

Inside the Atoms: Ranking on a Network of Networks

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The 20th ACM SIGKDD Conference on Knowledge Discovery and Data Mining



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KDD2014

This year's special theme:
Data Science for Social Good

20th ACM SIGKDD Conference on Knowledge Discovery and Data Mining
August 24-27, 2014 New York City



Background: Ranking in a Network

❑ Network: Data are naturally networks

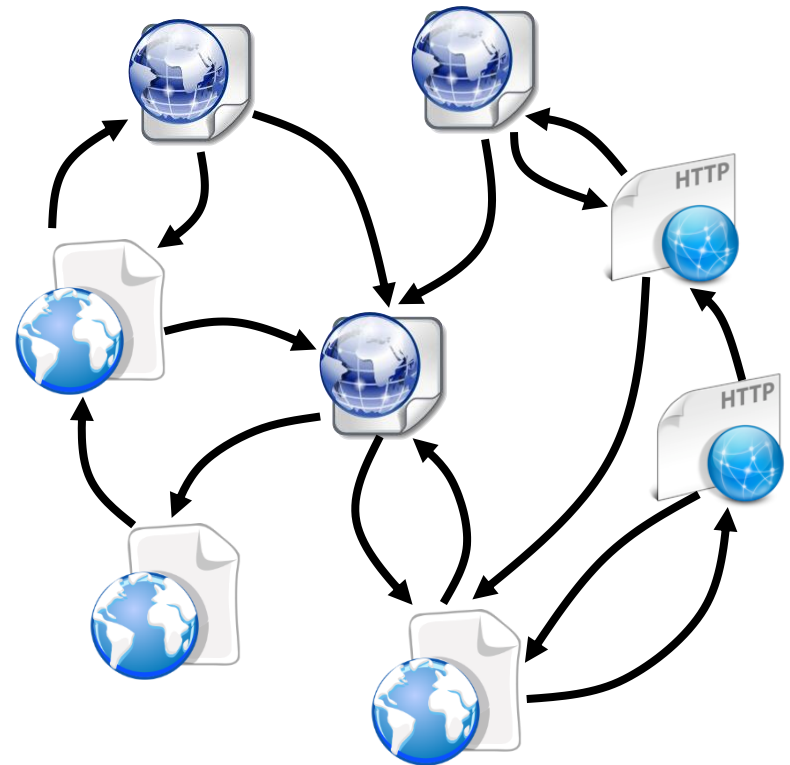
- Webs are linked by hyperlink
- Users are linked by friendship
- Proteins are linked by interactions

❑ Ranking without query

- Rank all nodes based on certain measures, e.g., Pagerank, HITS
- Who are most popular users?

❑ Ranking with query

- Find top-k most “similar” nodes for a query node based on certain measure, e.g., Personalized Pagerank, Simrank
- Who are potential friends of Jon?



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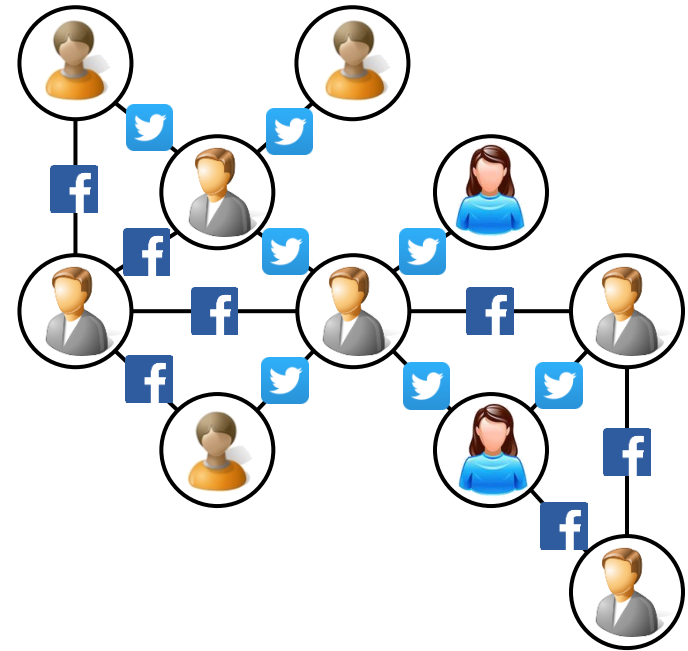
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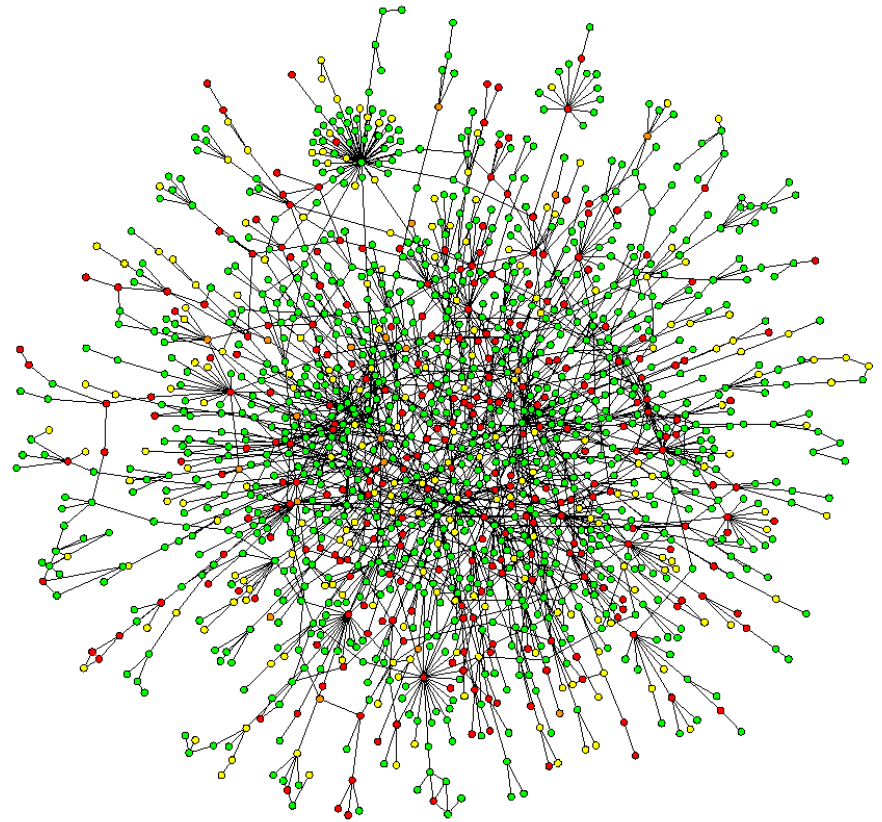
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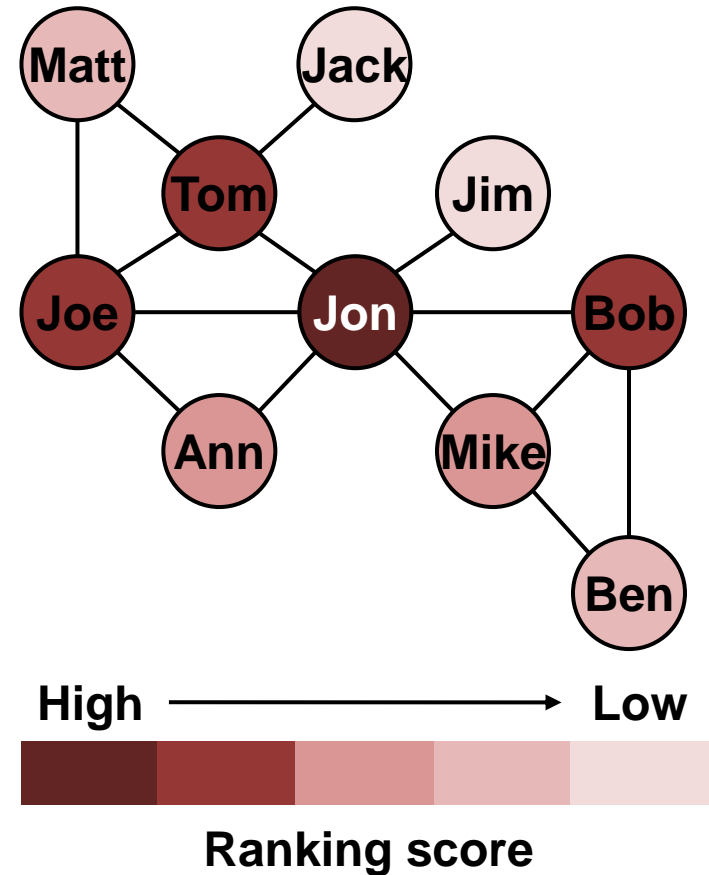
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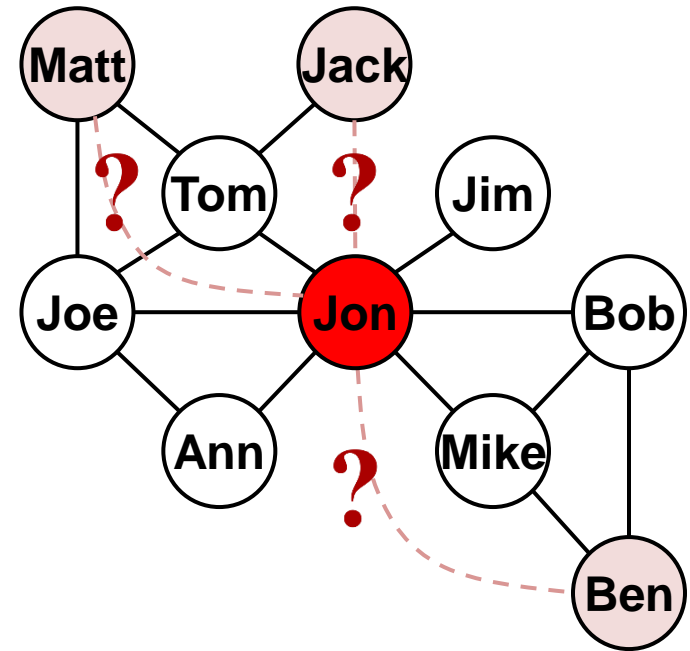


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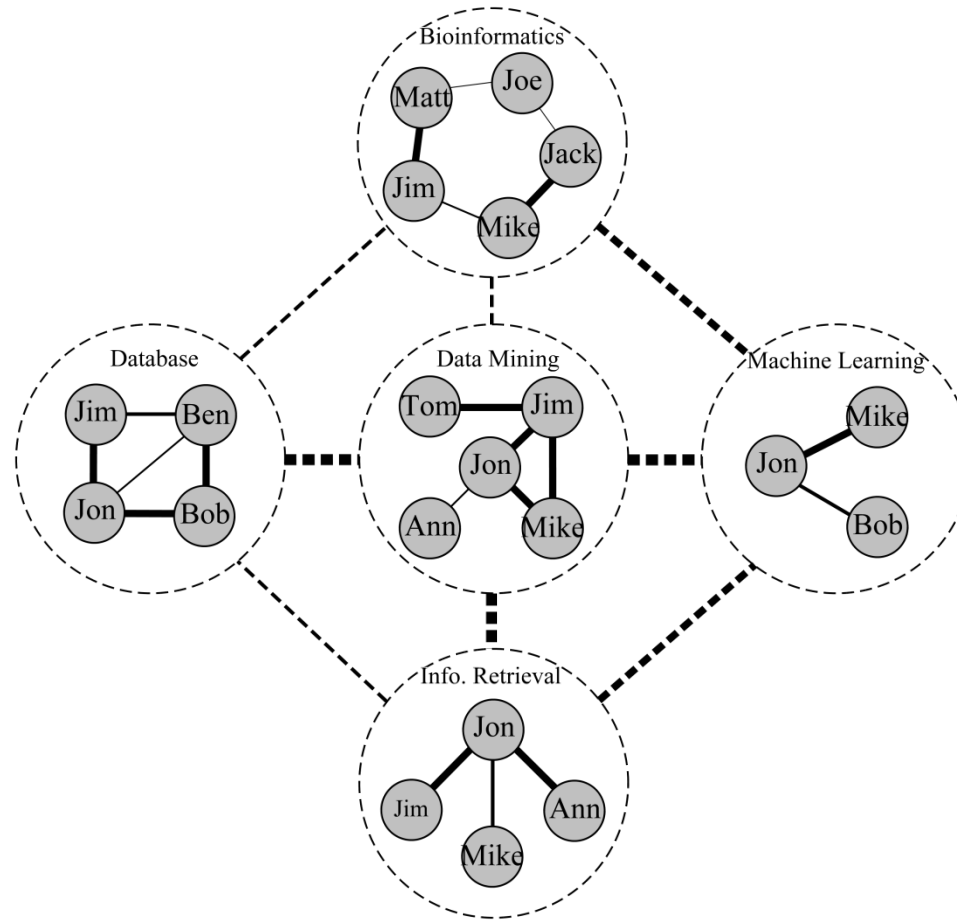
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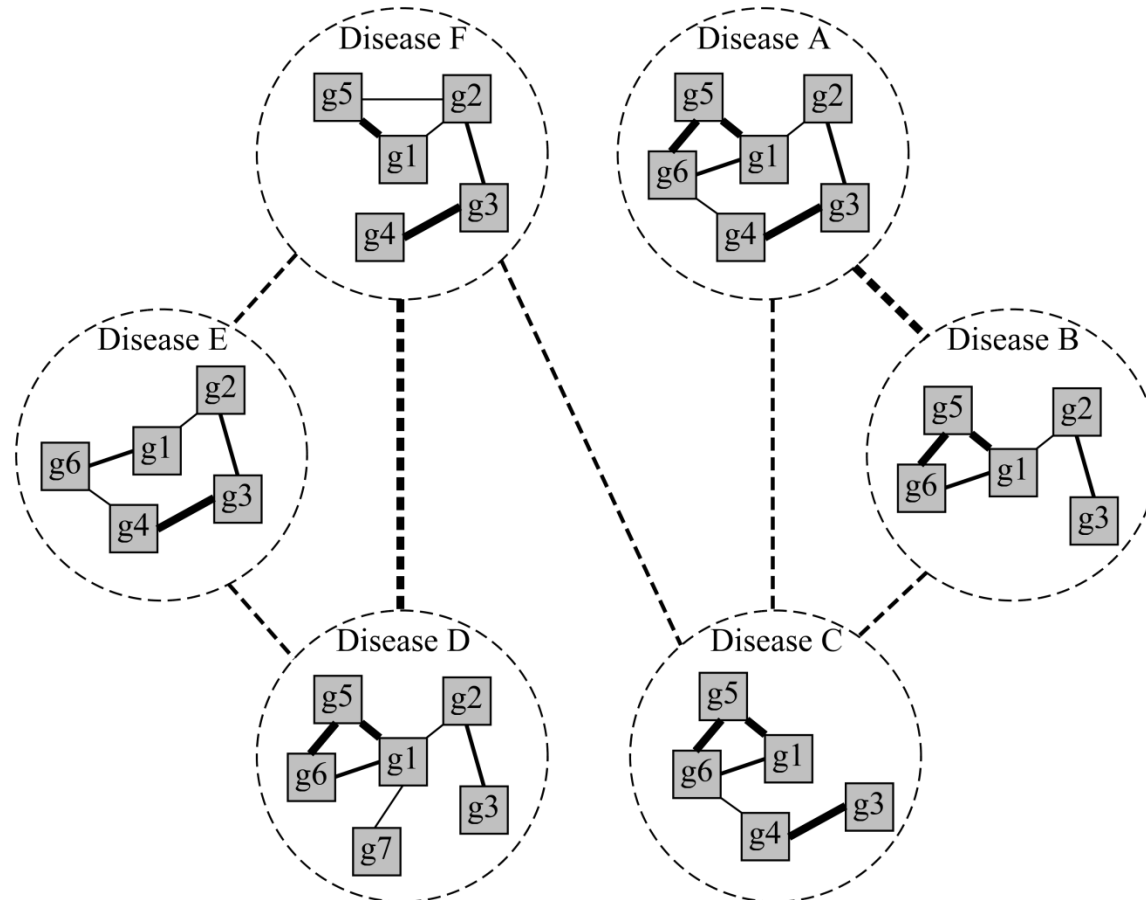
Motivation: Network of Networks (NoN)

Research Area Network of Co-author Networks



Motivation: Network of Networks (NoN)

Disease Network of Protein Interaction Networks



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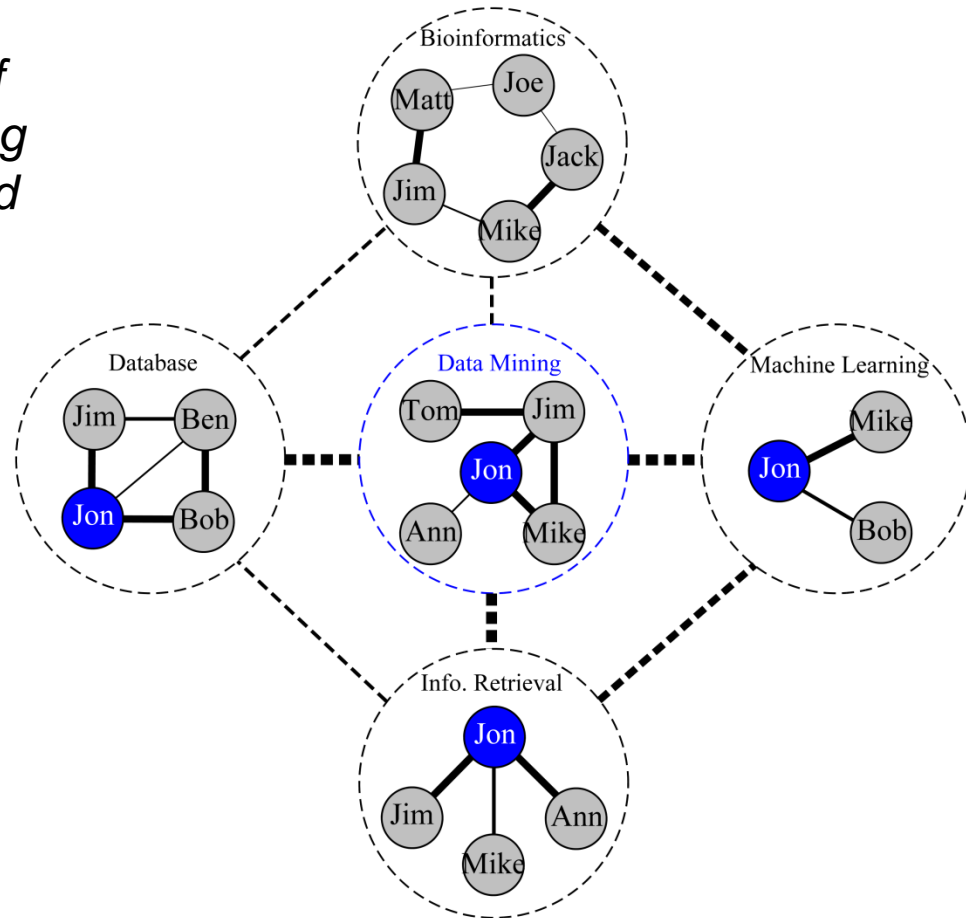
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Motivation: Ranking in NoN

Research Area Network of Co-author Networks

How to identify the importance of Jon in Data Mining by considering his overall contributions in related areas?



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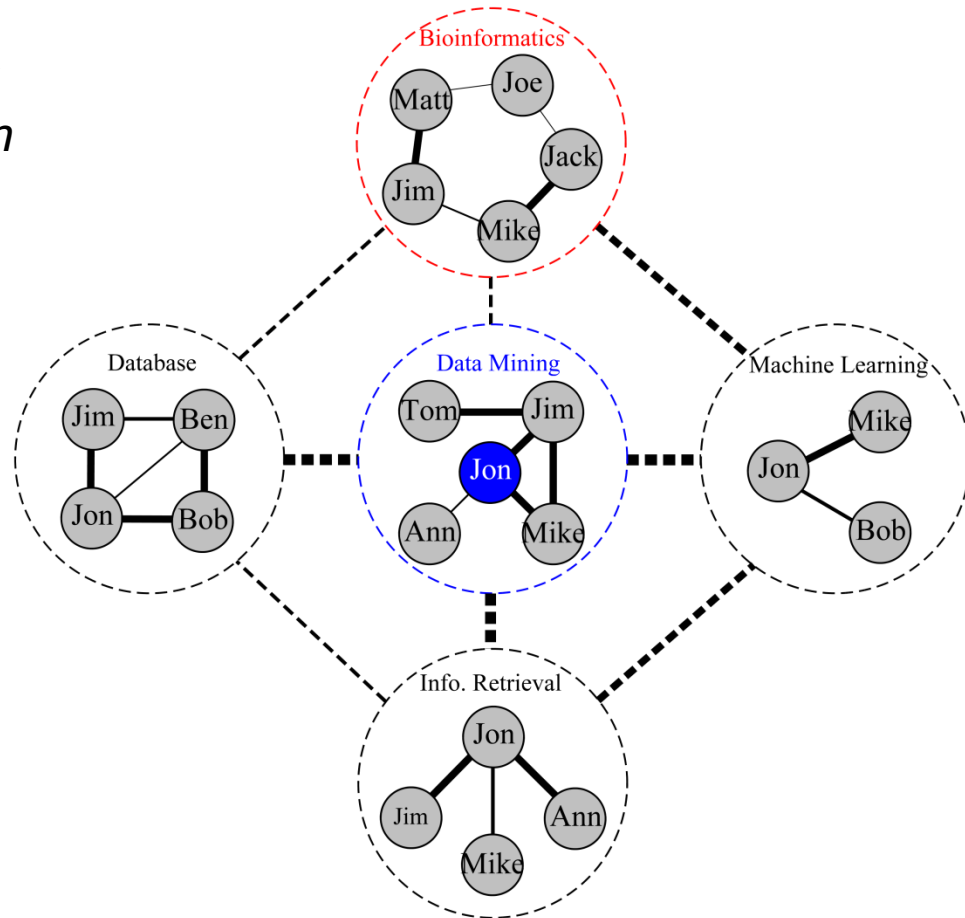
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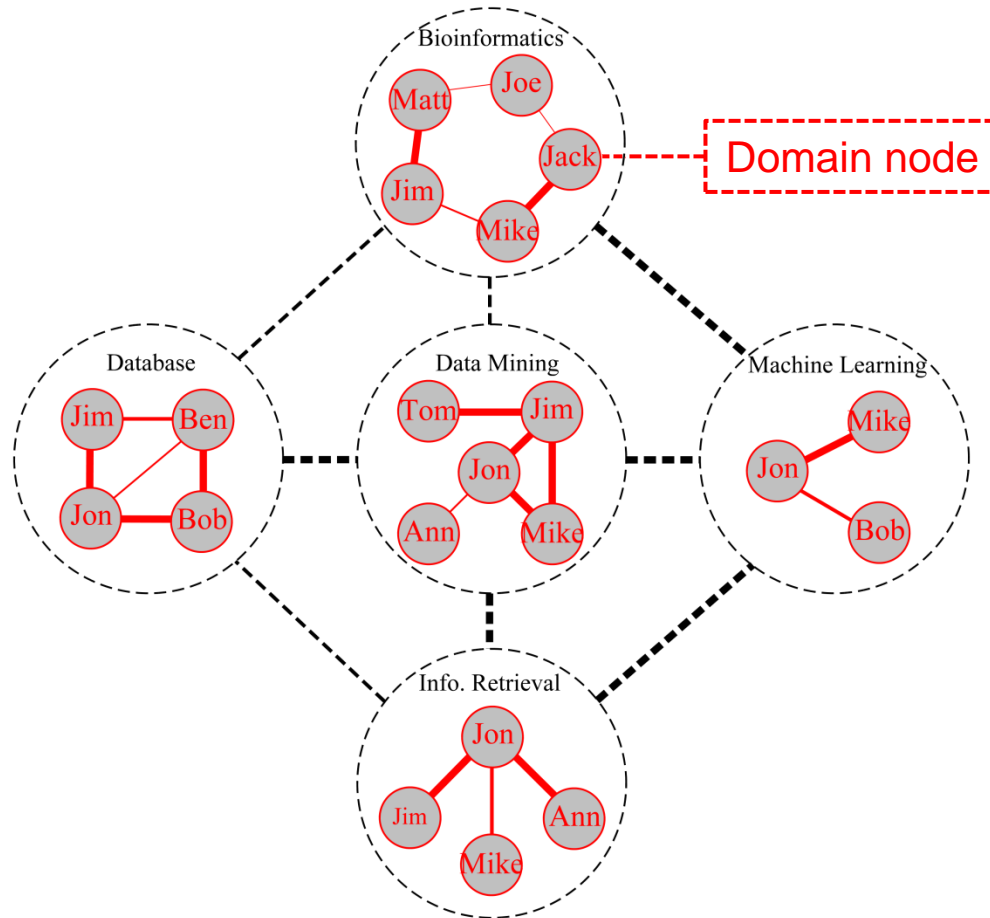
Research Area Network of Co-author Networks

Which Bioinformatics researcher are most likely to collaborate with Data Mining researcher Jon?



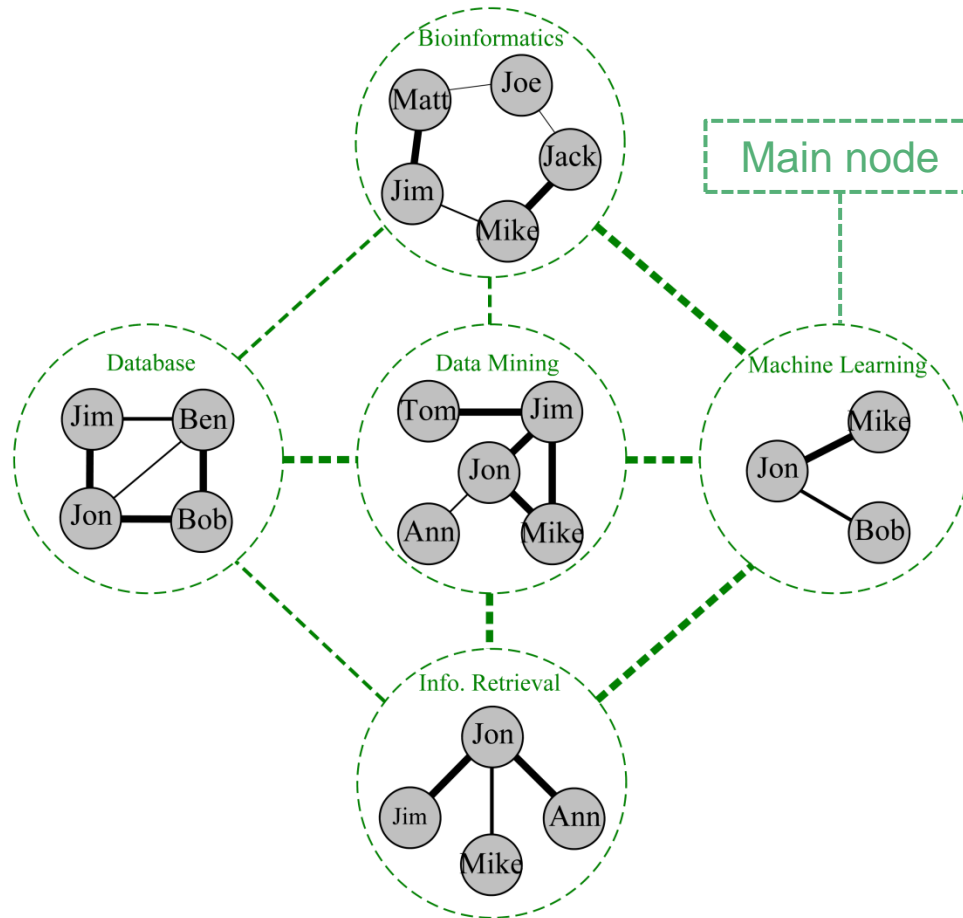
Problem Definitions

Domain-specific Network A_i



Problem Definitions

Main Network G

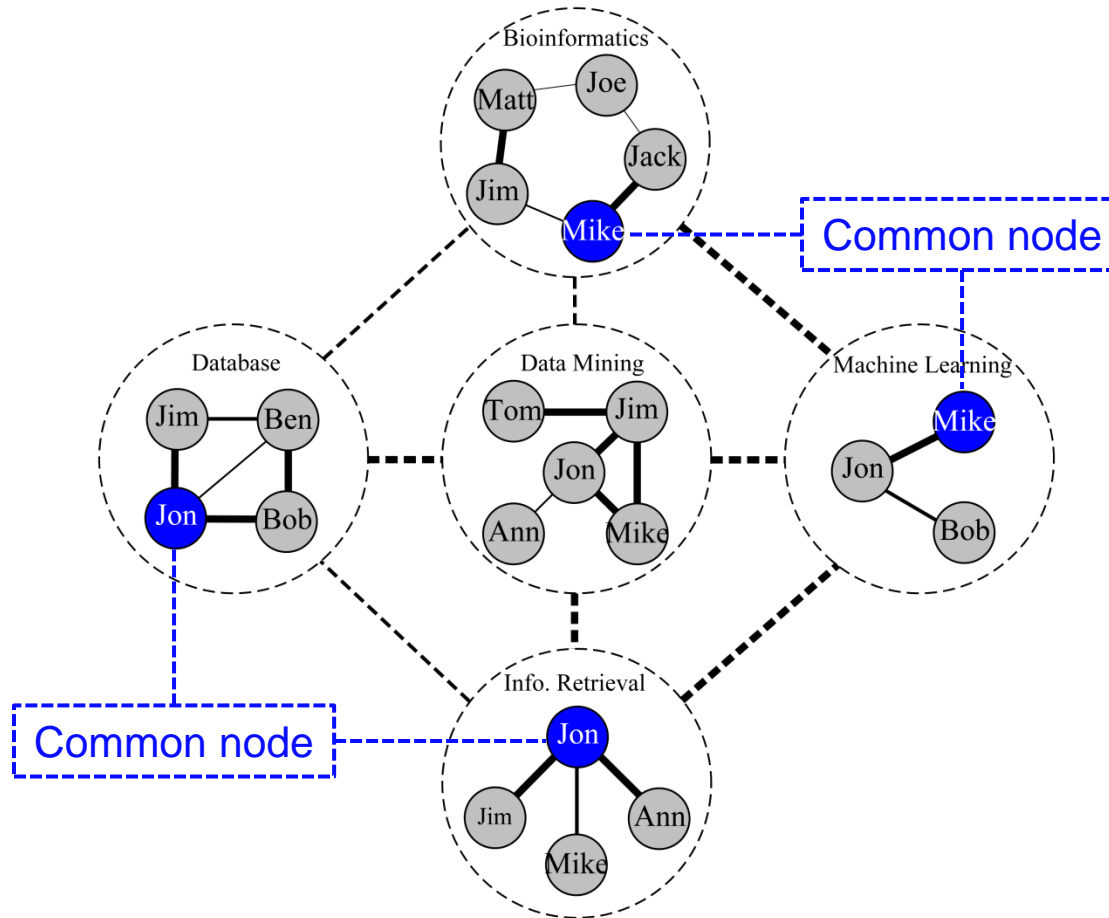


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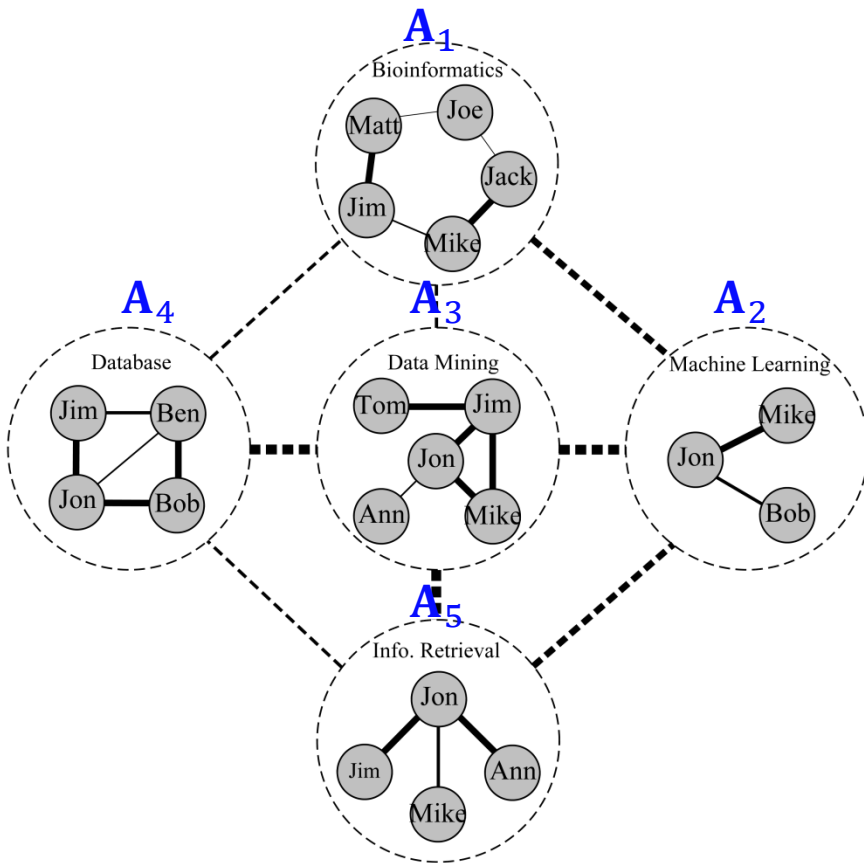
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Problem Definitions



CrossRank



Problem 1: CrossRank

Given: (1) an NoN, and (2) the query vectors \mathbf{e}_i ($i = 1, \dots, g$);

Find: ranking vectors \mathbf{r}_i for the nodes in the domain-specific networks A_i ($i = 1, \dots, g$).



CrossRank

Regularized Optimization Problem

$$J(\mathbf{r}_1, \dots, \mathbf{r}_g) = \underbrace{c \sum_{i=1}^g \mathbf{r}_i' (\mathbf{I}_{n_i} - \tilde{\mathbf{A}}_i) \mathbf{r}_i}_{\text{within-network smoothness}} + \underbrace{(1-c) \sum_{i=1}^g \|\mathbf{r}_i - \mathbf{e}_i\|^2}_{\text{query preference}} + \underbrace{a \sum_{i,j=1}^g \left\| \frac{\mathbf{r}_i(I_{ij})}{\sqrt{d_m(i)}} - \frac{\mathbf{r}_j(I_{ij})}{\sqrt{d_m(j)}} \right\|^2}_{\text{cross-network consistency}} \mathbf{G}(i,j)$$

- \mathbf{r}_i is the ranking vector of the domain-specific network \mathbf{A}_i
- $d_m(i)$ is the degree of main node i in the main network \mathbf{G}
- $\tilde{\mathbf{A}}_i$ is the symmetric normalized adjacency matrix \mathbf{A}_i
- I_{ij} is the set of common nodes between \mathbf{A}_i and \mathbf{A}_j



CrossRank

Matrix Form of the Objective Function

$$J(\mathbf{r}) = c\mathbf{r}'(\mathbf{I}_n - \tilde{\mathbf{A}})\mathbf{r} + (1 - c)\|\mathbf{r} - \mathbf{e}\|^2 + 2a\mathbf{r}'\mathbf{X}\mathbf{r}$$

$$\tilde{\mathbf{A}} = \begin{bmatrix} \tilde{\mathbf{A}}_1 & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \tilde{\mathbf{A}}_g \end{bmatrix} \quad \mathbf{r} = \begin{bmatrix} \mathbf{r}_1 \\ \vdots \\ \mathbf{r}_g \end{bmatrix} \quad \mathbf{e} = \begin{bmatrix} \mathbf{e}_1 \\ \vdots \\ \mathbf{e}_g \end{bmatrix}$$

\mathbf{X} encodes the cross-network consistency

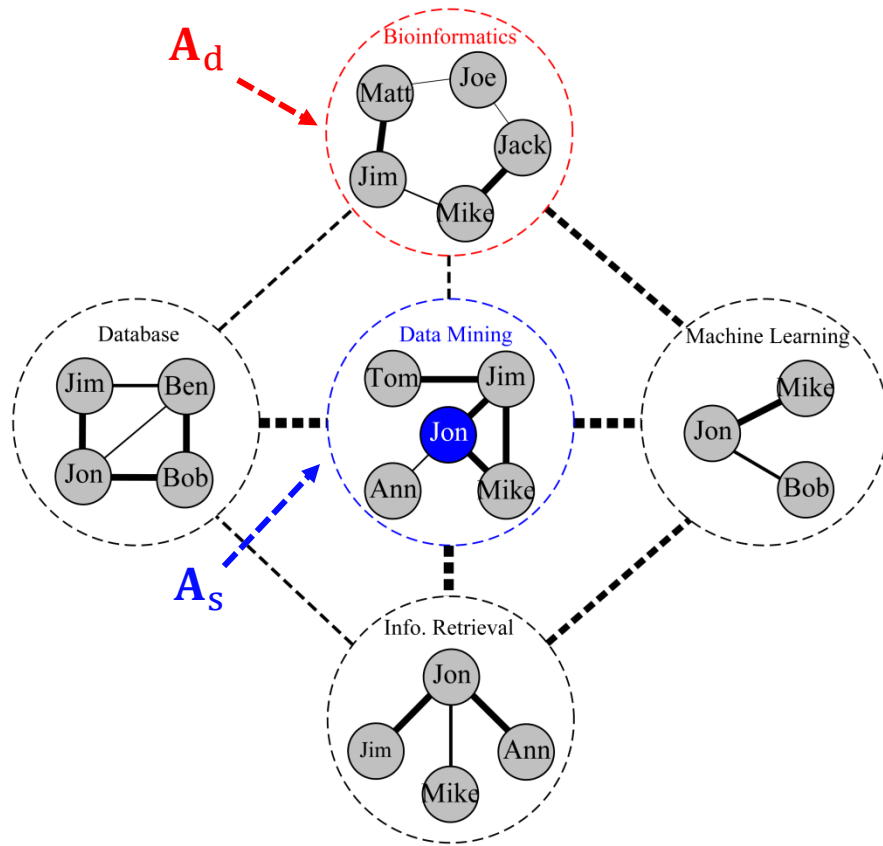
RWR-like Update rule

$$\mathbf{r} = \left(\underbrace{\frac{c}{1 + 2a} \tilde{\mathbf{A}}}_{\text{within-network walk}} + \underbrace{\frac{2a}{1 + 2a} \tilde{\mathbf{Y}}}_{\text{cross-network walk}} \right) \mathbf{r} + \frac{1 - c}{1 + 2a} \mathbf{e}$$

within-network walk cross-network walk



CrossQuery



Problem 2: CrossQuery

Given: (1) an NoN, (2) a query node from a *source* domain-specific network A_s , (3) a *target* domain-specific network A_d , and (4) an integer k ;

Find: the top- k most relevant nodes from the *target* domain-specific network A_d w.r.t. the query node



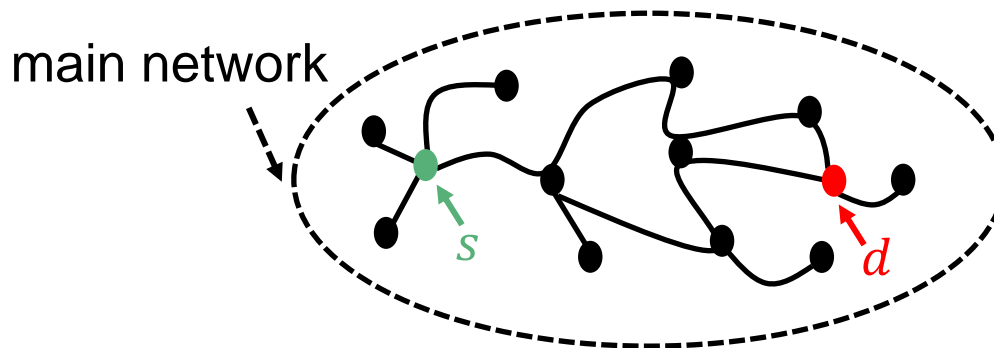
CrossQuery

CrossQuery-Basic

- Idea: our RWR-like update rule allows us to apply existing fast random walk with restart algorithm¹ where there is no accuracy loss. The candidate nodes can be restricted to those in the target domain-specific network.

CrossQuery-Fast

- Idea: given source and target domain-specific networks A_s and A_d of main nodes s and d respectively, prune less relevant main nodes². Then apply CrossQuery-Basic on the pruned NoN.



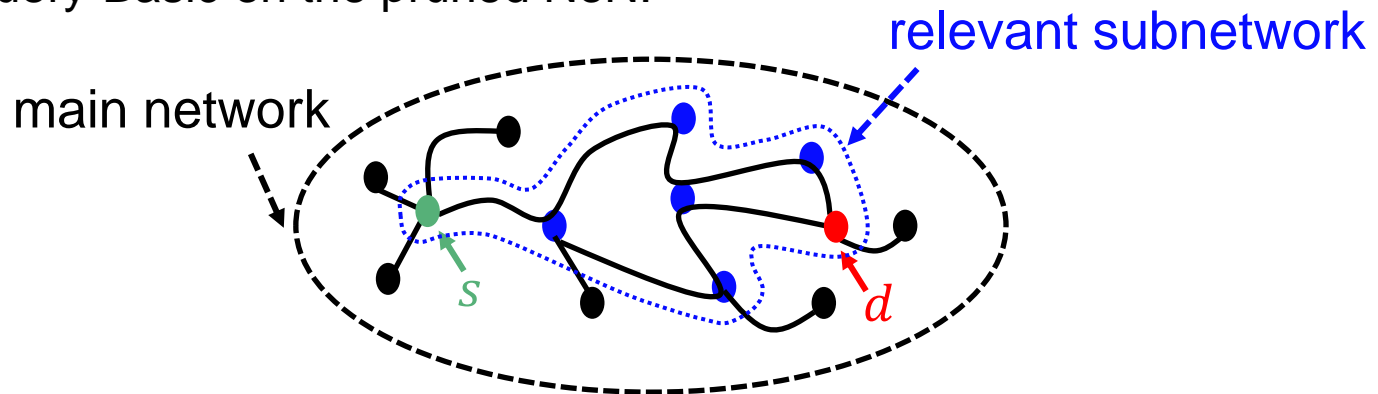
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CrossRank Effectiveness

Co-Author NoN

Areas in the main network

Area	Conference included
DM	KDD, ICDM, SDM, PKDD, PAKDD
ML	ICML, NIPS, AAAI, IJCAI, UAI, ECML
DB	VLDB, SIGMOD, ICDE, ICDT, EDBT, PODS
IR	SIGIR, WWW, ACL, ECIR, CIKM
BIO	ISMB, RECOMB, ECCB, BIBE, BIBM, WABI

CrossRank Effectiveness

Top ranked authors in the database area when varying α

Rank	$\alpha = 0$	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.3$	$\alpha = 0.5$
1	Divesh Srivastava	Jiawei Han	Jiawei Han	Jiawei Han	Jiawei Han
2	Jiawei Han	Divesh Srivastava	Divesh Srivastava	Philip S. Yu	Philip S. Yu
3	Philip S. Yu	Philip S. Yu	Philip S. Yu	Divesh Srivastava	Christos Faloutsos
4	Hector Garcia-Molina	Hector Garcia-Molina	Hector Garcia-Molina	Christos Faloutsos	Michael Stonebraker
5	Raghu Ramakrishnan	Raghu Ramakrishnan	Christos Faloutsos	Michael Stonebraker	Divesh Srivastava
6	Gerhard Weikum	Gerhard Weikum	Michael Stonebraker	Hector Garcia-Molina	Hector Garcia-Molina
7	Beng Chin Ooi	Christos Faloutsos	Raghu Ramakrishnan	Michael J. Carey	Michael J. Carey
8	H. V. Jagadish	Michael Stonebraker	Gerhard Weikum	Raghu Ramakrishnan	Gerhard Weikum
9	Michael J. Carey	Michael J. Carey	Michael J. Carey	Gerhard Weikum	Raghu Ramakrishnan
10	Michael Stonebraker	Beng Chin Ooi	Beng Chin Ooi	Elke A. Rundensteiner	Elke A. Rundensteiner



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$$J(\mathbf{r}_1, \dots, \mathbf{r}_g) = c \sum_{i=1}^g \mathbf{r}_i' (\mathbf{I}_{n_i} - \tilde{\mathbf{A}}_i) \mathbf{r}_i + (1 - c) \sum_{i=1}^g \|\mathbf{r}_i - \mathbf{e}_i\|^2 + a \sum_{i,j=1}^g \left\| \frac{\mathbf{r}_i(J_{ij})}{\sqrt{d_m(i)}} - \frac{\mathbf{r}_j(J_{ij})}{\sqrt{d_m(j)}} \right\|^2 \mathbf{G}(i, j)$$

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CrossQuery Effectiveness

CrossQuery Effectiveness

Cross-area Co-authorship prediction results

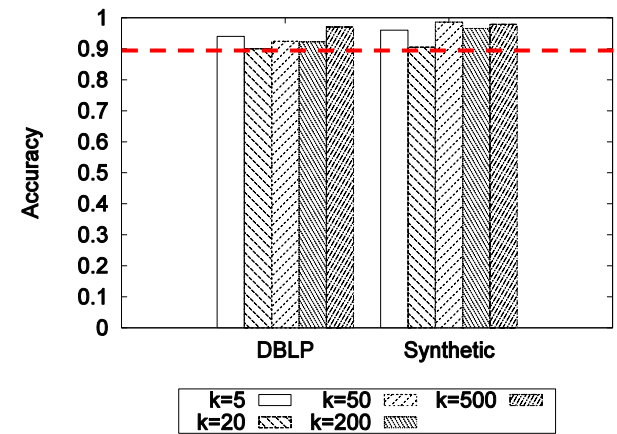
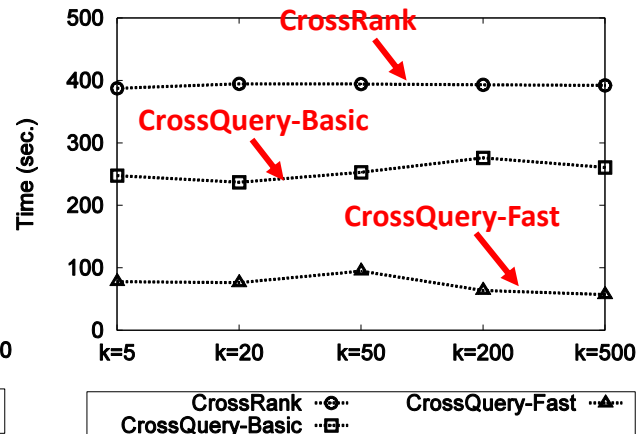
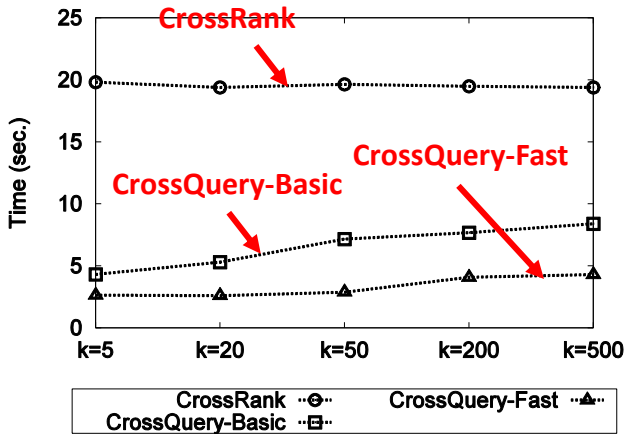
- *Which DB authors are most likely to collaborate with a DM author?*

#Papers	Hops	#Pairs	Methods	AUC	Accuracy
≥ 3	[3, 4]	45	PC	0.7196	0.4444
			Katz	0.7439	0.5556
			PropFlow	0.7558	0.6222
			PathSim	0.5636	0.2444
			PageRank	0.7417	0.5333
			CrossQuery	0.7685	0.6444
≥ 3	[3, 6]	70	PC	0.6009	0.3000
			Katz	0.6243	0.3714
			PropFlow	0.6268	0.4429
			PathSim	0.5278	0.2143
			PageRank	0.6378	0.3714
			CrossQuery	0.6632	0.4571
≥ 5	[3, 4]	23	PC	0.6521	0.2609
			Katz	0.6717	0.3478
			PropFlow	0.6850	0.3478
			PathSim	0.4279	0.1304
			PageRank	0.6743	0.3478
			CrossQuery	0.7099	0.3478
≥ 5	[3, 6]	38	PC	0.5692	0.2105
			Katz	0.5786	0.2368
			PropFlow	0.5950	0.2895
			PathSim	0.4362	0.1053
			PageRank	0.5880	0.2368
			CrossQuery	0.6308	0.2895



CrossQuery Efficiency

CrossQuery Efficiency



Query time on DBLP NoN

Query time on synthetic NoN

Accuracy of CrossQuery-Fast

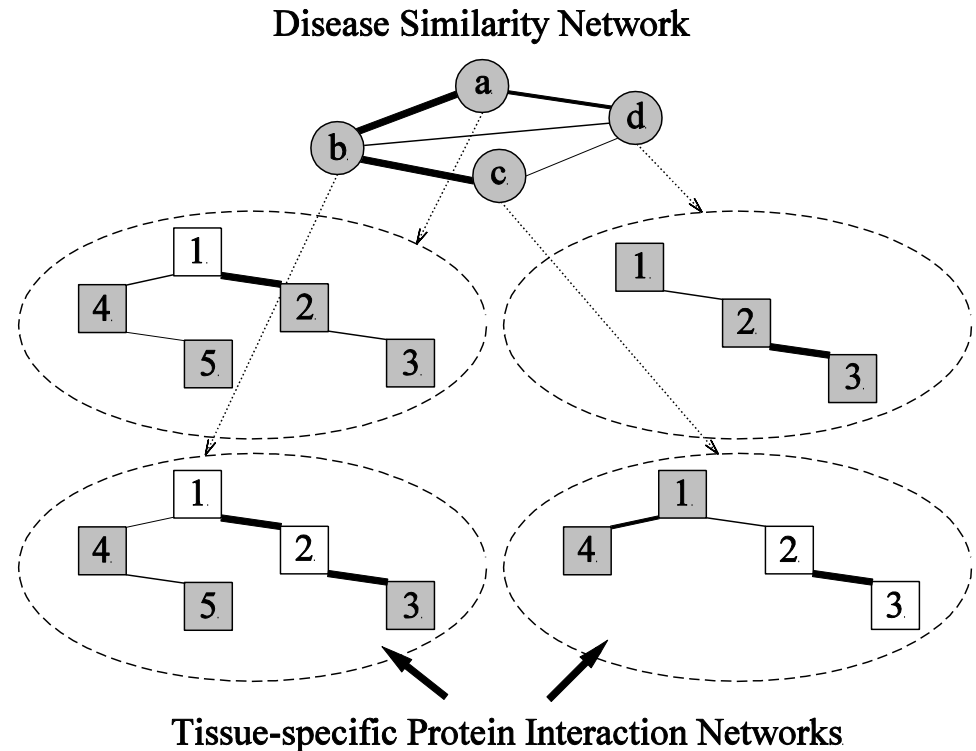
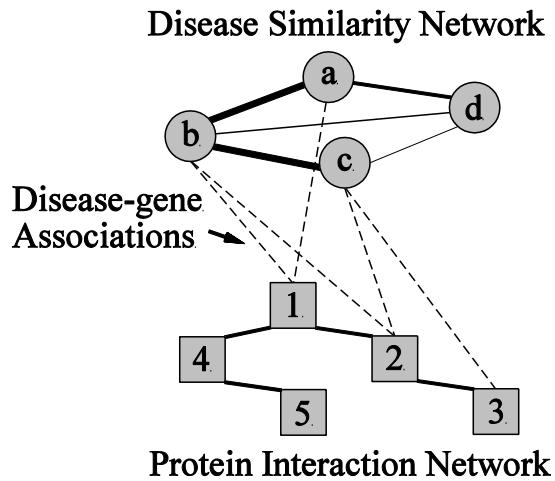


Candidate Gene Prediction

Protein Interaction NoN

Heterogeneous network structure

Network of Networks structure



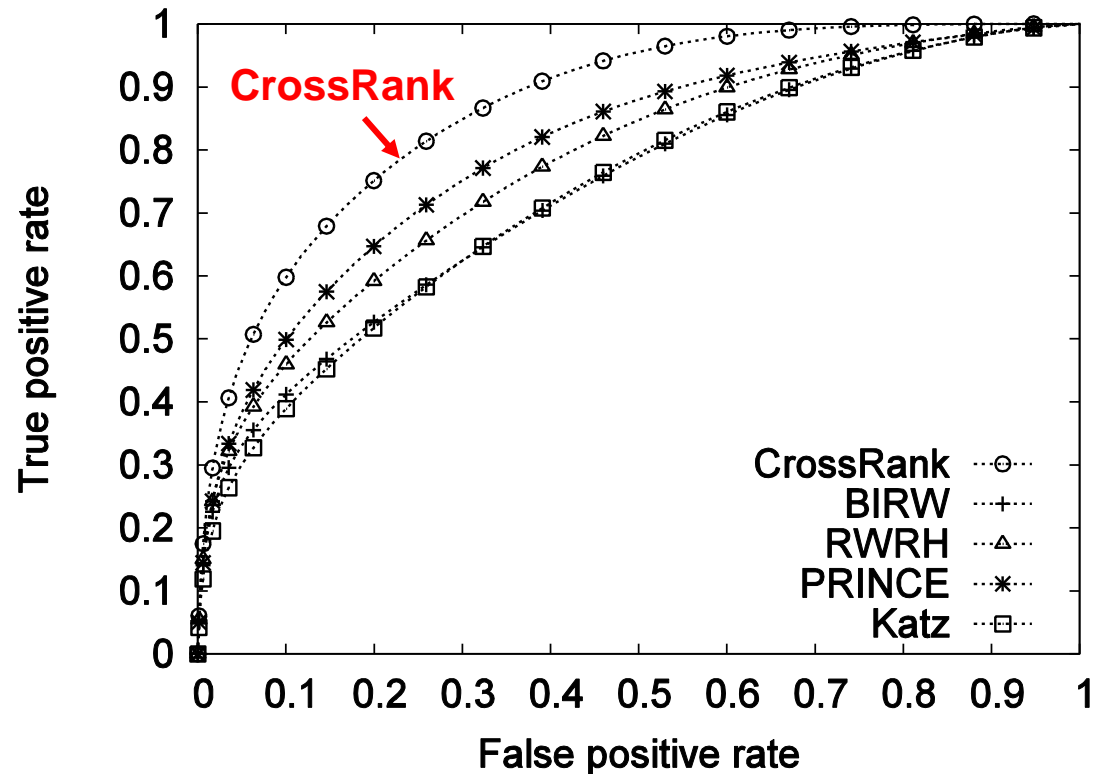
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Candidate Gene Prediction

Protein Interaction NoN



ROC curve comparison



Candidate Gene Prediction

Protein Interaction NoN

Ranking results comparison

Method	<i>p</i> -value
CrossRank vs. BIRW	1.82×10^{-11}
CrossRank vs. RWRH	2.04×10^{-11}
CrossRank vs. PRINCE	1.08×10^{-10}
CrossRank vs. Katz	2.32×10^{-12}



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Conclusion

- **New Data Model: Network of Networks (NoN)**
- **New Ranking Algorithm: CrossRank**
- **Efficient Query Algorithm: CrossQuery**



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Questions?



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