

Cross-domain Collaboration Recommendation

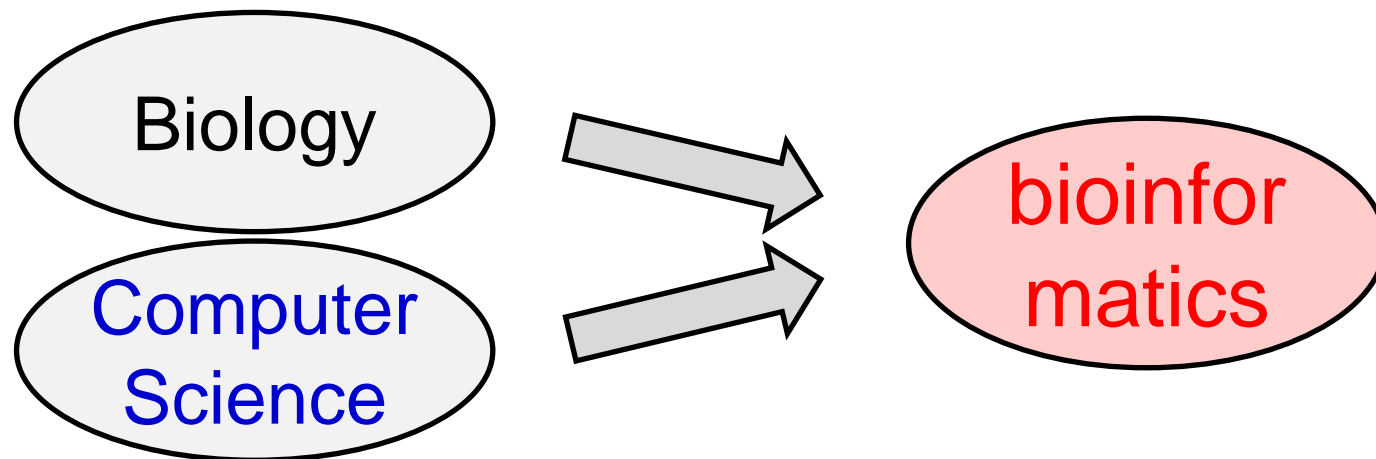
Jie Tang¹, Sen Wu¹, Jimeng Sun², Hang Su¹

¹Tsinghua University

²IBM TJ Watson Research Center

Cross-domain Collaboration

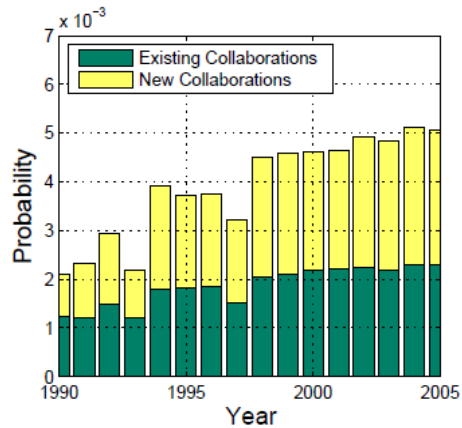
- Interdisciplinary collaborations have generated huge impact, for example,
 - 51 (>1/3) of the KDD 2012 papers are result of cross-domain collaborations between graph theory, visualization, economics, medical inf., DB, NLP, IR
 - Research field evolution



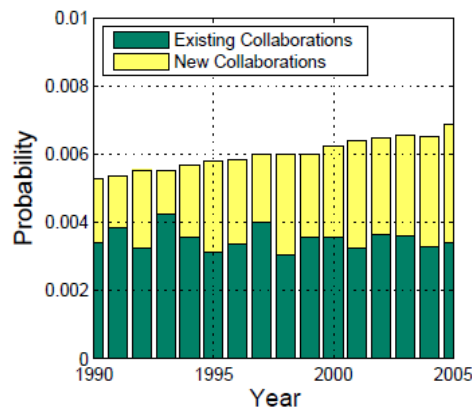
Cross-domain Collaboration (cont.)



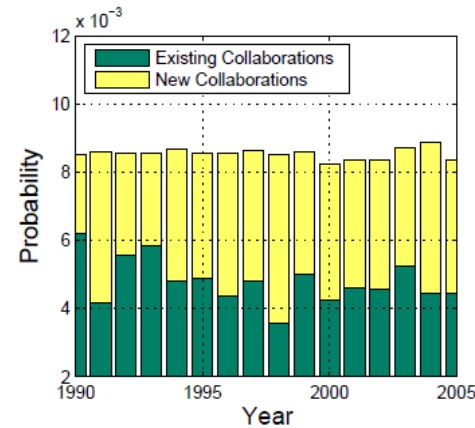
- Increasing trend of cross-domain collaborations



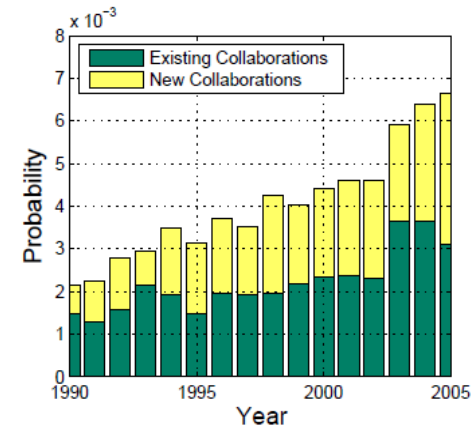
(a) DM - TH



(b) DM - MI



(c) DM - VIS



(d) MI - DB

Data Mining(DM), Medical Informatics(MI), Theory(TH), Visualization(VIS)

Challenges





Related Work-Collaboration recommendation

- Collaborative topic modeling for recommending papers
 - C. Wang and D.M. Blei. [2011]
- On social networks and collaborative recommendation
 - I. Konstas, V. Stathopoulos, and J. M. Jose. [2009]
- CollabSeer: a search engine for collaboration discovery
 - H.-H. Chen, L. Gou, X. Zhang, and C. L. Giles. [2007]
- Referral web: Combining social networks and collaborative filtering
 - H. Kautz, B. Selman, and M. Shah. [1997]
- Fab: content-based, collaborative recommendation
 - M. Balabanovi and Y. Shoham. [1997]



Related Work-Expert finding and matching

- Topic level expertise search over heterogeneous networks
 - J. Tang, J. Zhang, R. Jin, Z. Yang, K. Cai, L. Zhang, and Z. Su. [2011]
- Formal models for expert finding in enterprise corpora
 - K. Balog, L. Azzopardi, and M.de Rijke. [2006]
- Expertise modeling for matching papers with reviewers
 - D. Mimno and A. McCallum. [2007]
- On optimization of expertise matching with various constraints
 - W. Tang, J. Tang, T. Lei, C. Tan, B. Gao, and T. Li. [2012]

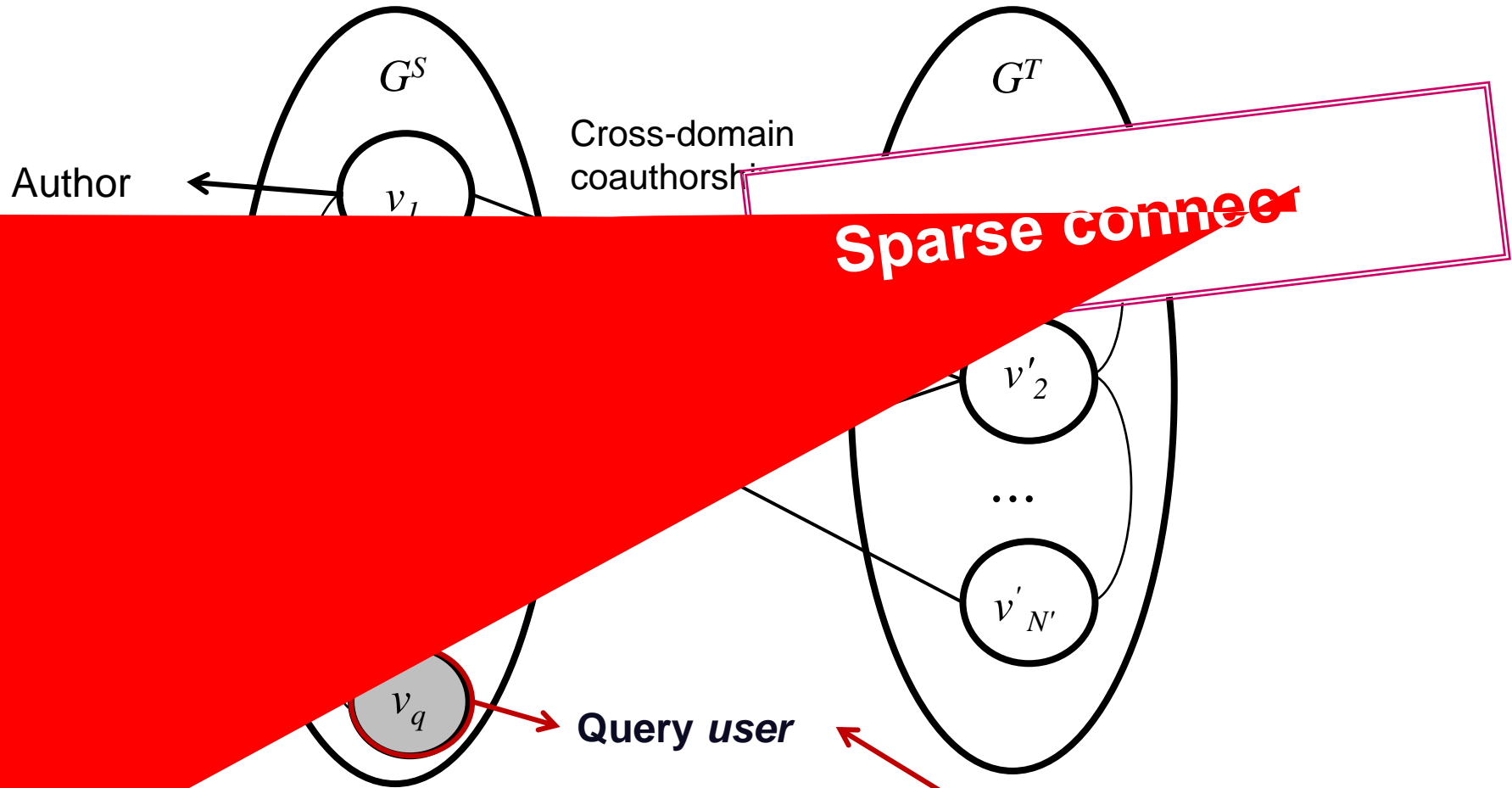
Approach Framework

—Cross-domain Topic Learning

Author Matching

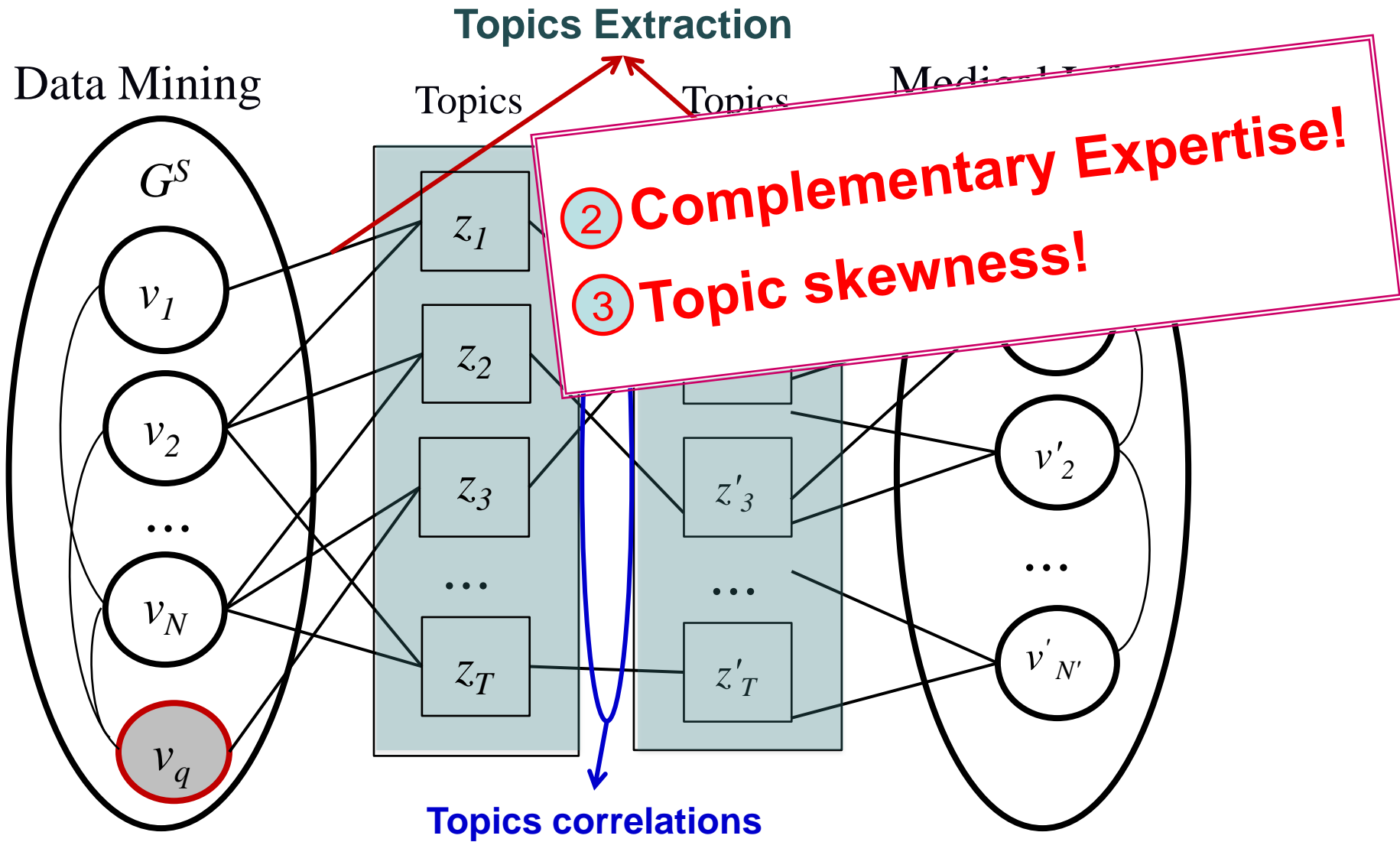
Data Mining

Medical Informatics

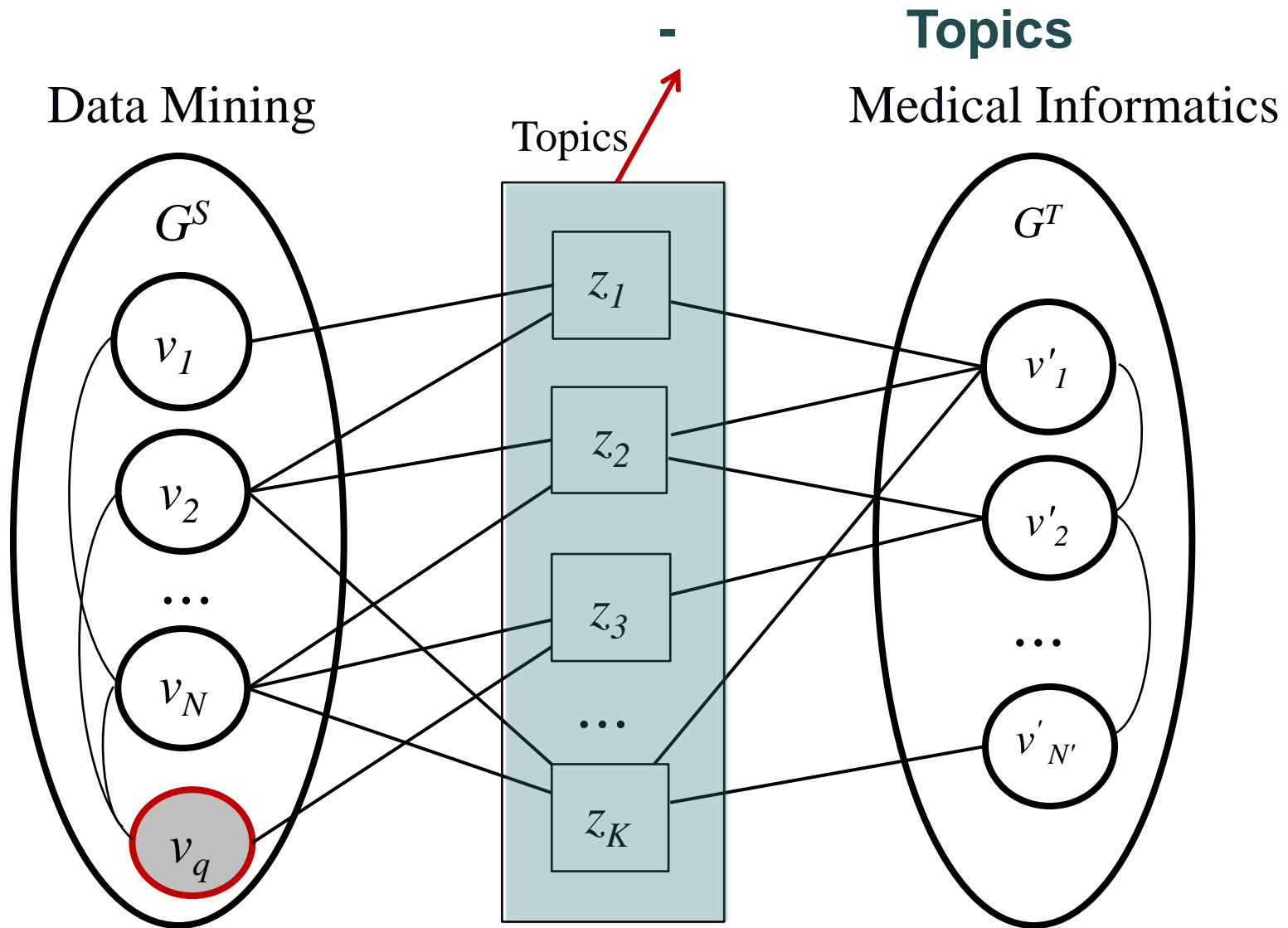


$$\mathbf{r}^{(t+1)} = (1 - \tau)\mathbf{S} \cdot \mathbf{r}^{(t)} + \tau \mathbf{a}$$

Topic Matching



Cross-domain Topic Learning



Collaboration Topics Extraction



Step 1:

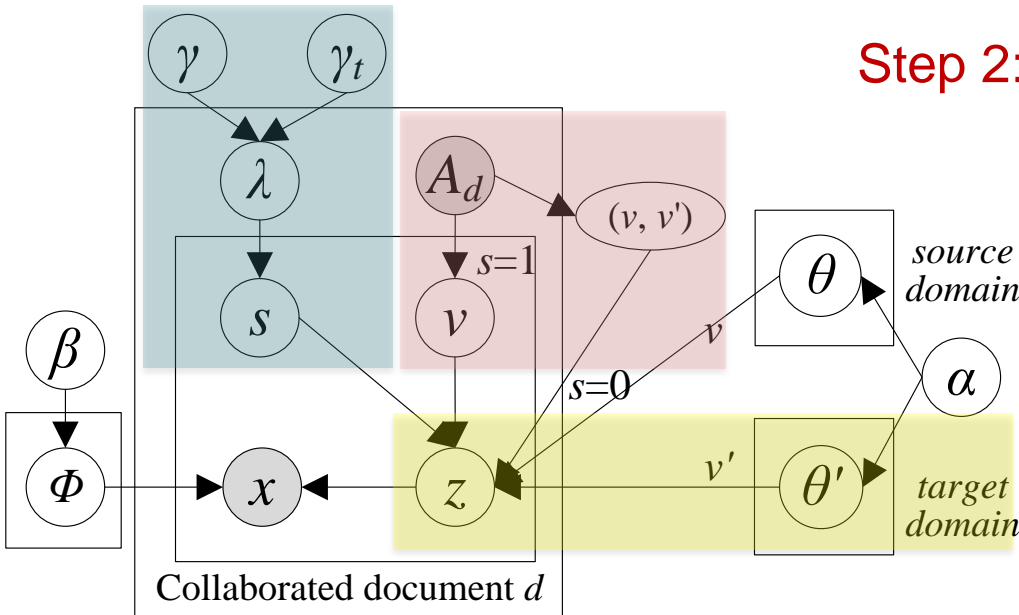
Input: a source domain G^S and a target domain G^T
Output: estimated parameters $\theta, \theta', \phi, \vartheta$, and λ

Initialize an ACT model in G^S by learning from documents written by authors only from G^S ;
 Similarly, initialize an ACT model for target domain G^T ;

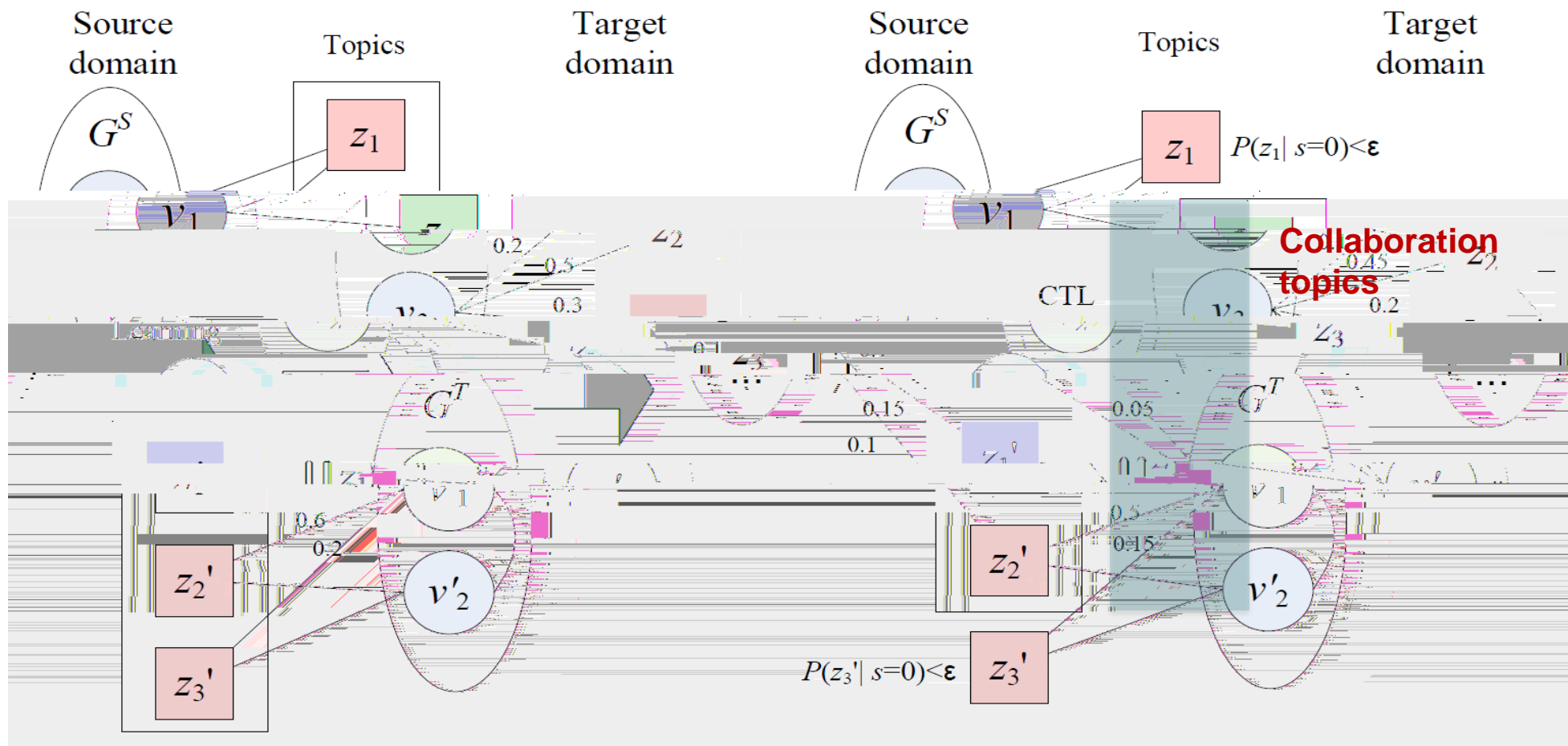
foreach collaborated document d **do**

Step 2:

foreach word $x_{di} \in d$ **do**
 Toss a coin s_{di} according to $bernoulli(s_{di}) \sim beta(\gamma_t, \gamma)$,
 where $s_{di} = 0$ if x_{di} is from G^S and $s_{di} = 1$ if x_{di} is from G^T .
if $s_{di} = 0$ **then**
 Randomly select a pair (v, v') from G^S authors, where v is an author from G^S and v' from G^T .
 Draw a topic $z_{di} \sim multi(\vartheta_{vv'})$ from the topic mixture $\vartheta_{vv'}$ specific to (v, v') .
end
if $s_{di} = 1$ **then**
 Randomly select a user v .
 Draw a topic $z_{di} \sim multi(\theta_v)$ from the topic model of user v .
end
 Draw a word $x_{di} \sim multi(\phi_{z_{di}})$ from z_{di} distribution.
end



Intuitive explanation of Step 2 in CTL



Experiments

Data Set and Baselines

- Arnetminer (available at <http://arnetminer.org/collaboration>)

Domain	Authors	Relationships	Source
Data Mining	6,282	22,862	KDD, SDM, ICDM, WSDM, PKDD
Medical Informatics	9,150	31,851	JAMIA, JBI, AIM, TMI, TITB

- Baselines
 - Content Similarity(Content)
 - Collaborative Filtering(CF)
 - Hybrid
 - Katz
 - Author Matching(Author), Topic Matching(Topic)

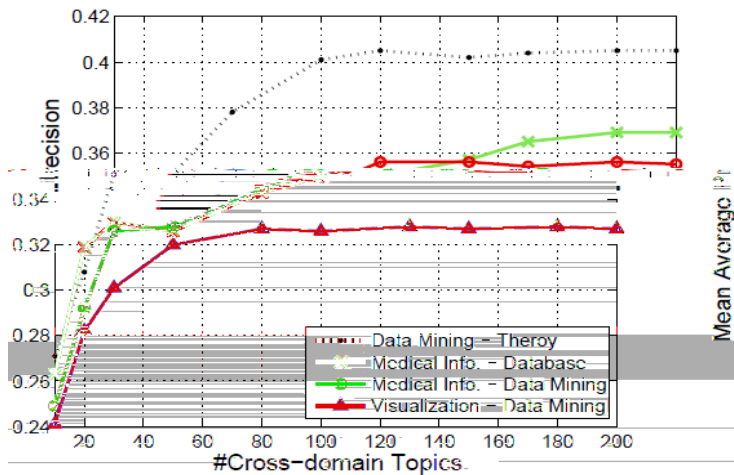


Performance Analysis

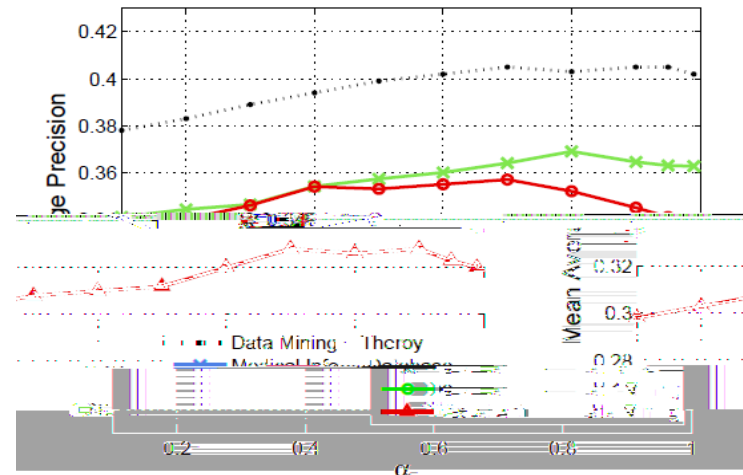
Training: collaboration before 2001 **Validation:** 2001-2005

Cross Domain	ALG	P@10	P@20	MAP	R@100	ARHR-10	ARHR-20
Data Mining(S) to Theory(T)	Content	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
	Hybrid	17.4	19.1	20.0	29.5	5.0	2.4
	Author	27.2	22.3	25.7	32.4	10.1	6.4
	Topic	28.0	26.0	32.4	33.5	13.4	7.1
	Katz	30.4	29.8	21.6	27.4	11.2	5.9
	CTL		37.7	36.4	40.6	35.6	14.3

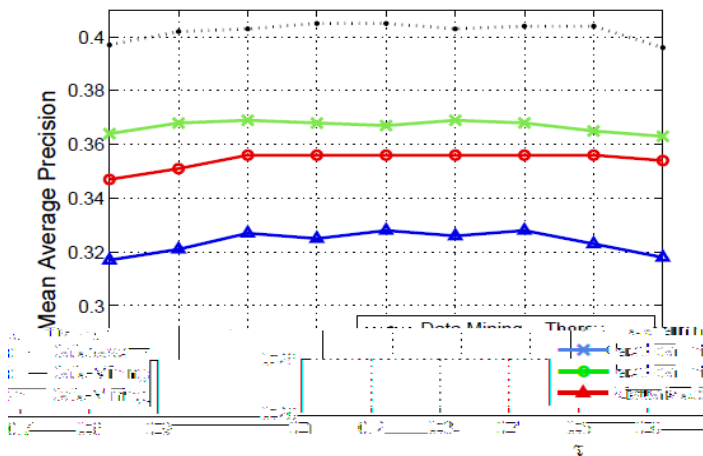
Parameter Analysis



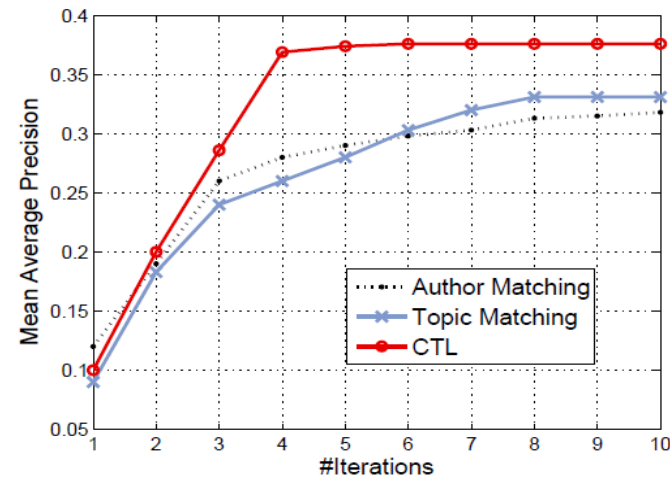
(a) number of topics T



(b) Hyperparameter α



(c) RWR parameter τ



(d) Convergence analysis

(a) varying the number of topics T

(c) varying the restart parameter τ in the random walk

(b) varying α parameter

(d) Convergence analysis



Conclusion

- Study the problem of cross-domain collaboration recommendation
- Propose the cross-domain topic model for recommending collaborators
- Experimental results in a coauthor network demonstrate the effectiveness and efficiency of the proposed approach



Future work

- Connect cross-domain collaborative relationships with social theories (e.g. social balance, social status, structural hole)
- Apply the proposed method to other networks

Thanks!

System: <http://arnetminer.org/collaborator>

Code&Data: <http://arnetminer.org/collaboration>

Challenge always be side with opportunity!



- Sparse connection:
 - cross-domain collaborations are rare;
- Complementary expertise:
 - cross-domain collaborators often have different expertise and interest;
- Topic skewness:
 - cross-domain collaboration topics are focused on a subset

Performance Analysis

Cross Domain	ALG	P@10	P@20	MAP	R@100	ARHR -10	ARHR -20
Medical Info.(S) to Database(T)	Content	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
	Hybrid	25.0	26.5	28.4	59.1	6.4	4.2
	Author	26.2	29.6	32.2	54.8	10.5	5.4
	Topic	29.4	26.3	34.7	59.3	11.5	5.2
	Katz	27.5	28.3	30.7	57.2	10.5	5.0
	CTL	32.5	30.0	36.9	59.8	11.4	5.4

Performance Analysis



Cross Domain	ALG	P@10	P@20	MAP	R@100	ARHR -10	ARHR -20
Medical Info.(S) to Data Mining(T)	Content	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
	Hybrid	18.0	19.0	19.8	36.7	3.4	1.3
	Author	20.1	23.8	29.3	64.4	5.3	2.1
	Topic	26.0	25.0	33.9	48.1	10.7	5.6
	Katz	21.2	23.8	32.4	48.1	10.2	4.8
	CTL	30.0					

Performance Analysis

Cross Domain	ALG	P@10	P@20	MAP	R@100	ARHR -10	ARHR -20
Visual.(S) to Data Mining(T)	Content	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
	Hybrid	16.0	20.0	27.6	30.1	6.3	4.4
	Author	22.0	25.2	27.7	31.1	11.9	6.7
	Topic	26.3	25.0	32.3	31.4	13.2	8.8
	Katz	23.0	25.1	29.3	30.2	10.4	5.4
	CTL	28.3	26.0	32.8	36.3	14.0	9.1