

# Cross-domain Collaboration Recommendation

Abstract: This paper proposes a cross-domain collaboration recommendation method based on matrix factorization. The method is designed to handle the problem of recommending items in a target domain based on user ratings in a source domain. The proposed method is evaluated on two real-world datasets, and the results show that it outperforms existing methods in terms of recommendation accuracy and diversity.

## ABSTRACT

In this paper, we propose a cross-domain collaboration recommendation method based on matrix factorization. The method is designed to handle the problem of recommending items in a target domain based on user ratings in a source domain. The proposed method is evaluated on two real-world datasets, and the results show that it outperforms existing methods in terms of recommendation accuracy and diversity.

Contributions: The proposed method has three main contributions: 1) **sparse connection:** The proposed method uses a sparse matrix factorization technique to reduce the number of parameters to be estimated. 2) **complementary expertise:** The proposed method leverages the complementary expertise of users in different domains to improve recommendation accuracy. 3) **topic skewness:** The proposed method handles the topic skewness problem by using a topic-based matrix factorization technique.

Organization: The paper is organized as follows. Section 2 describes the problem definition and related work. Section 3 describes the proposed method. Section 4 describes the experimental setup and results. Section 5 concludes the paper.

Index Terms: Cross-domain collaboration recommendation, matrix factorization, sparse connection, complementary expertise, topic skewness.

Introduction: In this paper, we propose a cross-domain collaboration recommendation method based on matrix factorization. The method is designed to handle the problem of recommending items in a target domain based on user ratings in a source domain. The proposed method is evaluated on two real-world datasets, and the results show that it outperforms existing methods in terms of recommendation accuracy and diversity.

Method: The proposed method is based on matrix factorization. The method is designed to handle the problem of recommending items in a target domain based on user ratings in a source domain. The proposed method is evaluated on two real-world datasets, and the results show that it outperforms existing methods in terms of recommendation accuracy and diversity.

Conclusion: In this paper, we propose a cross-domain collaboration recommendation method based on matrix factorization. The method is designed to handle the problem of recommending items in a target domain based on user ratings in a source domain. The proposed method is evaluated on two real-world datasets, and the results show that it outperforms existing methods in terms of recommendation accuracy and diversity.

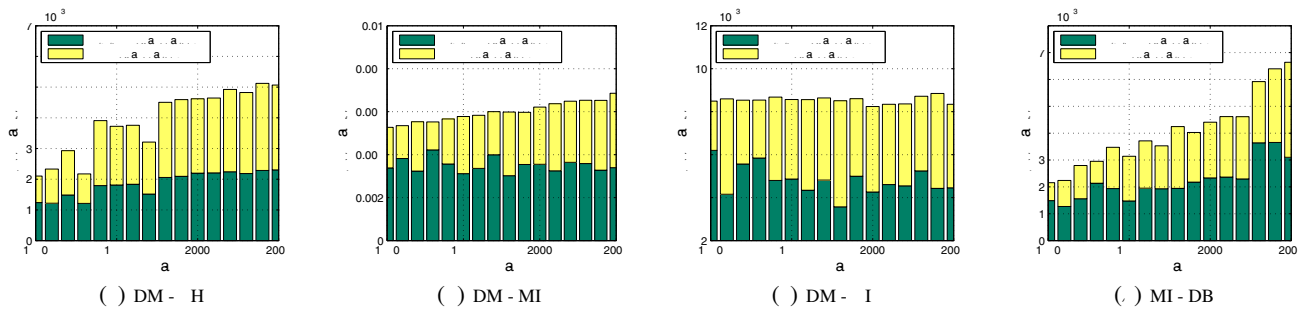


Figure 1: The comparison of existing collaboration and new collaboration trends over years. DM - Data Mining domain; MI - Medical Informatics domain; TH - Theory domain; VIS - Visualization domain; DB - Database domain. The trends of cross-domain collaborations in all but one case are growing (The exception between DM and VIS remain roughly constant over time). Newly formed cross-domain collaborations are significantly in all cases.

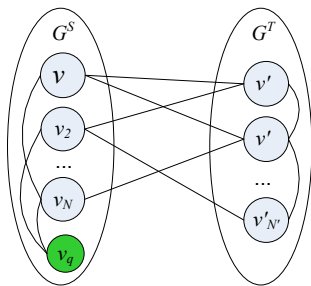
D. I. F. 1. B. C. C L. C L. B. C L. F. C L. C L. 2. 3. 4. 5. 6.

## 2. PROBLEM DEFINITION

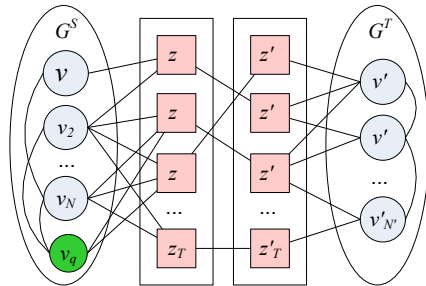
$\forall E$ .  $\forall E$ . D. 1. Source/Target domain.  $\mathcal{AG} = (V, E, X)$ ,  $V$ ,  $|V| = N$ ,  $E \subseteq V \times V$ ,  $X$ ,  $N \times d$ .  $\forall E$ ,  $x_j$ ,  $j^{th}$ .  $\forall E$ ,  $S$ ,  $T$ . I.  $S$ .  $v_i$ ,  $d$ . F.

G. 2. Domain-specific topic models. A.  $\{P(x_j | i)\}_{j,i}$ .  $P(x | i)$ . LDA/ LI. 4, 15. A. F. D. M.  $G^S$ ,  $G^T$ .  $V^S \cap V^T \neq \emptyset$ . G. P. b. 1. Cross-domain collaboration recommendation. G. (1)  $G^S$ ,  $G^T$ , (2).  $V_q$ .

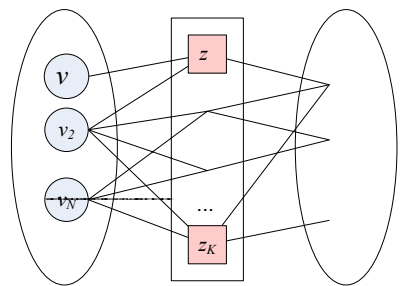
$\forall E$ .  $\forall E$ . H. I.  $w$ ,  $c$ . 3. CROSS-DOMAIN TOPIC LEARNING. A. 28.



(A) Bipartite graph



(B) Bipartite graph with intermediate nodes



(C) Bipartite graph with a single intermediate node

```

Input:  $G^S, G^T$ 
Output:  $\theta, \theta', \phi, \vartheta, \lambda$ 
Algorithm 1:
foreach  $c \in \{ab, add, c, d\}$  do
  foreach  $w \in d$   $d_i \in d$  do
     $be_{di} \sim \text{ll}(d_i) \sim \text{be}_a(\gamma_t, \gamma)$ 
    if  $d_i = 0$  then
       $D \sim \text{ll}(\vartheta_{vv'})$ 
    end if
    if  $d_i = 1$  then
       $D \sim \text{ll}(\theta_v)$ 
    end if
  end foreach
end foreach
   $D \sim \text{ll}(\phi_{z_{d_i}})$ 

```

Algorithm 1: C L.

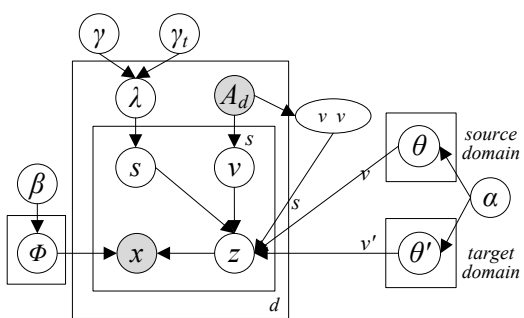


Figure 3: Graphical representation of CTL model.

$P(z|v)$  AC

E. 1

### 3.3 Cross-domain Topic Learning (CTL)

A

( )

C

(C L)

#### Model description.

F

B

F, 3

**Table 1: Notations in the CTL model.**

MB L	DE C I I
$T$	
$d$	
$A_d$	$d$
$d_i$	$( )$
$d_i$	$d_i$
$d_i$	$d_i$
$\theta_v$	
$\vartheta_{vv'}$	$( , ')$
$\phi_z$	
$\alpha, \beta$	D $\theta, \theta', \phi$
$\lambda$	
$\gamma, \gamma_t$	B $\lambda$

C L (F

C L

$I$   $A_d$

$d; v$   $(v, V)$

$x; s$

$(s = 1)$   $s = 0;$

$(v, V); D$   $S; B$

1  $C L$

F  $G^S, G^T$   $A, 1;$

C L

$p(v| )$   $p(v'| )$

D F

$p(s|d) \sim \text{beta}(t, )$   $\text{beta}(\cdot)$   $E$

$s = 1, v(V)$

$Z_{d_i} \sim v, v(V)$   $s = 0,$

$(v, V)$   $v, v'$

$( )$   $M$   $F$

10  $5$

$5$   $(10$

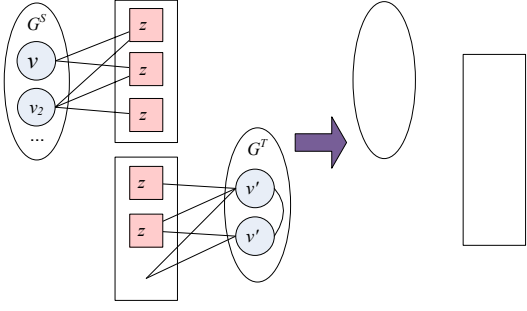
$v = \langle v, 0, \dots, 0 \rangle$   $0$

$v' = \langle 0, \dots, 0, v' \rangle$   $v, v'$

$v + v', v' S, F$   $X_{d_i}$

$Z_{d_i}$   $v, v'$

F, 4  $C L$   $B$   $C L$



1,932,442 (1990-2005)

- **Data Mining:** KDD, DM, ICDM, E DM, KDD, 6,282, 22,862
- **Medical Informatics:** J, A, M, I, A, J, B, I, A, I, M, IEEE, M, I, IEEE, I, B, 9,150, 31,851
- **Theory:** C, F, C, DA, 5,449, 27,712
- **Visualization:**

**Table 2: Recommendation performance by different methods on the four cross-domain test cases (%). Content– Content Similarity; CF– Collaborative Filtering; Author– Author Matching; Topic– Topic Matching.**

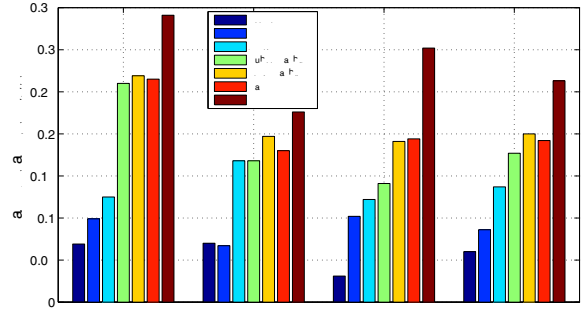
Cross domain	ALG	P@10	P@20	MAP	R@100	ARHR -10	ARHR -20
D M <sub>1</sub> → ( )	C	10.3	10.2	10.9	31.4	4.9	2.1
	CF	15.6	13.3	23.1	26.2	4.9	2.8
	H	17.4	19.1	20.0	29.5	5.0	2.4
	A	27.2	22.3	25.7	32.4	10.1	6.4
		28.0	26.0	32.4	33.5	13.4	7.1
	K	30.4	29.8	31.6	27.4	11.2	5.9
	C L	<b>37.7</b>	<b>36.4</b>	<b>40.6</b>	<b>35.6</b>	<b>14.3</b>	<b>7.5</b>
M <sub>2</sub> I <sub>1</sub> → ( )	C	10.1	10.9	12.5	45.9	3.6	2.1
	CF	18.3	20.2	21.4	47.6	5.3	3.9
	H	25.0	26.5	28.4	59.1	6.4	4.2
	A	26.2	29.6	32.2	54.8	10.5	<b>5.4</b>
		29.4	26.3	34.7	59.3	<b>11.5</b>	5.2
	K	27.5	28.3	30.7	57.2	10.5	5.0
	C L	<b>32.5</b>	<b>30.0</b>	<b>36.9</b>	<b>59.8</b>	11.4	<b>5.4</b>
D M <sub>2</sub> → ( )	C	5.8	5.7	9.5	19.8	1.9	0.9
	CF	13.7	17.8	18.9	34.3	2.7	1.3
	H	18.0	19.0	19.8	36.7	3.4	1.3
	A	20.1	23.8	29.3	<b>64.4</b>	5.3	2.1
		26.0	<b>25.0</b>	33.9	48.1	10.7	5.6
	K	21.2	23.8	32.4	48.1	10.2	4.8
	C L	<b>30.0</b>	24.0	<b>35.6</b>	49.6	<b>12.2</b>	<b>6.0</b>
D M <sub>1</sub> → ( )	C	9.6	11.8	13.2	18.9	3.1	1.8
	CF	14.0	20.8	26.4	29.4	6.9	4.3
	H	16.0	20.0	27.6	30.1	6.3	4.4
	A	22.0	25.2	27.7	31.1	11.9	6.7
		26.3	25.0	32.3	31.4	13.2	8.8
	K	23.0	25.1	29.3	30.2	10.4	5.4
	C L	<b>28.3</b>	<b>26.0</b>	<b>32.8</b>	<b>36.3</b>	<b>14.0</b>	<b>9.1</b>

( $< 80$ ), ... C L

**Hyperparameter analysis.** ... C L ...  $F_{10}$  5( ) ... C L ...  $T = 120$  ... 0.03 ... C L

**Restart parameter analysis.** ... C L ...  $F_{10}$  5( ) ... C L ... I ... B ...

**Convergence analysis.** ... C L ...  $F_{10}$  5( ) ... -D M ... 10 ... C L



**Figure 6: Performance on new collaboration prediction of all algorithms.**

( ... 5 ... ). ... C L ...

**New Collaboration Prediction** ... I ... C ... 2001 ... 2001-2005 ... Figure 6 ... 2. I ... C L ... 0.3 ... MA

**4.3 Prototype System**

... C L ... 5 ... ( ... 1,932,442 ... ) A ... C L ... A ... 1 ... ( ... ) ... (C ... 3.3) ... C L ...

**5. RELATED WORK**

C ... C ... 7 ... C ... K ... 17 ...





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**8. APPENDIX**

A ... (B ... ) ... 10 4075(10 . 0 / (-)-256( ... )-255 / 1 01 1 2115. \_ 7,-)145() J/ 1 41 0 -1.1660.0001 (I ) / 1 11