461544601390 52

0.1578
0.0935
0.2245
0.1108

CONCLUSIÓN

01 Aborda los desafíos de la dispersión de datos y el sesgo de popularidad.

02 Experimentos demuestran que supera rendimiento de los métodos de ultima generación.

03 Uso de SVD elimina necesidad de aumentaciones de datos que impliquen ruido.

04 Se propone explorar integración de análisis causal en el framework.

NUESTRAS OPINIONES

01

- En la práctica notamos la importancia de usar gpu y no cpu

02

- Análisis completo, que abarca comparativas importantes con SOTA. Pero...

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DATOS Y PROTOCOLOS

METRICAS

$$Recall = \frac{True\ Positive(TP)}{True\ Positive(TP) + False\ Negative(FN)}$$

$$NDCG@K = \frac{DCG@K}{IDCG@K} = \frac{\displaystyle\sum_{i=1}^{k\ (actual\ order)} \frac{Gains}{log_2(i+1)}}{\displaystyle\sum_{i=1}^{k\ (ideal\ order)} \frac{Gains}{log_2(i+1)}}$$