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cover

previous [R]1

common

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previous

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**.5>l >X< 2023 6**

# Dissertation Submitted to Zhejiang Gongshang University for Master's Degree of Engineering

Tag-aware recommender systems based on graph nerual networks and contrastive learning

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**Jun. 2023**

**School of Information and Electronic Engineering**

**Zhejiang Gongshang University**

**Hangzhou, 310018, P.R. China**

previous

Web 3.0

1 Folksonomy Graph FG < - > < - >

2 Light Folksonomy Graph Collaborative Filtering, LFGCF

3 Tag-aware Graph Contrastive Learning TAGCL

4 LFGCF TAGCL normalized Discounted cumulative Gain NDCG Mean Peciprocal Rank MRR MovieLens Last.FM Delicious TAGCL 4.6% 5.0% NDCG 4.21% MRR 1.62% TAGCL 5.18% 8.0% NDCG 7.22% MRR 5.64% MovieLens Last.FM 17% BibSonomy TAGCL TAGCL 1%

## Abstract

With the rapid development of information technology and big data on the Internet, modern society has entered the era of information explosion. However, data resources are accumulated in large quantities in the data platforms of applications, and information overload has become one of the important challenges faced by Internet users. As one of the effective tools to relieve information overload in the era of big data, recommendation system can provide personalized recommendation service for users. In the Web 3.0 era, the relationship between users and data resources is richer. On some websites, users can create and share various items, and tag them with various labels. These tags not only reflect the user's own interests and preferences and attitudes towards the items, but also provide more information to the recommendation system with the rich content of the items themselves. Therefore, label-aware recommendation systems use such socially labeled data as collaborative filtering information to provide users with more accurate personalized recommendation services.

Currently, label-aware recommendation systems have become an effective way to solve the problems of sparsity and fairness in recommendation systems. However, label-aware recommendation systems also have their limitations. Among them, the label data's own problems of multi-word meaning and multi-word synonymy limit the recommendation performance of label-aware recommendation systems. Although label-aware recommendation models for these problems have been proposed by some researchers,

there are still problems such as how to systematically organize social label data, how to effectively migrate existing deep learning models, and how to set appropriate optimization directions for algorithms. In order to make better use of social labeling data and improve recommendation performance, this thesis proposes the definition of social labeling graph for the above research problems, and based on this, two novel label-aware recommendation models are proposed. The models proposed in this thesis improve the performance of label-aware recommendation algorithms through lightweight graph neural networks and contrast learning methods, respectively, and reduce the training difficulty and mitigate the prevalence bias in the data. The main research contributions are as follows:

(1) This thesis proposes a new social labeling graph Folksonomy Graph consisting of <user-label> graph and <item-label> graph, which reduces the complexity of the social labeling graph and facilitates the design and optimization of subsequent models.

(2) Based on graph neural network, this thesis proposes a Light Folksonomy Graph Collaborative Filtering (LFGCF). In order to adapt to the characteristics of recommender systems, the model removes the feature transformation and nonlinear activation components of graph convolutional neural networks, and uses weighting and aggregation functions for message propagation. This approach improves the accuracy of the model and reduces the training difficulty of the model.

(3) This thesis explores the data bias present in recommender systems

and proposes a Tag-aware Graph Contrastive Learning framework (TAGCL). The model uses contrast learning and knowledge graph to jointly optimize the model and sample tags simultaneously during the training process, thus effectively improving the recommendation accuracy and fairness of the model.

(4) In order to evaluate the performance of LFGCF and TAGCL, a series of experiments are designed and compared with the current mainstream recommendation algorithm models in terms of recall, accuracy, Normalized Discounted cumulative Gain, Mean Peciprocal Rank metrics are compared. On three publicly available academic datasets MovieLens, Last.FM, and Delicious, the proposed model TAGCL has a 4.6% improvement in recall, 5.0% improvement in accuracy, 4.21% improvement in NDCG, and 1.62% improvement in MRR compared to the generic recommendation model. Compared with the tag-aware recommendation model, TAGCL has a 5.18% improvement in recall, 8.0% improvement in accuracy, 7.22% improvement in NDCG, and 5.64% improvement in MRR. For MovieLens and Last.FM, which have large data bias, the average recommendation popularity is reduced by 17%. Finally, this thesis also tests TAGCL performance on a real-running recommendation system BibSonomy, and the experimental results demonstrate that TAGCL improves the recall rate by 1% compared to the baseline model.

**Keywords: Tag-aware recommender systems; Graph neural networs; Contrastive learning; Contrastive Learning; Personalized recommender**

common

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# 1

Recommender Systems user item “ ” “ ”

Sequential Recommender Knowledge-based Recommender

Conversational Recommender Tag-aware Recommender

## 1.1

information overload [?]

[?]

[?] [?] [?]

“ ” [?]

1-5

[?]

Top-K

[width=1]figure/movie.pdf

1.1:

Web 3.0 [?]

folksonomy tag < > folksonomy

records ?? “ ” “ ” “ ” tagging behavior

Tag Recommender Systems

redundancy ambiguity ?? “IMDB top 250” Tag-aware Recommender Systems

**??**

[?]

long-tail [?]

## 1.2

### 1.2.1

Zhen [?] TagiCofi

Shepisten shepitsen$_{p}ersonalized_{2}008Peng[?]-Zhang[?, ?]--$
$Zhao[?]FolkRank++Randle[?]RTFLi[?]RandleBPR-T$

Multi-layer Perceptron, MLP [?, ?, ?, ?] Autoencoder, AE [?, ?] Neural Attention Network, NAN [?, ?] Graph Neural Network, GNN [?, ?]

embedding

-

Bayesian Personalized Ranking BPR Mean Squared Error MSE

[?, ?] Mao [?]

Cosine Contrastive Loss CCL

Hao [?]

[?]

Xu [?] DSPR

Zuo [?] CFA Sparse Autoencoder, SAE

Chen [?] AIRec

Huang [?]

Chen [?] heterogeneous graph

### 1.2.2

1 [?, ?]

[?, ?]

2 [?, ?]

3 BPR

## 1.3

### 1.3.1

- -

Top-K

1

\- -

2

3

4

Top-K

## 1.3.2

Folksonomy Graph FG Light Folksonomy Graph Collaborative Filtering, LFGCF Tag-aware Graph Contrastive Learning TAGCL

1 - -

2 LFGCF

3 TAGCL

4 LFGCF TAGCL

## 1.4

1 - -

2 LFGCF

3 TAGCL

## 1.5

6 ?? ?? ??

?? ?? ??

[width=0.7]figure/structure.drawio.pdf

1.2:

??

??

——

?? LFGCF

?? InfoNCE TAGCL

TransT TAGCL

?? LFGCF TAGCL

??

# 2

## 2.1

### 2.1.1

[?, ?]

Folksonomy

Top-K [?, ?, ?]

-

< - > < - >

[?]

?? “ ” “ ”

“ ” “ ”

[width=0.4]figure/tags.drawio.pdf

2.1:

- - -

- - - -

### 2.1.2

[?, ?] [?]

$a = (u, t, i) \in \mathcal{A}$ $\mathcal{E}_{u,t}$ $\mathcal{E}_{i,t}$ $\mathcal{E}_{u,t}$ $\mathcal{E}_{i,t}$

$\mathcal{E}_{u,t}$ $\mathcal{E}_{i,t}$ $\mathrm{e}_{u,t} = \{$ 1 , $if$(u,t) $\in \mathcal{E}_{u,t}$

0,otherwise , $\mathrm{e}_{i,t} = \{$ 1 , $if$(i,t) $\in \mathcal{E}_{i,t}$

0,otherwise .

$\mathcal{A}$ - - $\mathcal{G}_{UT} = (\mathcal{U}, \mathcal{T}, \mathcal{E}_{u,t})$

$\mathcal{G}_{IT} = (\mathcal{I}, \mathcal{T}, \mathcal{E}_{i,t})$

## 2.2

“ ” learning to recommend

“ ”

$f$ $\mathcal{A}$ $u$ $\mathcal{U}$ $i$ $\mathcal{I}$ $t$ $\mathcal{T}$ $\hat{y}$ $f : \mathcal{U} \times \mathcal{T} \times \mathcal{I}$

$K$ Top-K

[?] ID

[?, ?, ?] ID $\hat{y}_{ui} = f(u, i, t)$,

$min_{\Theta}$ $\mathbf{E}_{\mathcal{A}^+}$ $\mathcal{L}(f)$, $\mathcal{L}(\cdot)$ $f$ $\mathcal{A}^+$ $\Theta$

“ ” Top-K Top(u, K) =

$argmax^{(K)}_{i \in \mathcal{I}}\, \hat{y}_{u,i}$.

## 2.3

# 3

—— (Light Folksonomy Graph Collaborative Filtering, LFGCF)

## 3.1

### 3.1.1

euclidean structure Tensor

non-euclidean structure

- [?]

Message Passing Neural Network MPNN [?] Graph Convolutional Network GCN Thomas 2017 [?]

1 $A$ ;

2 $N \times D$ $X$ $N$ $D$

$Z \in \mathbf{R}^{N \times F}$ $F$

$\mathrm{H}^{(k+1)} = f(H^{(k)}, A)$ $H^{(0)} = X$ $H^{(K)} = Z$ $K$

$f(\cdot, \cdot)$

$\mathrm{f}(\mathrm{H}^{(k+1)}, A) = \sigma(AH^{(k)}W^{(k)})$ $W^{(k)}$ $k$ $\sigma$

$ReLU$ $A$ [?]

$A$

self-loops $A$ $A$ $I$ $\hat{A} = A + I$

$A$ $D$ $A$ : Norm(A) $=$ D$^{-1}A$ Norm(A) $=$ D$^{-\frac{1}{2}}AD^{-\frac{1}{2}}$ f(H$^{(k)}, A) =$ $\sigma(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(k)}W^{(k)})$ $H^{(k)}$ $k$ $k$ $k-1$ $H^{(0)} = X$

[width=]figure/gcn.drawio.pdf

3.1:

**??** $v_4$ $v_2$ $v_3$ $v_5$ $v_7$ $v_4$ $v_i$ $k$ $h_i^{(k)}$ h$_i^{(k)} = f^{(k)}(W^{(k)} \cdot \frac{\sum_{u \in \mathcal{N}(i)} h_u^{k-1}}{|\mathcal{N}(i)|} + B^{(k)} \cdot h_i^{(k-1)})$ $\mathcal{N}(i)$ $v_i$ $h_u^{(k-1)}$ $v_i$ $v_u$ $k-1$ $h_i^{(k-1)}$ $v_i$ $k-1$ $|\mathcal{N}(i)|$ $B^{(k)}$

(receptive field) oversmoothing [**?**] GCN GraphSAGE[**?**] GAT[**?**] GraphSAGE $O(|V|)$ Pinterest[171+] GAT GCN GAT

## 3.1.2

[**?**] **??** **??** **??** **??** Koren SVD++ [**?**] Gori ItemRank [**?**] - SVD++ ItemRank

[171+] https://www.pinterest.com/

0.45 [width=.88]figure/ui-graph.drawio.pdf

3.2: -

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3.3:

0.45 [width=.5]figure/social$_{g}raph.drawio.pdf$

3.4:

0.45 [width=.95]figure/ssk.drawio.pdf

3.5:

3.6:

- [?]

1 - - -

2 side information

ID

Wang [?] NGCF GCN feature transformation neighborhood aggregation nonlinear activation [?] attributed graph - ID

He [?] LightGCN NGCF LightGCN

3.1.2.1 NGCF

ID $u$ $e_u^{(0)}$ $i$ $e_i^{(0)}$ NGCF -

$$e_u^{(k)} = \sigma(W_1 e_u^{(k-1)} + \sum_{i \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}}(W_1 e_i^{(k-1)} + W_2(e_i^{(k-1)} \odot e_u^{(k-1)})))e_i^{(k)} = \sigma(W_1 e_i^{(k-1)} + \sum_{u \in \mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i||\mathcal{N}_u|}} \tag{3-1}$$

$\sigma(\cdot)$ $e_u^{(k-1)}$ $e_i^{(k-1)}$ $u$ $i$ $k-1$ $\mathcal{N}_u$ $u$ $\mathcal{N}_i$ $i$ $W_1$ $W_2$ $K$ $K+1$ $(e_u^{(0)}, e_u^{(1)}, \ldots, e_u^{(k)})$ $(e_i^{(0)}, e_i^{(1)}, \ldots, e_i^{(k)})$ NGCF concatenates

NGCF $\sigma(\cdot)$ $W_1$ $W_2$ [?] [?] - ID

3.1.2.2 LightGCN

NGCF LightGCN LightGCN -

$$e_u^k = \sum_{i \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}} e_i^{(k-1)} e_i^k = \sum_{u \in \mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i||\mathcal{N}_u|}} e_u^{(k-1)} \tag{3-2}$$

$\frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}}$ $\sigma(\cdot)$ $W_1$ $W_2$ NGCF LightGCN $K$ $(e_u^{(0)}, e_u^{(1)}, \ldots, e_u^{(k)})$ $(e_i^{(0)}, e_i^{(1)}, \ldots, e_i^{(k)})$

LightGCN NGCF LightGCN - LightGCN

## 3.2 LFGCF

LFGCF

[width=0.88]figure/lfgcf.drawio.pdf

3.7: LFGCF

### 3.2.1

GCN[?] GAT[?]

aggregation function

[?] [?] Top(u, K) = $argmax_{i \in \mathcal{I}}^{(K)}(\hat{y}_{u,i})$

LFGCF **??** LFGCF - -

BPR TransRT

### 3.2.2

[?]

$$e_u^{(k+1)} = \mathcal{AGG}(e_u^{(k)}, e_t^{(k)} : t \in \mathcal{N}_u) e_i^{(k+1)} = \mathcal{AGG}(e_i^{(k)}, e_t^{(k)} : t \in \mathcal{N}_i) \qquad (3\text{-}3)$$

$e_u, e_i \in \mathbf{R}^d$ $G_{UT}$ or $G_{IT}$ $\mathcal{AGG}$ $k$

[?] GIN[?] GraphSage[?] LSTM

BGCNN[?] TGCN

Top-K

### 3.2.3

$\mathcal{G}_{UT}$ $\mathcal{G}_{IT}$

$\mathcal{G}_{UT}$

$$e_u^{(k+1)} = \sum_{t \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u|}\sqrt{|\mathcal{N}_t|}} e_t^{(k)} e_t^{(k+1)} = \sum_{u \in \mathcal{N}_t} \frac{1}{\sqrt{|\mathcal{N}_t|}\sqrt{|\mathcal{N}_u|}} e_u^{(k)} \qquad (3\text{-}4)$$

$\frac{1}{\sqrt{|\mathcal{N}_u|}\sqrt{|\mathcal{N}_t|}}$ GCN $\mathcal{G}_{UT}$ $\mathcal{G}_{IT}$

$$e_i^{(k+1)} = \sum_{t \in \mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i|}\sqrt{|\mathcal{N}_t|}} e_t^{(k)} e_t^{(k+1)} = \sum_{u \in \mathcal{N}_t} \frac{1}{\sqrt{|\mathcal{N}_t|}\sqrt{|\mathcal{N}_i|}} e_i^{(k)} \tag{3-5}$$

### 3.2.4

LFGCF 0 K

e =COMB($\mathrm{e}^{(k)} : k \in K$). $\mathcal{COMB}$ $K$

[?]

$$\mathrm{e}_u = \textstyle\sum_{k=0}^{K} a_k e_u^{(k)}, \quad e_i = \sum_{k=0}^{K} a_k e_i^{(k)}, \quad e_t = \sum_{k=0}^{K} a_k e_t^{(k)}$$

$a_k \geq 0$ K $a_k$ $1/(K+1)$

$K$ 1 [?] 2

[?]

$$\hat{y}_{ui} = e_u^T e_i$$

### 3.2.5

TransRT TransR [?] TransRT $e_u + e_t \approx e_i$

$e_u, e_i, e_t \in \mathbf{R}^d$ $u$ $i$ $t$ $e_u, e_i$ $(u, t, i)$

g(u, t, i) $= ||\mathrm{e}_u + e_t - e_i||_2^2$ $e_u, e_i, e_t$ $g(u, t, i)$

### 3.2.6

LFGCF 0 BPR

BPR $\mathrm{L}_{rec} =$

$\sum_{(u,i,i') \in \mathcal{O}} -ln(\sigma(\hat{y}_{u,i} - \hat{y}_{u,i'}))$ $\mathcal{O} = \{(u, i, i')|(u, i) \in \mathcal{A}, (u, i') \notin \mathcal{A}\}$ $(u, i)$

$(u, i')$ $u$ $i'$

TransRT $L_T = \alpha ReLU(g_u(u, t_u, i) - g_i(u, t_i, i))$.

$\alpha$ $g_u(u, t_u, i)$ $g_i(u, t_i, i)$ BPR BPR

$\nabla e_u = -\eta(1 - \sigma(\hat{y}_{ui} - \hat{y}_{ui'}))(e_i - e_{i'})$ $e_u$ $i$ $e_i$

$e_u$ $e_i$ $G_{UT}$ and $G_{IT}$ TrnasRT

Top-K TransRT LFGCF

$L = L_{rec} + \mathcal{L}_T + \gamma||\Theta||_2$. $\gamma$ Adam[?] $\mathcal{L}_{rec}$ $\mathcal{L}_T$

## 3.3

NGCF LightGCN LightGCN

NGCF LFGCF Top-K

# 4

TAGCL

## 4.1

InfoNCE NCE

### 4.1.1

Contrastive Learning, CL Self-Supervised Learning SSL

**??** [171+] **??** 1 **??** 1

"1 " **??** "one dollar"

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4.1:

0.49 [width=.88]figure/Inline-Detailed.jpg

4.2:

4.3:

Encoder Noise Contrastive Estimation NCE

### 4.1.2

[171+] https://aeon.co/essays/your-brain-does-not-process-information-and-it-is-not-a-computer

4.1.2.1

language model $s$ $w$ $s = \{w_1, \cdots, w_m\}$ $w_i$ $i$ $c_i$

$$p(w_1, w_2, \cdots, w_m) = p(w_1) \times p(w_2|w_1) \times p(w_3|w_1, w_2) \times \cdots \times p(w_m|w_1, \cdots, w_m) = \prod_{i=1}^{m} p(w_i|w_1, \cdot \quad (4\text{-}1)$$

$p(w|c)$ $w$ “ $n$ ” n-gram **??** $\mathrm{p}(\mathrm{w}_1, w_2, \cdots, w_m) = \prod_{i=1}^{m} p(w_i|w_{i-n+1}, \cdots, w_{i-1})$ **??** $\mathrm{L}_{MLE} = \sum_{w_i \in s} logp_\theta(w_i|c_i)$ $\mathcal{L}_{MLE}$ $p(w|c)$ $w$ $c$ $\theta$ $\mathrm{p}_\theta(w|c) = F(w, c; \theta)$ $\theta^*$ $F$ $p(w|c)$ $F(w, c; \theta^*)$

Bengio [**?**] Neural Probabilistic Language Model NPLM $w$ $V = \{v_1, v_2, \cdots, v_|V|\}$ $(w, c)$ SoftMax $\hat{y} = [\hat{y}_{i,1}, \hat{y}_{i,2}, \cdots, \hat{y}_{i,|V|}]$ $\hat{y}_{i,j}$ $c_i$ $i$ $j$ $v_j$ $w_i$ $c_i'$ $w_i'$ SoftMax $s_{theta}(w, c)$ $w$ $c$ $w$

$$p_\theta(w|c) = \frac{exp(s_\theta)(w, c)}{\sum_{w' \in V} exp(s_\theta)(w, c)} = \frac{u_\theta(w, c)}{Z(c)} \quad (4\text{-}2)$$

$u_\theta(w, c) = exp(s_\theta)(w, c)$ $w$ $Z(c) = \sum_{w' \in V} exp(s_\theta)(w, c)$ $Z(c)$

4.1.2.2 NCE

[**?**] $\theta^*$ $c$ $\tilde{p}(w|c)$ $D = 1$ $c$ $q(w)$ $D = 0$

$k_d$ $k_n$ $p(w|c)$

$$p(D=1)=\frac{k_d}{k_d+k_n}p(D=0)=\frac{k_n}{k_d+k_n}p(w|D=1,c)=\tilde{p}(w|c)p(w|D=0,c)=q(w) \tag{4-3}$$

$k_n/k_d=k$

$$p(D=0|w,c)=\frac{k\times q(w)}{\tilde{p}(w|c)+k\times q(w)}p(D=1|w,c)=\frac{\tilde{p}(w|c)}{\tilde{p}(w|c)+k\times q(w)} \tag{4-4}$$

$Z(c)$ $z_c$ **??**

$$p_\theta(D=0|w,c)=\frac{k\times q(w)}{u_\theta(w,c)+k\times q(w)}p_\theta(D=1|w,c)=\frac{\tilde{p}(w|c)}{u_\theta(w,c)+k\times q(w)} \tag{4-5}$$

$D_t$

$$\mathcal{L}_{NCE}=\sum_{t=1}^{k_d+k_n}[D_t logp(w|D=1,c)+(1-D_t)logp(w|D=0,c)]=\sum_{t=1}^{k_d}log\frac{u_\theta(w,c)}{u_\theta(w,c)+k\times q(w)}+\sum_{t=1}^{k_n}log\frac{}{u_\theta} \tag{4-6}$$

**??**

$$J_{NCE}^c=\mathbf{E}_{w\sim p\tilde{p}(w|c)}log\frac{u_\theta(w,c)}{u_\theta(w,c)+k\times q(w)}+k\mathbf{E}_{w\sim q(w)}log\frac{k\times q(w)}{u_\theta(w,c)+k\times q(w)} \tag{4-7}$$

NCE $c$ $1:k$

1

4.1.2.3 InfoNCE

InfoNCE NCE InfoNCE NCE [**?**]

$c_i$ $w_{i+k}$ $\mathrm{I}(\mathrm{w}_{i+k};c_i)=\sum_{x,c}p(w_{i+k},c_t)log\frac{p(w_{i+k}|c_i)}{p(w_{i+k})}$

**??** $I(w_{i+k};c_i)$ $\frac{p(w_{i+k}|c_i)}{p(w_{i+k})}$ $p(w_{i+k}|c_i)$ $c_i$ $w_{i+k}$

$p(w_{i+k})$ $w_{i+k}$ **??** $c_i$ $w_{i+k}$ $\mathrm{p}(\mathrm{x}_{i+k}|c_i) = \frac{f_k(w_{i+k},c_t)}{\sum_{w_j \in X} f_k(w_j,c_t)}$ InfoNCE $\mathrm{L}_N = -\mathbf{E}_X[log\frac{f_k(w_{i+k},c_t)}{\sum_{w_j \in X} f_k(w_j,c_t)}]$ InfoNCE $c_i$ $w_{i+k}$

$$\mathcal{L}_N^{opt} = -\mathbf{E}_X log[\frac{\frac{p(w_{i+k}|c_i)}{p(w_{i+k})}}{\frac{p(w_{i+k}|c_i)}{p(w_{i+k})} + \sum_{w_j \in X_{neg}} \frac{p(w_j|c_i)}{p(w_j)}}] = \mathbf{E}_X log[1+\frac{p(w_{i+k})}{p(w_{i+k}|c_i)} \sum_{w_j \in X_{neg}} \frac{p(w_j|c_i)}{p(w_j)}] \approx -\mathbf{E} \tag{4-8}$$

InfoNCE InfoNCE InfoNCE

### 4.1.3

point-aware

pair-aware

SoftMax

SoftMax NDCG[?]

SoftMax

## 4.2

### 4.2.1

[?] 1 Collection 2 Learning 3 Serving

[?] bias in user selection bias exposure

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4.4:

0.49 [width=.88]figure/rs-bias.drawio.pdf

4.5:

4.6:

bias conformity bias position bias bias in data : popularity bias unfairness bias in model inductive bias bias amplification in loop

1 Missing Not at Random MNAR

2

3

4

5

6

7

8

### 4.2.2

[?] 1

2

3 – ” ”

## 4.3 TAGCL

TAGCL

### 4.3.1

TAGCL LFGCF - - ?? - -

[width=.66]figure/tagcl.drawio.pdf

4.7: TAGCL

$d$ embedding $e_u$ $e_i$ LFGCF TAGCL

- - $e_{t(u)}$ $(e_{t(i)})$ - -

### 4.3.2

[?, ?, ?, ?]

Wang [?] SGL

Yu [?] SimGCL SimGCL SimGCL

TAGCL TAGCL

$u$

$$e'_u = e_u + \epsilon\delta'_u \quad e''_u = e_u + \epsilon\delta''_u \tag{4-9}$$

$\delta'/\delta''$ $\epsilon$ SoftMax

## 4.3.3

TAGCL BPR BPR

$$\mathcal{L}_{rec} = -\sum_{u\in\mathcal{U}}\sum_{i\in\mathcal{N}_u}\sum_{i'\notin\mathcal{N}_u} ln\sigma(\hat{y}_{ui} - \hat{y}_{ui'}) + \lambda||\Theta||^2 \quad (4\text{-}10)$$

$\lambda$ $L_2$

4.3.3.1

SoftMax $\tau$

InfoNCE [**?**] -

$$\mathcal{L}_{cl}^{user} = \sum_{u\in\mathcal{U}} -ln\frac{exp(e_u^{\prime T} e_u^{\prime\prime}/\tau)}{\sum_{v\in\mathcal{U}} exp(e_u^{\prime T} e_v^{\prime\prime}/\tau)} \quad u \neq v \mathcal{L}_{cl}^{tag(u)} = \sum_{t\in\mathcal{T}} -ln\frac{exp(e_{t(u)}^{\prime T} e_{t(u)}^{\prime\prime}/\tau)}{\sum_{s\in\mathcal{T}} exp(e_{t(u)}^{\prime T} e_{s(u)}^{\prime\prime}/\tau)} \quad t \neq s \mathcal{L}_{cl}^{\mathcal{G}_{UT}} = \mathcal{L}_{c}^{u} \quad (4\text{-}11)$$

$\tau$ SoftMax - $\mathcal{L}_{cl}^{\mathcal{G}_{IT}}$ TAGCL

$$\mathcal{L}_{cl} = \mathcal{L}_{cl}^{\mathcal{G}_{UT}} + \mathcal{L}_{cl}^{\mathcal{G}_{IT}} \quad (4\text{-}12)$$

4.3.3.2

TransT $< u, t, i >\in \mathcal{A}$

TAGCL $\mathcal{D}$ $(u, t, t', i, i')$

$$\mathcal{D} = \{(u, t, t', i, i')|(u, t, i) \in \mathcal{A} \cap (u, t', i) \notin \mathcal{A} \cap (u, t, i') \notin \mathcal{A}\} \quad (4\text{-}13)$$

$(u, t, t', i, i')$

$$\mathcal{L}_{nt} = -\sum_{(u,t,t',i,i')\in\mathcal{D}} ln[\sigma(e_{t(i)}^T e_i - e_{t'(i')}^T e_{i'})] \quad (4\text{-}14)$$

$\sigma$ -

TransT - $\mathcal{G}_{IT}$ $e_{t(i)}$ -

$mathcalG_{IT}$ TransTag[?] LFGCF TransRT $\mathcal{G}_{UT}$ $\mathcal{G}_{IT}$

$e_{t(u)} - e_{t(i)}$ $(u, t, i) \in \mathcal{A}$ $i$ $e_i$ $e_u + e_{t(u)} - e_{t(i)}$

$i$ $e_u$ $e_i$ $e_u$ $e_i$ $e_t$

$e_{t(u)} - e_{t(i)}$ $e_t$ TransT

$$\mathcal{L}_T = \sum_{(u,t,i)\in\mathcal{A}} ||e_u + (e_{t(u)} - e_{t(i)}) - e_i||_2 \tag{4-15}$$

## 4.3.4

BPR TransT TAGCL

$$\mathcal{L} = \mathcal{L}_{rec} + \alpha\mathcal{L}_{cl} + \beta\mathcal{L}_{nt} + \gamma\mathcal{L}_T \tag{4-16}$$

$\alpha$, $\beta$ $\gamma$ TAGCL 0 $\Theta = \{e_u^{(0)}, e_{t(u)}^{(0)}, e_{t(i)}^{(0)}, e_i^{(0)}\}$

Adam

## 4.4

NCE InfoNCE

NCE InfoNCE TAGCL TAGCL

TransE TransT

# 5

LFGCF

TAGCL TAGCL

## 5.1

MovieLens Last.FM Delicious HetRec2011[?]

LFGCF TAGCL BibSonomy

1 **MovieLens** MovieLens[171+] Movie-

Lens ID ID ID

2 **Last.fm** Last.fm[171+]

MovieLens ID ID ID

3 **Delicious** Del.icio.us[171+]

ID ID ID

4 **BibSonomy** BibSonomy[171+] SQL

BibSonomy-BM BibSonomy-BT BibSonomy-BM

ID ID ID BibSonomy-BT ID ID ID

[?] Last.Fm 5 Delicious 15

BibSonomy 15 **??**

**??** Last.FM MovieLens Delicious

[171+]https://movielens.org/

[171+]https://www.last.fm/

[171+]https://del.icio.us/

[171+]https://www.bibsonomy.org/

5.1:

| | | | | | (%) |
|---|---|---|---|---|---|
| Last.FM | 1808 | 12212 | 2305 | 175641 | 99.20% |
| MovieLens | 1651 | 5381 | 1586 | 36728 | 99.59% |
| Delicious | 1843 | 65877 | 3508 | 330744 | 99.73% |
| BibSonomy-BM | 5996 | 576232 | 8092 | 1622320 | 99.95% |
| BibSonomy-BT | 9721 | 750514 | 9721 | 1972556 | 99.97% |

## 5.2

### 5.2.1

2 8 E5-2620V4 2.0GHz DDR4 ECC REG 128G 2400MHz 1 256G SATA SSD 4TB 2 GPU NVIDIA TITAN Xp Pascal Dacrema [?] PyTorch RecBole[?] 1.0.1 RecBole RecBole

1 HetRec2011

2 ID

3 6:2:2

4 RecBole LFGCF TGCN

5

6

7

5.2.1.1

Recall@K Precision@K [?] Normalized Discounted Cumulative Gain NDCG@K [?] Mean Reciprocal Rank MRR@K [?] —— Average Recommendation Popularity ARP@K [?] Top-K

Confusion Matrix

True Positive TP False Negative FN False Positive FP True Negative TN Accuracy Sensitivity **??**

5.2:

| 2* | | |
|---|---|---|
| | TP | FN |
| | FP | TN |

$$R = \frac{TP}{TP + FN}, P = \frac{TP}{TP + FP} \tag{5-1}$$

$$Recall@K = \frac{|R^N(u) \bigcap T(u)|}{|T(u)|} \tag{5-2}$$

$T(u)$ $R^N(u)$ $Recall@N$ $K$

$$Precision@K = \frac{|R^N(u) \bigcap T(u)|}{N} \tag{5-3}$$

$N$ $R^N(u)$ $Precision@N$ $K$

NDCG

$$nDCG@K = \frac{1}{\mathcal{U}} \sum_{u \in \mathcal{U}} \frac{\sum_{n=1}^{N} \frac{I(R_n^N(u) \in T(u))}{log(n+1)}}{\sum_{n=1}^{N} \frac{1}{log(n+1)}} \tag{5-4}$$

$R_n^N(u)$ Top-K $n^{th}$ $R^N(u)$ $NDCG@N$ $K$

$$MRR@K = \frac{1}{\mathcal{U}} \sum_{u \in \mathcal{U}} \frac{1}{rank_u^*} \tag{5-5}$$

$rank_u^*$

$$AveragePopularity@K = \frac{1}{|U|} \sum_{u \in U} \frac{\sum_{i \in R_u} \phi(i)}{|R_u|} \tag{5-6}$$

$\phi(i)$ $i$

### 5.2.2

LightGCN[**?**]

SimGCL[**?**] BPR-T[**?**] TGCN[**?**]

1 **LightGCN**

2 **SimGCL** LightGCN

3 **BPR-T** BPR BPR-T

4 **TGCN**

# 5.3

LFGCF TAGCL MovieLensLast.FM Delicious LFGCF TAGCL

## 5.3.1

Minibatch Adam [?] BatchSize 2048 500 [?] {0.0005 0.001 0.005 0.01} {1e-5 1e-4 1e-3 1e-2} 64 Xavier [?] 20

## 5.3.2

**?? ?? ??** imp. LFGCF TAGCL LFGCF TGCN LFGCF TAGCL Last.FM MovieLens Delicious TAGCL

SimGCL LightGCN SimGCL LightGCN TGCN TGCN BPR-T

### 5.3.2.1 MovieLens

**??** MovieLens MovieLens LightGCN SimGCL BPR-T TGCN LFGCF TAGCL TAGCL TAGCL Pre. 0.0405 NDCG TAGCL 0.2338 MRR TAGCL 0.2356 Rec. ARP TAGCL LFGCF Rec. ARP Prec. SimGCL Prec. NDCG MRR

BPR-T LightGCN TGCN

5.3: MovieLens

| 2* | | | | | 2***LFGCF** | 2***TAGCL** | 2***im** |
|---|---|---|---|---|---|---|---|
| | **LightGCN** | **SimGCL** | **BPR-T** | **TGCN** | | | |
| Rec. | 0.2788 | 0.2835 | 0.2826 | 0.2812 | <u>0.2929</u> | **0.3180** | |
| Pre. | 0.0349 | <u>0.0383</u> | 0.0365 | 0.0372 | 0.0365 | **0.0405** | |
| NDCG | 0.2015 | <u>0.2274</u> | 0.2209 | 0.2187 | 0.2140 | **0.2338** | |
| MRR | 0.2101 | **0.2383** | 0.2273 | 0.2218 | 0.2183 | <u>0.2356</u> | - |
| ARP | 26.78 | 18.15 | 22.76 | 25.25 | <u>18.10</u> | **14.96** | 1 |

5.3.2.2 Last.FM

**??** Last.FM TAGCL Rec. Pre. NDCG MRR ARP 0.5199 0.1611 0.4949 0.5541 42.99 SimGCL Pre. NDCG MRR ARP TAGCL 0.5055 LFGCF NDCG SimGCL SimGCL BPR-T TGCN BPR-T NDCG TGCN TGCN

5.4: Last.FM

| 2* | | | | | 2***LFGCF** | 2***TAGCL** | 2***im** |
|---|---|---|---|---|---|---|---|
| | **LightGCN** | **SimGCL** | **BPR-T** | **TGCN** | | | |
| Rec. | 0.4835 | 0.5055 | 0.4714 | 0.4736 | <u>0.5057</u> | **0.5199** | |
| Pre. | 0.1375 | <u>0.1534</u> | 0.1363 | 0.1332 | 0.1465 | **0.1611** | |
| NDCG | 0.4087 | <u>0.4680</u> | 0.4321 | 0.4225 | 0.4482 | **0.4949** | |
| MRR | 0.4664 | <u>0.5263</u> | 0.5083 | 0.4874 | 0.5033 | **0.5541** | |
| ARP | 111.99 | <u>51.67</u> | 103.74 | 78.88 | 80.65 | **42.99** | 1 |

5.3.2.3 Delicious

?? Delicious LightGCN SimGCL NDCG MRR LightGCN BPR-T TGCN Rec. Pre. TGCN BPR-T LFGCF TAGCL TAGCL LFGCF TAGCL Delicious

5.5: Delicious

| 2* | | | | | 2***LFGCF** | 2***TAGCL** | 2***imp. SOT** |
|---|---|---|---|---|---|---|---|
| | **LightGCN** | **SimGCL** | **BPR-T** | **TGCN** | | | |
| Rec. | 0.3337 | <u>0.3351</u> | 0.3150 | 0.3284 | 0.3300 | **0.3432** | 2.42% |
| Pre. | 0.3525 | <u>0.3554</u> | 0.3409 | 0.3519 | 0.3498 | **0.3705** | 4.25% |
| NDCG | <u>0.4213</u> | 0.4177 | 0.3984 | 0.4160 | 0.4080 | **0.4385** | 4.08% |
| MRR | <u>0.5786</u> | 0.5529 | 0.5373 | 0.5589 | 0.5395 | **0.5828** | 0.73% |
| ARP | **3.11** | <u>4.67</u> | 6.32 | 6.21 | 4.69 | 5.61 | -80.39% |

## 5.3.3 LFGCF

Last.FM Delicious LFGCF ?? LFGCF LFGCF-L LFGCF-T TransRT

5.3.3.1

LFGCF LFGCF NGCF LFGCF-L ?? Last.FM LFGCF-L Recall@10 Recall@20 0.4208 0.4958 ?? Delicious LFGCF Delicious Recall@10 Recall@20 0.1615 0.2838 Delicious LFGCF

| [t]0.49 | **Recall@10** | **Recall@20** |
|---|---|---|
| LFGCF-L | 0.4208 | 0.4958 |
| LFGCF-T | 0.4336 | 0.5027 |
| LFGCF | 0.4362 | 0.5132 |

5.6: Last.FM LFGCF

| [t]0.49 | **Recall@10** | **Recall@20** |
|---|---|---|
| LFGCF-L | 0.1615 | 0.2838 |
| LFGCF-T | 0.1903 | 0.3270 |
| LFGCF | 0.1955 | 0.3286 |

5.7: Delicious LFGCF

5.8: LFGCF

5.3.3.2 TransRT

LFGCF TransRT LFGCF

TransRT LFGCF LFGCF-T **??** Last.FM LFGCF

Recall@10 Recall@20 0.4362 0.5132 **??** Delicious LFGCF

LFGCF-T TransRT LFGCF LFGCF-T

LFGCF TransRT LFGCF LFGCF LFGCF-T

LFGCF

### 5.3.4 TAGCL

Last.FM Delicious TAGCL **??** TAGCL

TAGCL-A LFGCF-T TAGCL-CL TAGCL-NT

TAGCL-T TransT

Last.FM **??** TAGCL-NT Rec.@20 0.5212 ARP.@20

[t]0.49

| | **Rec.@20** | **ARP.@20** |
|---|---|---|
| TAGCL-A | 0.4502 | 92.05 |
| TAGCL-CL | 0.4141 | 89.42 |
| TAGCL-NT | **0.5212** | 43.92 |
| TAGCL-T | 0.5193 | 52.17 |
| TAGCL | 0.5199 | **42.99** |

5.9: Last.FM TAGCL

[t]0.49

| | **Rec.@20** | **ARP.@20** |
|---|---|---|
| TAGCL-A | 0.3188 | 5.33 |
| TAGCL-CL | 0.3301 | **5.24** |
| TAGCL-NT | 0.3425 | 5.48 |
| TAGCL-T | 0.3396 | 5.58 |
| TAGCL | **0.3432** | 5.61 |

5.10: Delicious TAGCL

5.11: TAGCL

TAGCL 42.99 TAGCL 20 TAGCL-CL TAGCL TAGCL-NT

Delicious **??** TAGCL Rec.@20 0.3432 ARP.@20 TAGCL-CL 5.24 TAGCL TAGCL Rec.@20 ARP.@20

5.3.4.1

TAGCL

InfoNCE TAGCL InfoNCE TAGCL TAGCL-CL TAGCL-CL TAGCL TAGCL TAGCL-CL

?? TAGCL TAGCL-A TAGCL

TAGCL TAGCL

5.3.4.2

-

TAGCL-NT TAGCL-NT TAGCL TAGCL-CL TAGCL-A

TAGCL Delicious 85

67

TransT TransT TransT

TAGCL-T TransT TAGCL TAGCL

5.3.4.3

TAGCL Last.FM Delicious GNN

TAGCL ??

?? TAGCL Last.FM Delicious GNN

TAGCL GNN Last.FM Delicious Recall@20

ARP@20 TAGCL

0.49 [width=.88]figure/tagcl$_{p}aram_{l}astfm_{l}ayer.pdf$

5.1: Last.FM TAGCL

0.49 [width=.88]figure/tagcl$_{p}aram_{d}e_{l}ayer.pdf$

5.2: Delicious TAGCL

5.3: TAGCL

TAGCL ?? Last.FM ?? TAGCL

Delicious ?? TAGCL TAGCL

0.49 [width=.88]figure/tagcl$_{p}aram_{l}astfm_{e}mb.pdf$

5.4: Last.FM TAGCL

0.49 [width=.88]figure/tagcl$_{p}aram_{d}e_{e}mb.pdf$

5.5: Delicious TAGCL

5.6: TAGCL

Delicious 64 TAGCL

5.3.4.4

TAGCL Last.FM Delicious TAGCL

$K$ TAGCL Recall NDCG $K$ NDCG

TAGCL 5% TAGCL $K$ Delicious

TAGCL $K$ TAGCL

### 5.3.5

LFGCF **??** LFGCF

LFGCF LFGCF $0.22 \times 10^6$

**??** $0.15s$ Delicious TGCN

[width=1]figure/topk$_{c}omparison.pdf$

5.7: TAGCL

### 5.3.6

TAGCL BibSonomy [**?**]

BibTeX 15 BibSonomy-BM BibSonomy-BT

BibSonomy BibTeX BibSonomy-BM 1622320 5996 8092

576232 BibSonomy-BT 1972556 9721 11313 750514

99.95% 99.97% BibSonomy LightGCN

?? TAGCL LightGCN TAGCL

BibSonomy TAGCL 1% 2% Delicious TAGCL

BibSonomy Delicious

5.12: Delicious

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2* (×10^6) | 2*[c] | | | | | | | |
| | | | | | | LightGCN | ~4.33 | -5.18% |
| | | | | | | NGCF | ~4.36 | -4.58% |
| 2*[c] | (%) | 2*[c] | (s) | 2*[c] | (%) | LFGCF | ~4.55 | [c]- |
| | | | | | | GNN-PTR | ~4.57 | +0.18% |
| | | | | | | TGCN | ~5.01 | +9.15% |
| | | | | ~0.14 | +5.13% | | | |
| | | | | ~0.15 | +13.91% | | | |
| | | | | ~0.13 | [c]- | | | |
| | | | | ~0.17 | +16.33% | | | |
| | | | | ~2.12 | +93.81% | | | |

## 5.4

LFGCF TAGCL

MovieLens Last.FM Delicious TAGCL 4.6% 5.0%

NDCG 4.21% MRR 1.62% TAGCL 5.18% 8.0%

NDCG 7.22% MRR 5.64% MovieLens Last.FM 17% BibSonomy TAGCL TAGCL LightGCN 1%

# 6

## 6.1

Top-K

1 2

3

LFGCF TAGCL LFGCF

TAGCL

1

2 LFGCF

3 TAGCL

4 LFGCF TAGCL

LFGCF TAGCL

## 6.2

1 hypergraph

2 over-fitting gradient vanishing

over-smoothing

3

4

post

[title= ]

1. “ ” 2017C03058

1. Pursuit and evasion strategy of a differential game based on deep reinforcement learning. Frontiers in Bioengineering and Biotechnology, 2022, 10: 827408.

2. A fairness-aware graph contrastive learning recommender framework for social tagging systems. Information Sciences 2023: 119064.

1. 202110178862.3

2. 202210119309.7

1. ——“ ”

2.

“ ”

“ ”

“ ”

X c X : :

/ /

“ ”

X c X : :