Mining Knowledge from Data: An Information Network Analysis Approach

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Outline

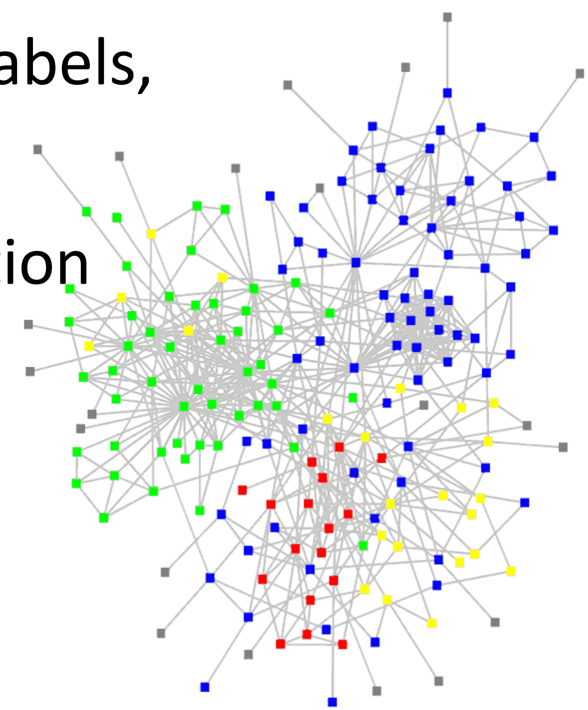
- **Motivation:** Why Mining Information Networks?
- **Part I:** Clustering, Ranking and Classification
  - Clustering and Ranking in Information Networks
  - Classification of Information Networks
- **Part II:** Meta-Path Based Exploration of Information Networks
  - Similarity Search in Information Networks
  - Relationship Prediction in Information Networks
- **Part III:** Advanced Topics on Information Network Analysis
  - Role Discovery and OLAP in Information Networks
  - Relation Strength Learning in Information Networks
  - Mining Evolution and Dynamics of Information Networks
- **Conclusions**

Motivation

- Traditional view of a database
  - Database: a data repository
  - Database system: supports organized and efficient data storage, update, retrieval, management, …
- Our view of a database: an organized info. network!
  - Information-rich, inter-related data relations and records form one or a set of gigantic, interconnected, multi-typed heterogeneous information networks
  - Surprisingly rich knowledge can be derived from such database-information network (DB-InfoNet)
- How to uncover knowledge “buried” in databases?
  - Exploring the power of multi-typed, heterogeneous links
  - Mining “semi-structured” heterogeneous information networks!

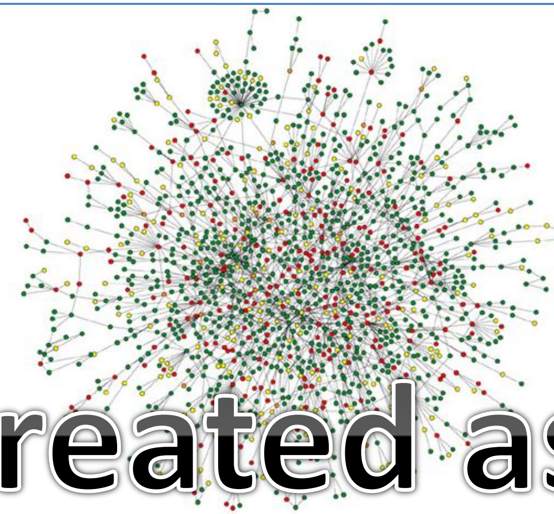
What Are Information Networks?

- Information network: A network where each node represents an entity (e.g., actor in a social network) and each link (e.g., tie) a relationship between entities
  - Each node/link may have attributes, labels, and weights
  - Link may carry rich semantic information



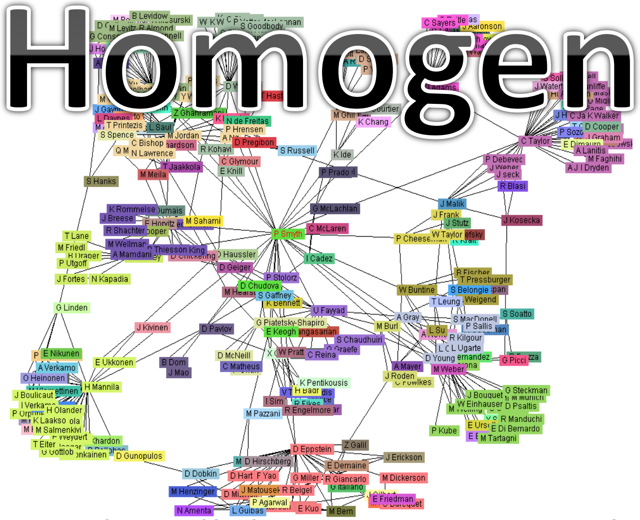
Information Networks Are Everywhere

Social Networking Websites

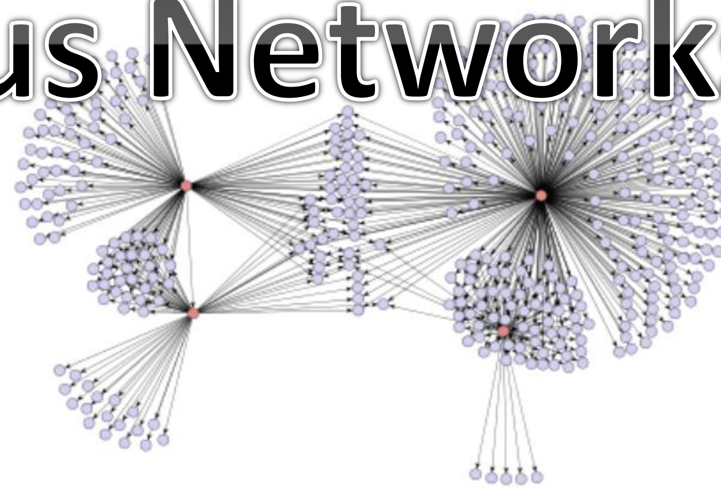


Biological Network: Protein Interaction

They are all treated as Homogeneous Networks!



Research Collaboration Network

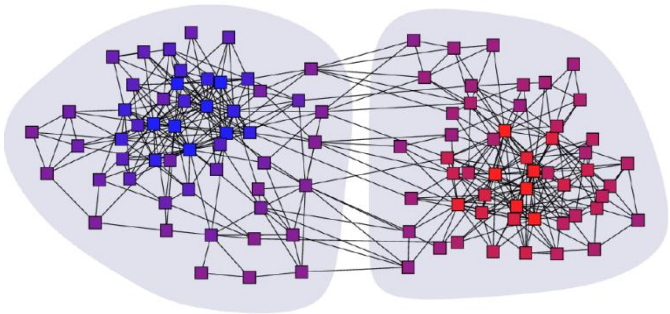


Product Recommendation Network via Emails

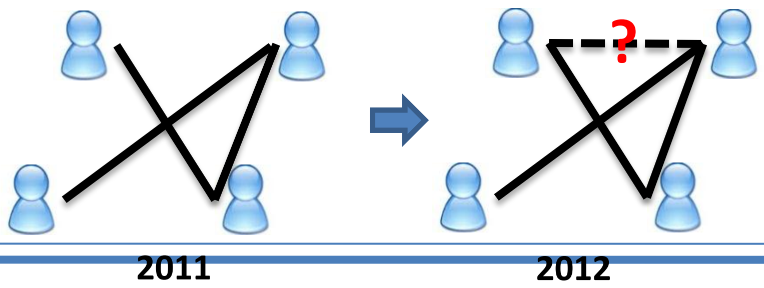
Homogeneous Information Networks

- Single object type and single link type
  - Link analysis based applications

Ranking web pages [Brin and Page, 1998]



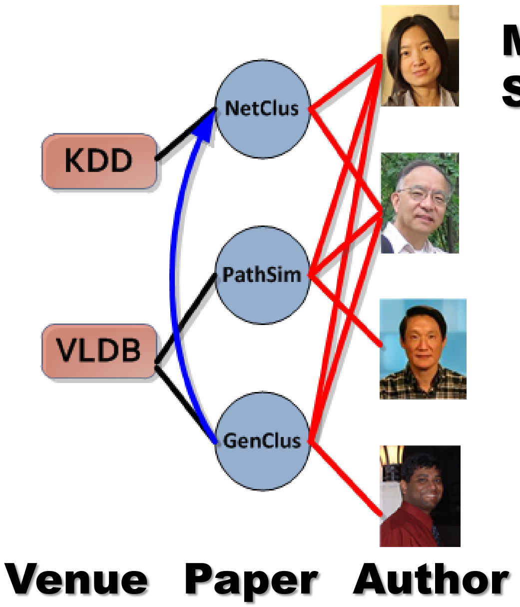
Clustering books about politics [Newman, 2006]



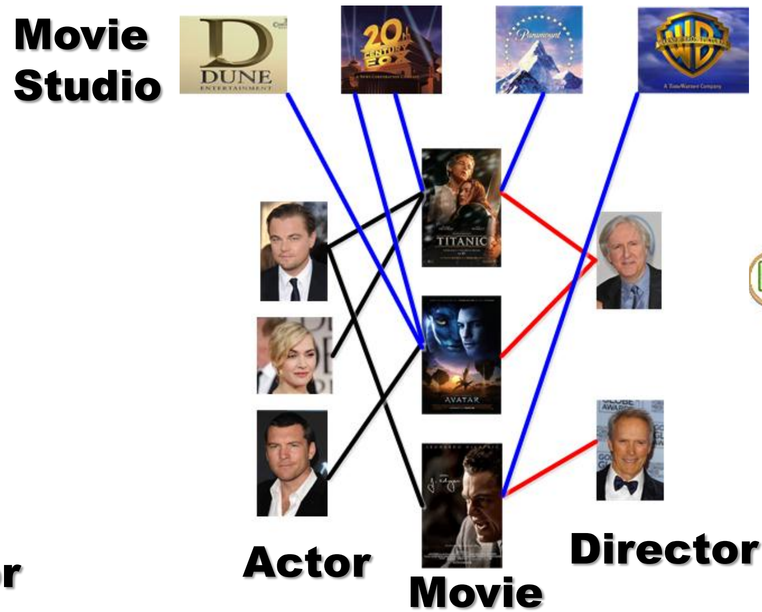
Link Prediction [Kleinberg, 2003]

Heterogeneous Information Networks

- Multiple object types and/or multiple link types



DBLP Bibliographic Network



The IMDB Movie Network

The Facebook Network

1. Homogeneous networks are ***Information loss*** projection of heterogeneous networks!
2. ***New problems*** are emerging in heterogeneous networks!

Heterogeneous Networks Are Ubiquitous

- Healthcare
  - Doctor, patient, disease, treatment

- Content sharing websites
  - Video, image, user, comment
- E-Commerce
  - Seller, buyer, product, review
- News
  - Person, organization, location, text

What Can be Mined from Heterogeneous Networks?

- DBLP: A Computer Science bibliographic database

26 Yizhou Sun, Jiawei Han, Charu C. Aggarwal, Nitesh V. Chawla: When will it happen?: relationship prediction in heterogeneous information networks. WSDM 2012: 663-672

A sample publication record in DBLP (>1.8 M papers, >0.7 M authors, >10 K venues)

Knowledge hidden in DBLP Network	Mining Functions	Publications
How are CS research areas **structured**?	Clustering	EDBT'09, KDD'09, ICDM'09
Who are the **leading** researchers on Web search?	Ranking	EDBT'09, KDD'09,
Who are the **peer** researchers of Jure Lescovec?	Similarity Search	VLDB'11
Whom **will** Christos Faloutsos **collaborate with** in the future?	Relationship Prediction	ASONAM'11
Whether **will** an author **publish** a paper in KDD, and **when**?	Relationship Prediction with Time	WSDM'12
Which types of **relationships** are most **influential** for an author to decide her topics?	Relation Strength Learning	VLDB'12, KDD'12 submission

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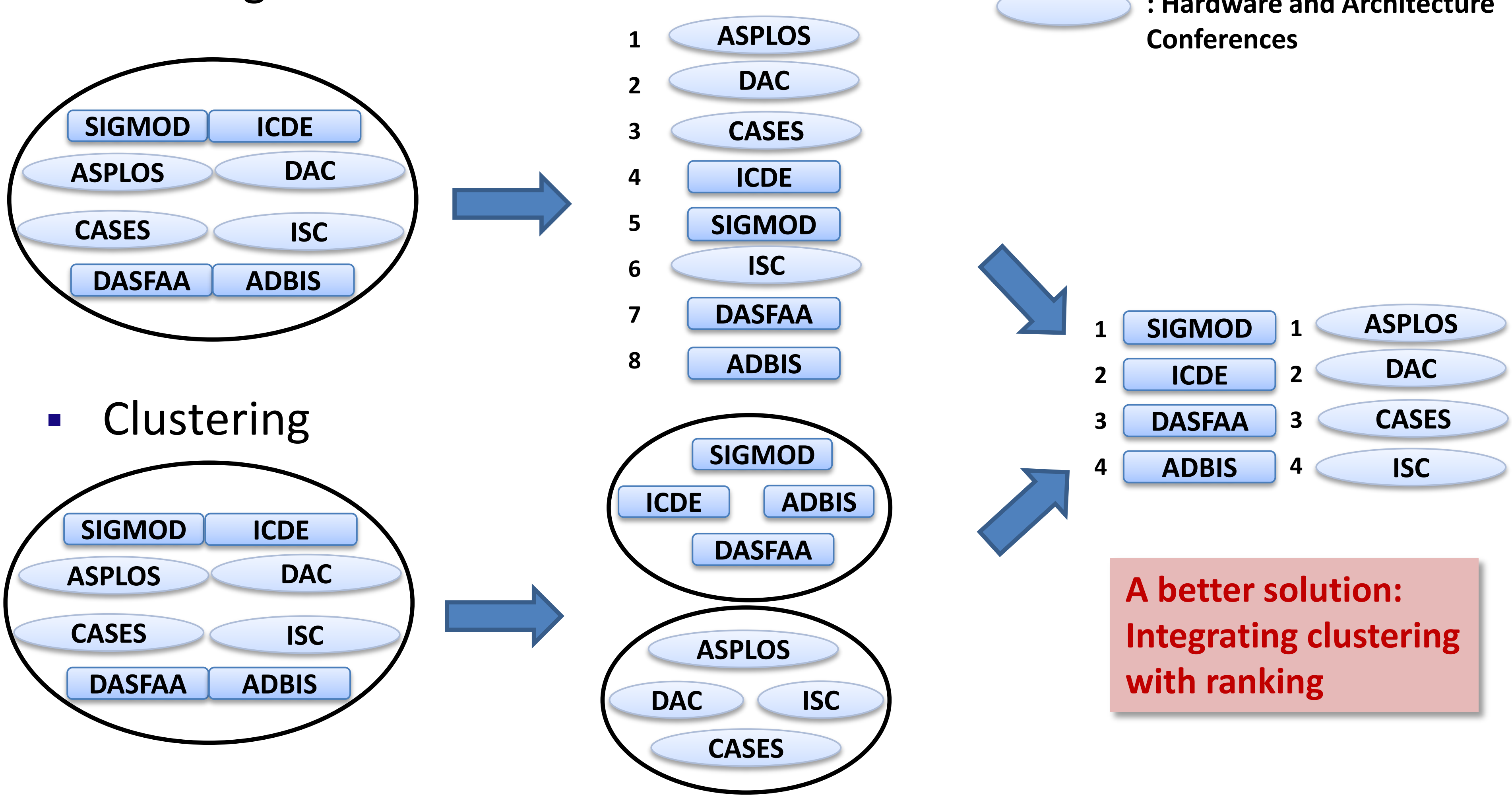
Ranking and Clustering: Two Critical Functions

- Ranking
- Clustering



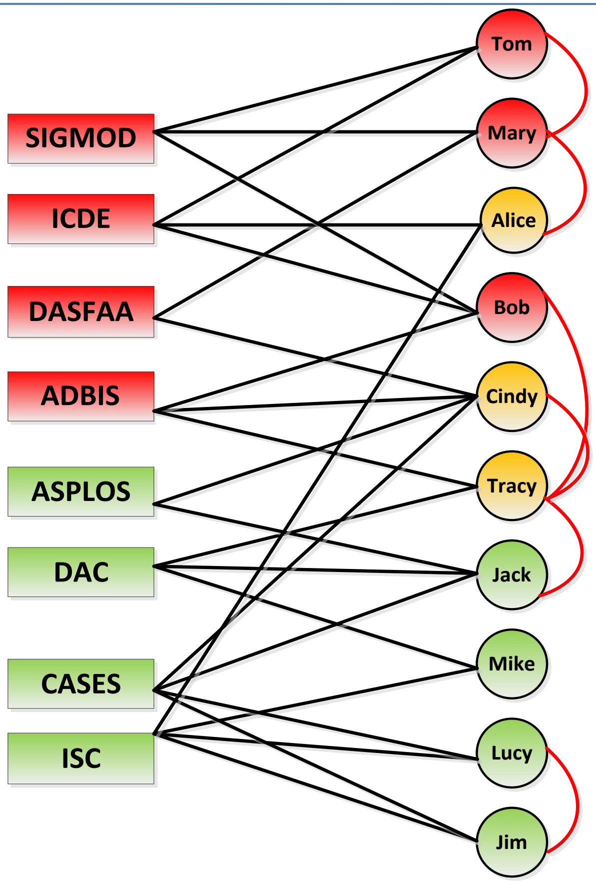
Comparing apples and oranges?

Not distinguishing objects in each cluster?

A better solution: Integrating clustering with ranking

RankClus: Integrating Clustering with Ranking [Sun, EDBT'09]

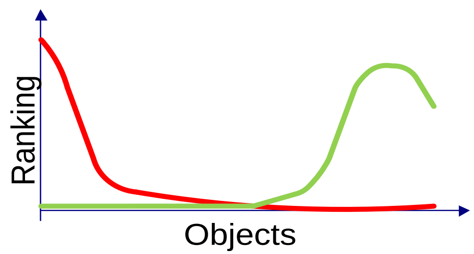
- A case study on bi-typed DBLP network
  - Links exist between
    - Conference (X) and author (Y)
    - Author (Y) and author (Y)
  - A matrix denoting the weighted links
    - $W = \begin{bmatrix} W_{XX} & W_{XY} \\ W_{YX} & W_{YY} \end{bmatrix}$
  - Goal:
    - Clustering and ranking conferences via authors
      - **Simple solution: Project the bi-typed network into homogeneous conference network + spectral clustering [Shi & Malik, 2000]**



Idea: Ranking and Clustering Mutually Enhance Each Other

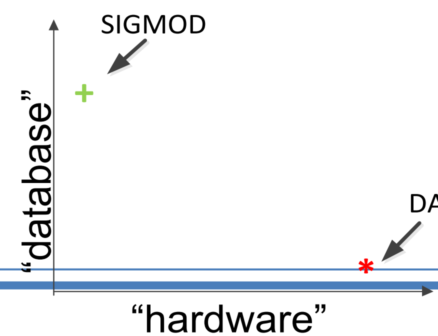
- Better clustering => Conditional ranking distributions are more distinguishing from each other
  - Conditional ranking distribution serves as the feature of each cluster

P(•|area = “database”) vs. P(•|area = “hardware”)

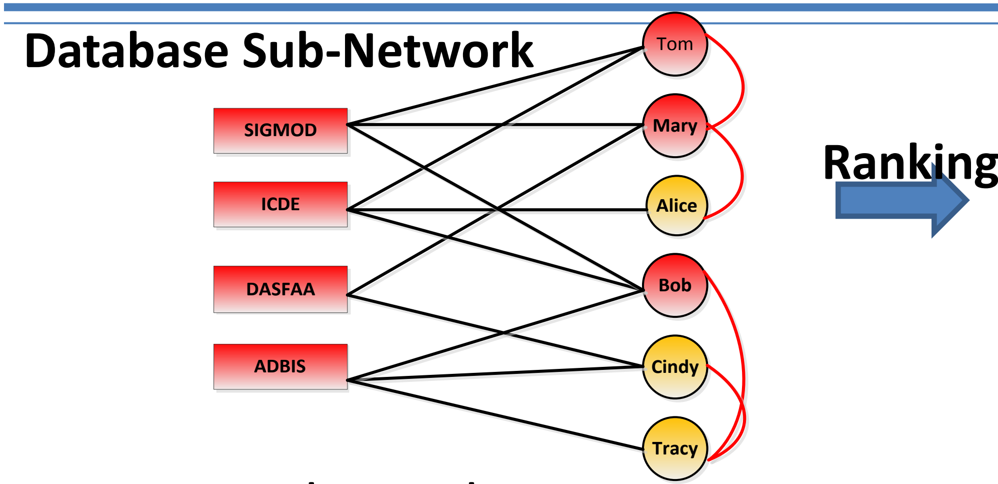


- Better ranking => Better metric for objects can be learned from the ranking for better clustering
  - Posterior probabilities for each object in each cluster serves as the new metric for each object

(P(area = “database”|SIGMOD), P(area = “hardware”|SIGMOD))



Simple Ranking vs. Authority Ranking



P(SIGMOD|area = "database")?
P(Tom|area = "database")?

- Simple Ranking
  - Proportional to # of publications of an author / a conference
  - Considers only **immediate neighborhood** in the network

What about an author publishing 100 papers in low reputation conferences?

- Authority Ranking:
  - More sophisticated "rank rules" are needed
  - **Propagate** the ranking scores in the network over different types

Rules for Authority Ranking

- Rule 1: Highly ranked authors publish *many* papers in highly ranked conferences

$$\vec{r}_Y(j) = \sum_{i=1}^{m} W_{YX}(j,i)\vec{r}_X(i)$$

- Rule 2: Highly ranked conferences attract *many* papers from *many* highly ranked authors

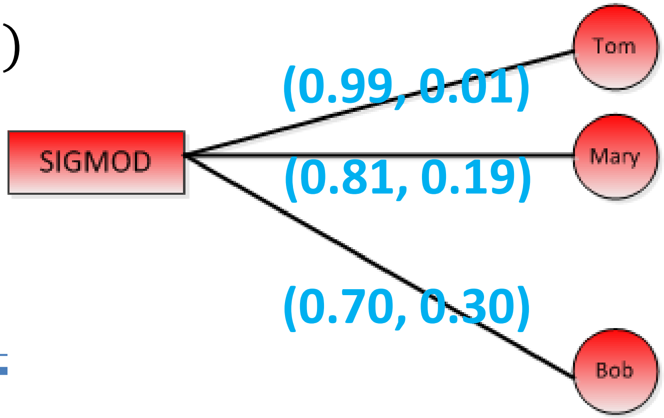
$$\vec{r}_X(i) = \sum_{j=1}^{n} W_{XY}(i,j)\vec{r}_Y(j)$$

- Rule 3: The rank of an author is enhanced if he or she co-authors with *many* highly ranked authors

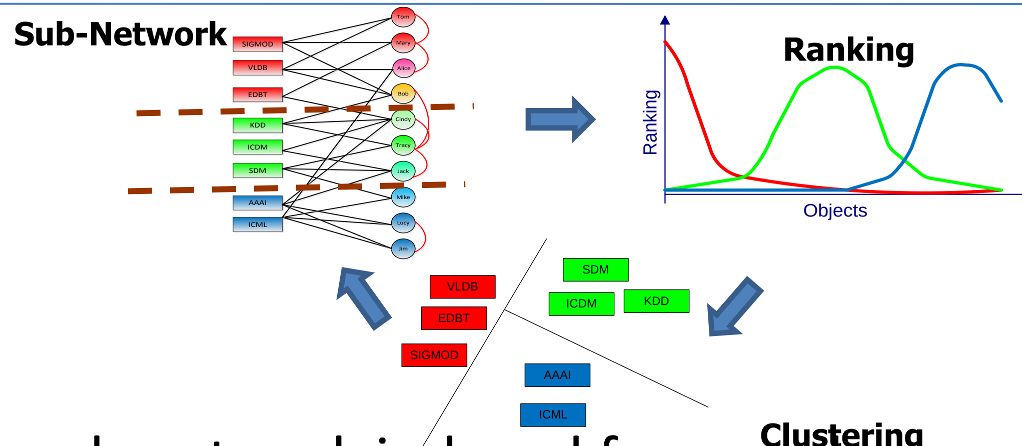
$$\vec{r}_Y(i) = \alpha \sum_{j=1}^{m} W_{YX}(i,j)\vec{r}_X(j) + (1-\alpha) \sum_{j=1}^{n} W_{YY}(i,j)\vec{r}_Y(j)$$

Generating New Measure Space

- Input: Conditional ranking distributions for each cluster
  - $P_X(i|k)$: $e.g.,$ $P_X(SIGMOD|area = \text{"database"})$
- Output: Each conference *i* is mapped into a new measure space
  - $i: (\pi_{i,1}, \ldots, \pi_{i,K}), where\ \pi_{i,k} = P_X(k|i)$
    - E.g., SIGMOD: $(P(\text{"}database\text{"}|SIGMOD), P(\text{"}hardware\text{"}|SIGMOD))$
- Solution
  - $P_X(k|i) \propto P(k) \times P_X(i|k)$
  - Calculate cluster size $P(k)$
    - Maximize the log-likelihood of generating all the links
      - $P(i,j) = \sum_k P(k) \times P_X(i|k) \times P_Y(j|k)$
    - EM algorithm
      - $P(k|i,j) \propto P(k) \times P_X(i|k) \times P_Y(j|k)$
      - $P(k) \propto \sum_{ij} W_{XY}(i,j) P(k|i,j)$



The Algorithm Framework



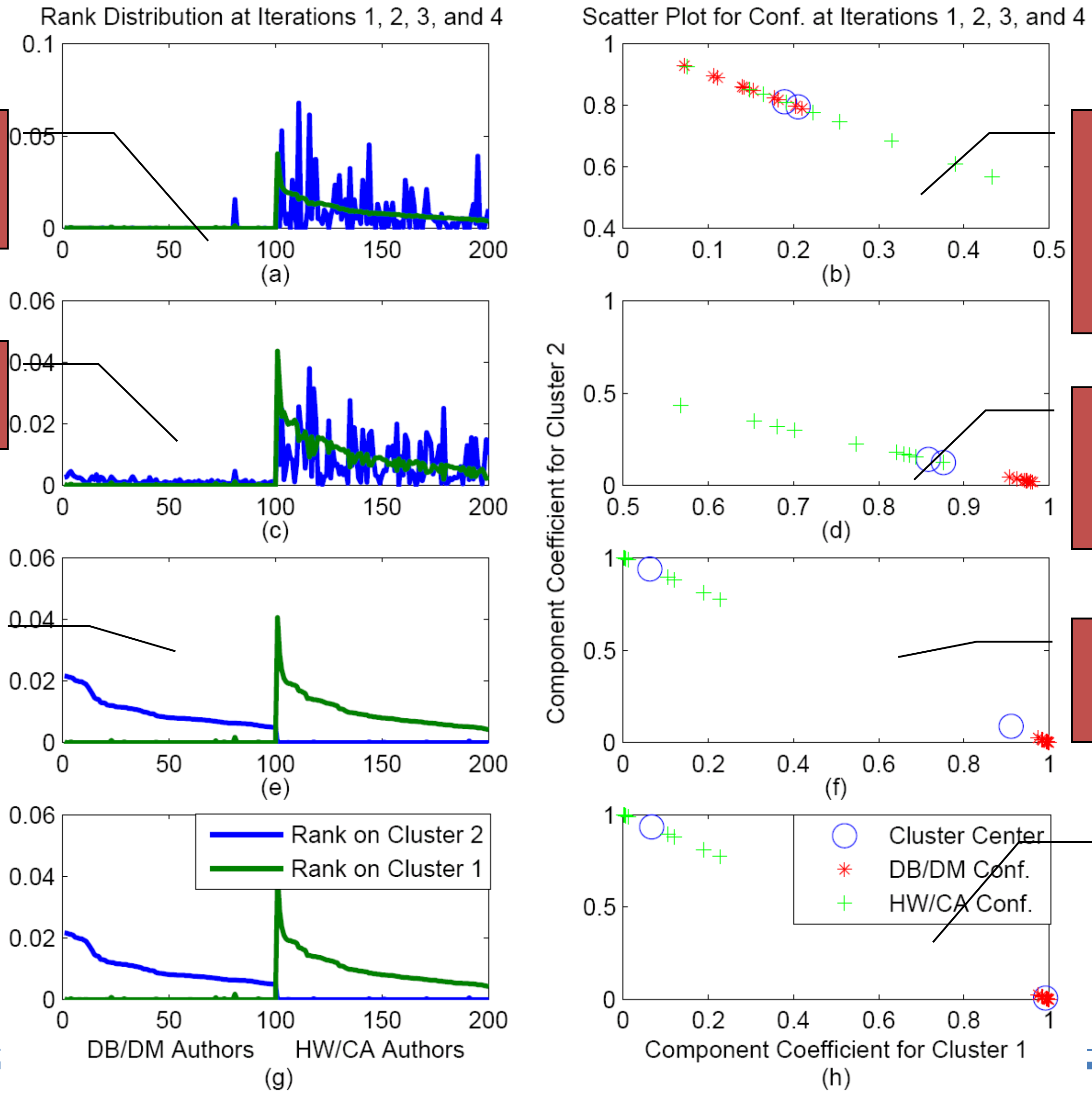
- Step 0: Initialization
  - Randomly partition
- Step 1: Ranking
  - Ranking objects in each sub-network induced from each cluster
- Step 2: Generating new measure space
  - Estimate **mixture model coefficients** for each target object
- Step 3: Adjusting cluster
- Step 4: Repeating Steps 1-3 until stable

Step-by-Step Running Case Illustration

Initially, ranking distributions are mixed together

Improved a little

Improved significantly



Two clusters of objects mixed together, but preserve similarity somehow

Two clusters are almost well separated

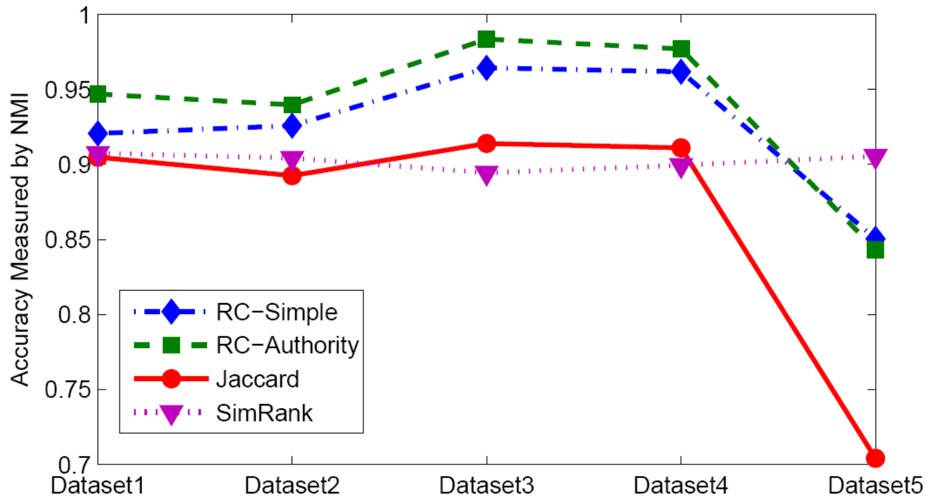
Well separated

Stable

Clustering and Ranking CS Conferences by RankClus

	DB	Network	AI	Theory	IR
1	VLDB	INFOCOM	AAMAS	SODA	SIGIR
2	ICDE	SIGMETRICS	IJCAI	STOC	ACM Multimedia
3	SIGMOD	ICNP	AAAI	FOCS	CIKM
4	KDD	SIGCOMM	Agents	ICALP	TREC
5	ICDM	MOBICOM	AAAI/IAAI	CCC	JCDL
6	EDBT	ICDCS	ECAI	SPAA	CLEF
7	DASFAA	NETWORKING	RoboCup	PODC	WWW
8	PODS	MobiHoc	IAT	CRYPTO	ECDL
9	SSDBM	ISCC	ICMAS	APPROX-RANDOM	ECIR
10	SDM	SenSys	CP	EUROCRYPT	CIVR

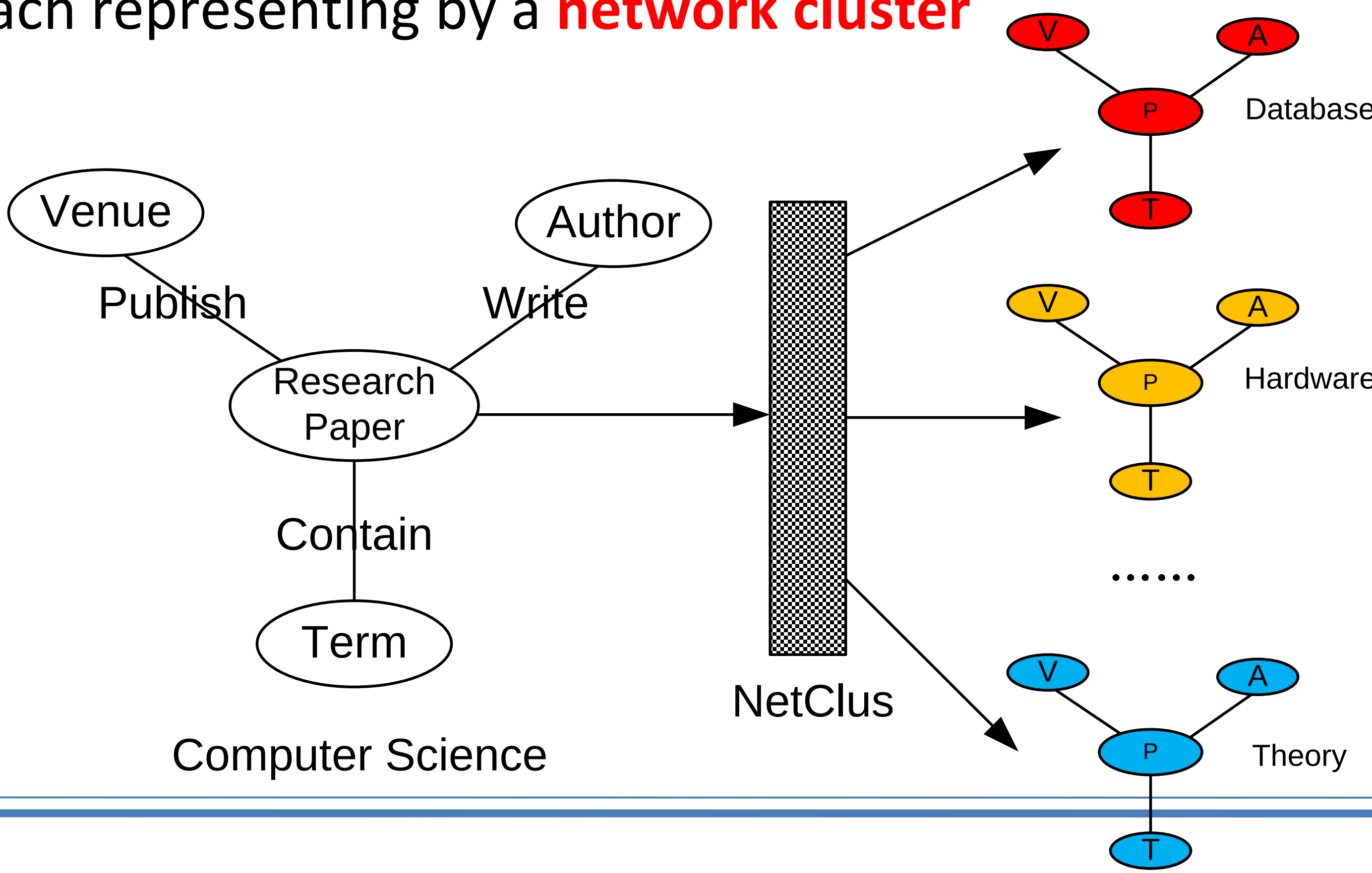
Top-10 conferences in 5 clusters using RankClus in DBLP



RankClus outperforms *spectral clustering [Shi and Malik, 2000]* algorithms on projected homogeneous networks

NetClus [Sun, KDD'09]: Beyond Bi-Typed Networks

- Beyond bi-typed information network
  - A Star Network Schema [**richer information**]
- Split a network into different layers
  - Each representing by a **network cluster**



Multi-Typed Networks Lead to Better Results

- The network cluster for database area: Conferences, Authors, and Terms
  - Better clustering and ranking than RankClus

Conference	Rank Score	Author	Rank Score	Term	Rank Score
SIGMOD	0.315	Michael Stonebraker	0.0063	database	0.0529
VLDB	0.306	Surajit Chaudhuri	0.0057	system	0.0322
ICDE	0.194	C. Mohan	0.0053	query	0.0313
PODS	0.109	Michael J. Carey	0.0052	data	0.0251
EDBT	0.046	David J. DeWitt	0.0051	object	0.0138
CIKM	0.019	H. V. Jagadish	0.0043	management	0.0113
...	...	...	...	...	...

  - NetClus vs. RankClus: **16%** higher accuracy on conference clustering in terms of Normalized Mutual Information

Impact of RankClus Methodology

- RankCompete [Cao et al., WWW'10]
  - Extend to the domain of web images
- RankClus in Medical Literature [Li et al., Working paper]
  - Ranking treatments for diseases
- RankClass [Ji et al., KDD'11]
  - Integrate classification with ranking
- Trustworthy Analysis [Gupta et al., WWW'11] [Khac Le et al., IPSN'11]
  - Integrate clustering with trustworthiness score
- Topic Modeling in Heterogeneous Networks [Deng et al., KDD'11]
  - Propagate topic information among different types of objects
- …

Interesting Results from Other Domains

RankCompete: Organize images automatically!

	Top 10 Treatments	Ranking
1	Zidovudine/therapeutic use	0.1679
2	Anti-HIV Agents/therapeutic use	0.1340
3	Antiretroviral Therapy, Highly Active	0.0977
4	Antiviral Agents/therapeutic use	0.0718
5	Anti-Retroviral Agents/therapeutic use	0.0236
6	Interferon Type I/therapeutic use	0.0147
7	Didanosine/therapeutic use	0.0132
8	Ganciclovir/therapeutic use	0.0114
9	HIV Protease Inhibitors/therapeutic use	0.0105
10	Antineoplastic Combined Chemotherapy	0.0103

Rank treatments for AIDS from MEDLINE

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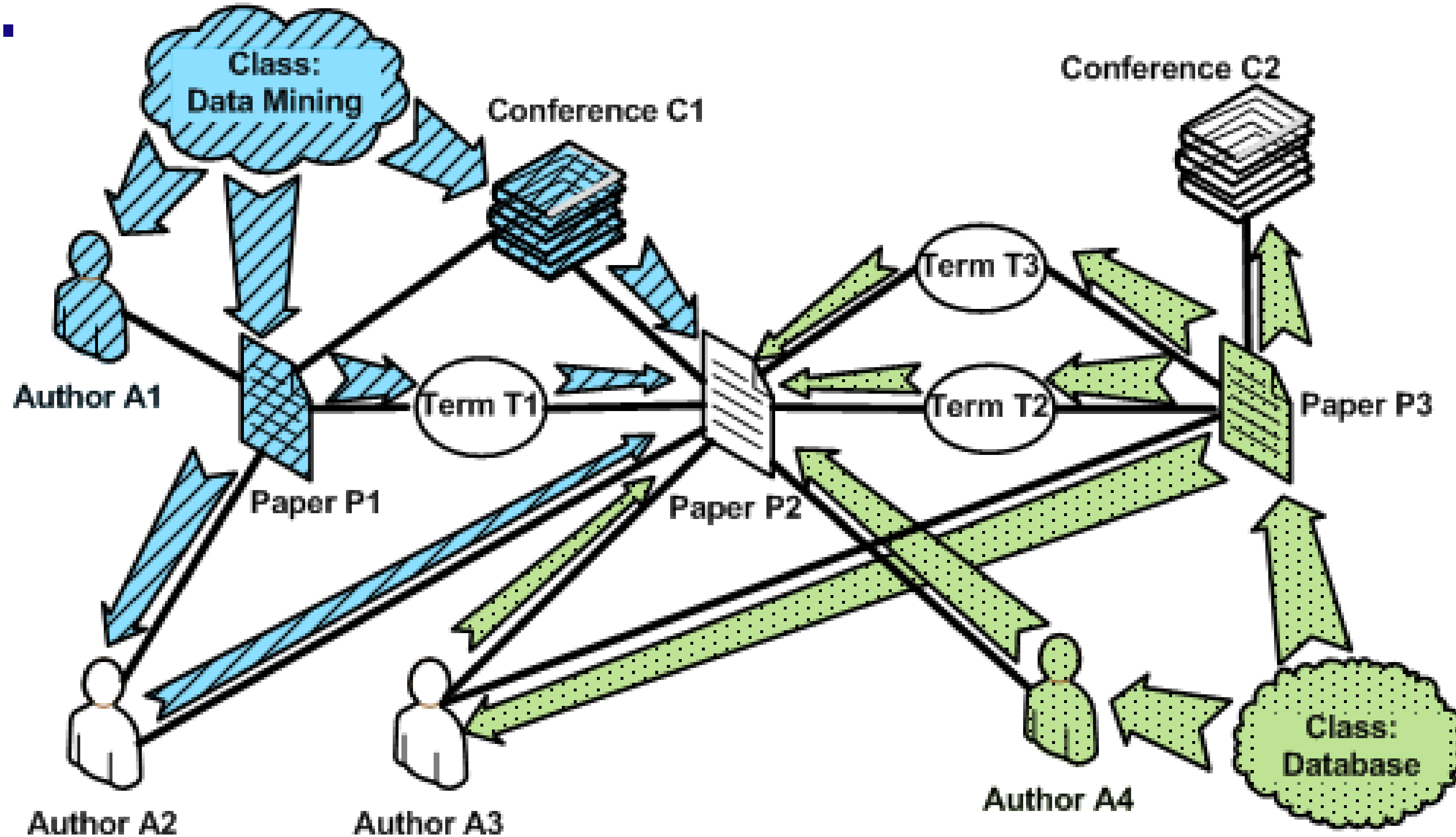
Classification: Knowledge Propagation



M. Ji, M. Danilevski, et al., "Graph Regularized Transductive Classification on Heterogeneous Information Networks", ECMLPKDD'10

GNetMine: Graph-Based Regularization [Ji, PKDD'10]

- Minimize the objective function

$$J(\boldsymbol{f}_1^{(k)}, \dots, \boldsymbol{f}_m^{(k)})$$

User preference: how much do you value this relationship / ground truth?

$$= \sum_{i,j=1}^{m} \lambda_{ij} \sum_{p=1}^{n_i} \sum_{q=1}^{n_j} R_{ij,pq} \left(\frac{1}{\sqrt{D_{ij,pp}}} f_{ip}^{(k)} - \frac{1}{\sqrt{D_{ji,qq}}} f_{jq}^{(k)} \right)^2$$

$$+ \sum_{i=1}^{m} \alpha_i (\boldsymbol{f}_i^{(k)} - \mathbf{y}_i^{(k)})^T (\boldsymbol{f}_i^{(k)} - \mathbf{y}_i^{(k)})$$

Smoothness constraints: objects linked together should share *similar* estimations of confidence belonging to class *k*

Normalization term applied to each type of link separately: reduce the impact of popularity of nodes

Confidence estimation on labeled data and their pre-given labels should be similar

From RankClus to GNetMine & RankClass

- **RankClus [EDBT'09]: Clustering and ranking working together**
  - No training, no available class labels, no expert knowledge
- **GNetMine [PKDD'10]: Incorp. prior knowledge in networks**
  - Classification in heterog. networks, but objects treated equally
- **RankClass [KDD'11]: Integration of ranking and classification in heterogeneous network analysis**
  - Ranking: informative understanding & summary of each class
  - Class membership is critical information when ranking objects
  - Let ranking and classification mutually enhance each other!
  - Output: Classification results + ranking list of objects within each class

Experiments on DBLP

- Class: Four research areas (communities)
  - Database, data mining, AI, information retrieval
- Four types of objects
  - Paper (14376), Conf. (20), Author (14475), Term (8920)
- Three types of relations
  - Paper-conf., paper-author, paper-term
- Algorithms for comparison
  - Learning with Local and Global Consistency (LLGC) [Zhou et al. NIPS 2003] – also the homogeneous version of our method
  - Weighted-vote Relational Neighbor classifier (wvRN) [Macskassy et al. JMLR 2007]
  - Network-only Link-based Classification (nLB) [Lu et al. ICML 2003, Macskassy et al. JMLR 2007]

Performance Study on the DBLP Data Set

Table 3: Comparison of classification accuracy on authors (%)

($a\%, p\%$) of authors and papers labeled	nLB (A-A)	nLB (A-C-P-T)	wvRN (A-A)	wvRN (A-C-P-T)	LLGC (A-A)	LLGC (A-C-P-T)	GNetMine (A-C-P-T)	RankClass (A-C-P-T)
(0.1%, 0.1%)	25.4	26.0	40.8	34.1	41.4	61.3	82.9	**83.9**
(0.2%, 0.2%)	28.3	26.0	46.0	41.2	44.7	62.2	83.4	**85.6**
(0.3%, 0.3%)	28.4	27.4	48.6	42.5	48.8	65.7	86.7	**88.3**
(0.4%, 0.4%)	30.7	26.7	46.3	45.6	48.7	66.0	87.2	**88.8**
(0.5%, 0.5%)	29.8	27.3	49.0	51.4	50.6	68.9	87.5	**89.2**
average	28.5	26.7	46.3	43.0	46.8	64.8	85.5	**87.2**

Table 4: Comparison of classification accuracy on papers (%)

($a\%, p\%$) of authors and papers labeled	nLB (P-P)	nLB (A-C-P-T)	wvRN (P-P)	wvRN (A-C-P-T)	LLGC (P-P)	LLGC (A-C-P-T)	GNetMine (A-C-P-T)	RankClass (A-C-P-T)
(0.1%, 0.1%)	49.8	31.5	62.0	42.0	67.2	62.7	**79.2**	77.7
(0.2%, 0.2%)	73.1	40.3	71.7	49.7	72.8	65.5	**83.5**	83.0
(0.3%, 0.3%)	77.9	35.4	77.9	54.3	76.8	66.6	83.2	**83.6**
(0.4%, 0.4%)	79.1	38.6	78.1	54.4	77.9	70.5	83.7	**84.7**
(0.5%, 0.5%)	80.7	39.3	77.9	53.5	79.0	73.5	84.1	**84.8**
average	72.1	37.0	73.5	50.8	74.7	67.8	82.7	**82.8**

Table 5: Comparison of classification accuracy on conferences (%)

($a\%, p\%$) of authors and papers labeled	nLB (A-C-P-T)	wvRN (A-C-P-T)	LLGC (A-C-P-T)	GNetMine (A-C-P-T)	RankClass (A-C-P-T)
(0.1%, 0.1%)	25.5	43.5	79.0	81.0	**84.5**
(0.2%, 0.2%)	22.5	56.0	83.5	85.0	**85.5**
(0.3%, 0.3%)	25.0	59.0	**87.0**	**87.0**	**87.0**
(0.4%, 0.4%)	25.0	57.0	86.5	89.5	**90.5**
(0.5%, 0.5%)	25.0	68.0	90.0	94.0	**95.0**
average	24.6	56.7	85.2	87.3	**88.5**

Experiments with Very Small Training Set

- DBLP: 4-fields data set (DB, DM, AI, IR) forming a heterog. info. network
- Rank objects within each class (with extremely limited label information)
- Obtain High classification accuracy and excellent rankings within each class

	Database	Data Mining	AI	IR
Top-5 ranked conferences	VLDB	KDD	IJCAI	SIGIR
	SIGMOD	SDM	AAAI	ECIR
	ICDE	ICDM	ICML	CIKM
	PODS	PKDD	CVPR	WWW
	EDBT	PAKDD	ECML	WSDM
Top-5 ranked terms	data	mining	learning	retrieval
	database	data	knowledge	information
	query	clustering	reasoning	web
	system	classification	logic	search
	xml	frequent	cognition	text

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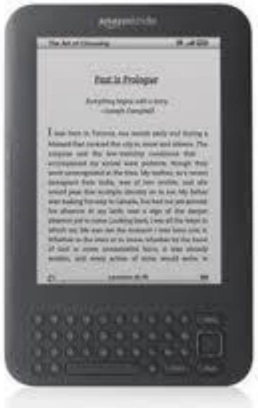
Similarity Search: Find Similar Objects in Networks [Sun, VLDB'11]

- DBLP
  - Who are the most similar to "Christos Faloutsos"?

- IMDB
  - Which movies are the most similar to "Little Miss Sunshine"?

- E-Commerce
  - Which products are the most similar to "Kindle"?



How to systematically answer these questions in heterogeneous information networks?

Existing Link-based Similarity Functions

- Existing similarity functions in networks
  - Personalized PageRank (P-PageRank) [Jeh and Widom, 2003]
  - SimRank [Jeh and Widom, 2002]

- Drawbacks
  - Do not distinguish object type and link type
  - Limitations on the similarity measures
    - To return highly visible objects or pure objects in the network

Network Schema and Meta-Path

Objects are connected together via different types of relationships!

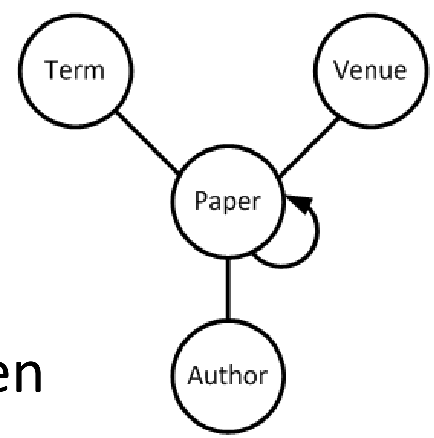
“Jim-P1-Ann”
“Mike-P2-Ann”
“Mike-P3-Bob”

Author-Paper-Author

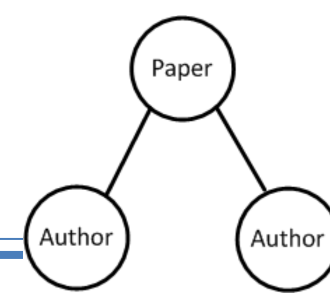
“Jim-P1-SIGMOD-P2-Ann”
“Mike-P3-SIGMOD-P2-Ann”
“Mike-P4-KDD-P5-Bob”

Author-Paper-Venue-Paper-Author

- Network schema
  - Meta-level description of a network

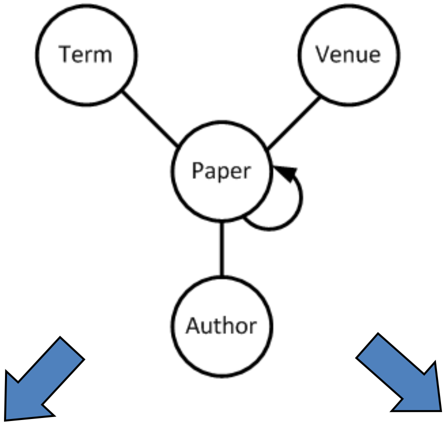


- Meta-Path
  - **Meta-level description** of a path between two objects
  - **A path** on network schema
  - Denote an existing or concatenated **relation** between two object types



Different Meta-Paths Tell Different Semantics

- Who are most similar to Christos Faloutsos?



Meta-Path: ***Author-Paper-Author***

Rank	Author	Score
1	Christos Faloutsos	1
2	Spiros Papadimitriou	0.127
3	Jimeng Sun	0.12
4	Jia-Yu Pan	0.114
5	Agma J. M. Traina	0.110
6	Jure Leskovec	0.096
7	Caetano Traina Jr.	0.096
8	Hanghang Tong	0.091
9	Deepayan Chakrabarti	0.083
10	Flip Korn	0.053

Christos's students or close collaborators

Meta-Path: ***Author-Paper-Venue-Paper-Author***

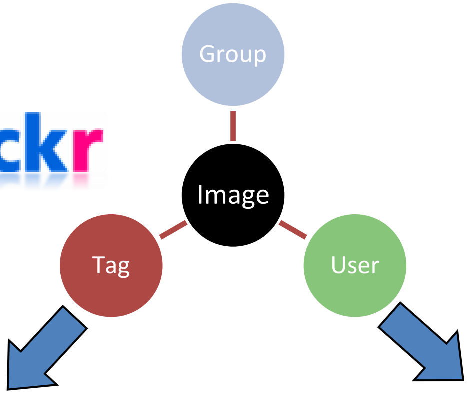
Rank	Author	Score
1	Christos Faloutsos	1
2	Jiawei Han	0.842
3	Rakesh Agrawal	0.838
4	Jian Pei	0.8
5	Charu C. Aggarwal	0.739
6	H. V. Jagadish	0.705
7	Raghu Ramakrishnan	0.697
8	Nick Koudas	0.689
9	Surajit Chaudhuri	0.677
10	Divesh Srivastava	0.661

Work on similar topics and have similar reputation

Some Meta-Path Is “Better” Than Others

- Which pictures are most similar to  ?

flickr

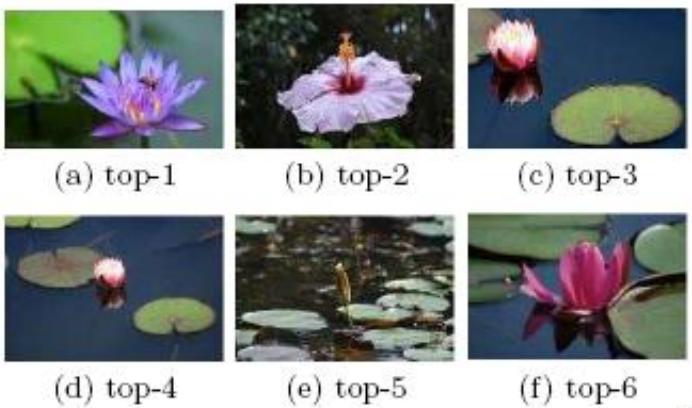


Evaluate the similarity between images according to their linked tags

Evaluate the similarity between images according to tags and groups

Meta-Path: ***Image-Tag-Image***

Meta-Path: ***Image-Tag-Image-Group-Image-Tag-Image***



PathSim: Similarity in Terms of "Peers"

- Why peers?
  - Strongly connected, while **similar visibility**

Amazon Kindle

B&N Nook

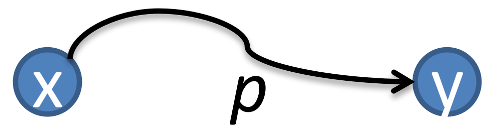
Sony Reader

Kobo eReader

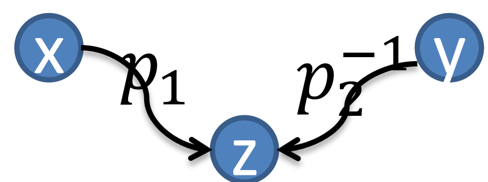
- In addition to meta-path
  - Need to consider **similarity measures**

Limitations of Existing Similarity Measures

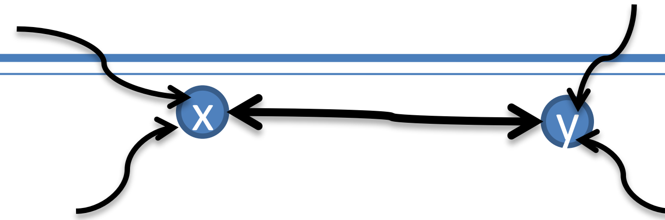
- Random walk (RW)
  - $s(x, y) = \sum_{p \in \mathcal{P}} Prob(p)$
  - Used in **Personalized PageRank (P-PageRank)**
  - Favor **highly visible** objects
    - objects with large degrees



- Pairwise random walk (PRW)
  - $s(x, y) = \sum_{(p_1, p_2) \in (\mathcal{P}_1, \mathcal{P}_2)} Prob(p_1) Prob(p_2^{-1})$
  - Used in **SimRank**
  - Favor **"pure"** objects
    - objects with highly skewed distribution in their in-links or out-links



Only PathSim Can Find Peers



- PathSim
  - Normalized path count between x and y following meta-path $\mathcal{P}$

$$s(x,y) = \frac{2 \times |\{p_{x \rightsquigarrow y} : p_{x \rightsquigarrow y} \in \mathcal{P}\}|}{\underbrace{\boxed{|\{p_{x \rightsquigarrow x} : p_{x \rightsquigarrow x} \in \mathcal{P}\}|}}_{\text{Visibility of x}} + \underbrace{\boxed{|\{p_{y \rightsquigarrow y} : p_{y \rightsquigarrow y} \in \mathcal{P}\}|}}_{\text{Visibility of y}}}$$

  - Favor **“peers”**:
    - objects with strong connectivity and similar visibility under the given meta-path
  - Calculation
    - For $\mathcal{P}$: $A_1 - A_2 - \cdots - A_l - A_{l-1} - \cdots - A_1$
      - $M = W_{A_1A_2} W_{A_2A_3} \ldots W_{A_{l-1}A_l} W_{A_lA_{l-1}} \ldots W_{A_3A_2} W_{A_2A_1}$
      - $s(x,y) = \frac{2M_{xy}}{M_{xx}+M_{yy}}$
      - A co-clustering based pruning algorithm is provided
        » 18.23% - 68.04% efficiency improvement over the baseline

Properties of PathSim

- Symmetric
  - $s(x, y) = s(y, x)$
- Self-Maximum
  - $s(x, y) \in [0,1], and\ s(x, x) = 1$
- Balance of visibility
  - $s(x, y) \le \frac{2}{\sqrt{M_{xx}/M_{yy}}+\sqrt{M_{yy}/M_{xx}}}$
    - M_{xx} is the number of path instances starting from *x* and ending with *x* following the given meta path
- Limiting behavior
  - If repeating a pattern of meta path infinite times, PathSim degenerates to authority ranking comparison

Long meta path without introducing new relationships is not that helpful!

Find Academic Peers by PathSim

- Anhai Doan
  - CS, Wisconsin
  - Database area
  - PhD: 2002

- Jignesh Patel
  - CS, Wisconsin
  - Database area
  - PhD: 1998

Meta-Path: ***Author-Paper-Venue-Paper-Author***

Rank	P-PageRank	SimRank	PathSim
1	AnHai Doan	AnHai Doan	AnHai Doan
2	Philip S. Yu	Douglas W. Cornell	Jignesh M. Patel
3	Jiawei Han	Adam Silberstein	Amol Deshpande
4	Hector Garcia-Molina	Samuel DeFazio	Jun Yang
5	Gerhard Weikum	Curt Ellmann	Renée J. Miller

- Amol Deshpande
  - CS, Maryland
  - Database area
  - PhD: 2004

- Jun Yang
  - CS, Duke
  - Database area
  - PhD: 2001

Meta-Path: A Key Concept for Mining Heterogeneous Networks

- Meta-path based mining
  - PathPredict [Sun et al., ASONAM'11]
    - Co-authorship prediction using meta-path based similarity
  - PathPredict_when [Sun et al., WSDM'12]
    - When a relationship will happen
  - Citation prediction [Yu et al., SDM'12]
    - Meta-path + topic
- Meta-path learning
  - User Guided Meta-Path Selection [Sun et al., KDD'12 Submission]
    - Meta-path selection + clustering

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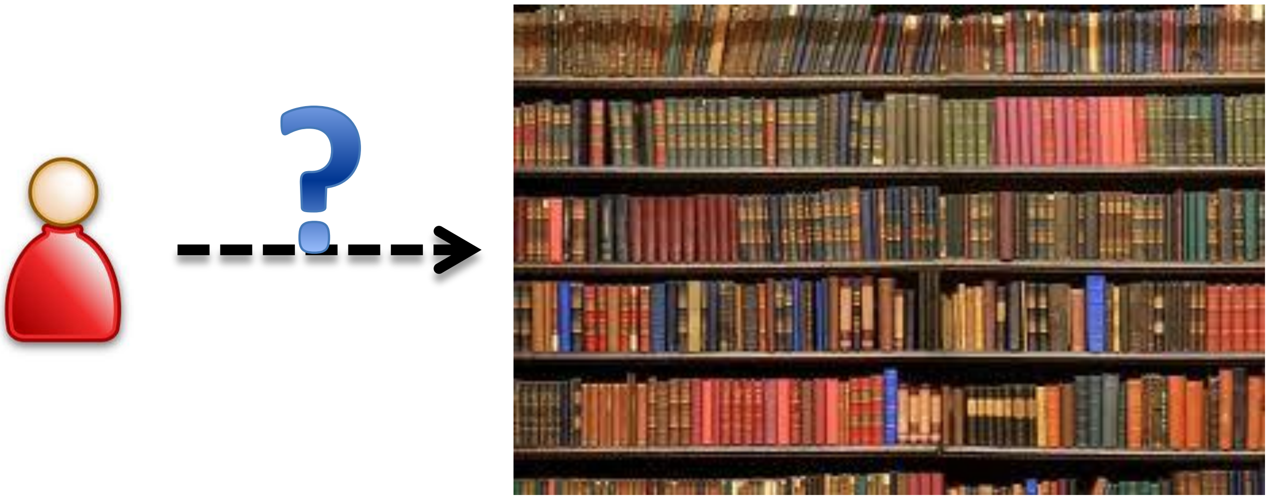
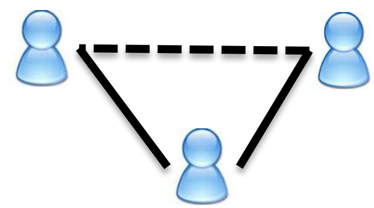
PathPredict: Meta-Path Based Relationship Prediction

- Wide applications
  - Whom should I **collaborate** with?
  - Which paper should I **cite** for this topic?
  - Whom else should I **follow** on Twitter?
  - Whether Ann will **buy** the book “Steve Jobs”?
  - Whether Bob will **click** the ad on hotel?
  - …



Relationship Prediction vs. Link Prediction

- Link prediction in homogeneous networks [Liben-Nowell and Kleinberg, 2003, Hasan et al., 2006]
  - E.g., friendship prediction

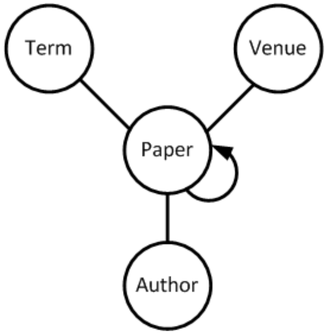


- Relationship prediction in heterogeneous networks
  - Target: Different types of relationships need different prediction models

  - Features: Different connection paths need to be treated separately!
    - **Meta-path based approach** to define topological features.

PathPredict: Meta-Path Based Co-authorship Prediction in DBLP [Sun, ASONAM'11]

- Co-authorship prediction problem
  - Whether two authors are going to collaborate for the first time
- Co-authorship encoded in meta-path
  - Author-Paper-Author
- Topological features encoded in meta-paths



Meta-Path	Semantic Meaning
$A - P \rightarrow P - A$	a_i cites a_j
$A - P \leftarrow P - A$	a_i is cited by a_j
$A - P - V - P - A$	a_i and a_j publish in the same venues
$A - P - A - P - A$	a_i and a_j are co-authors of the same authors
$A - P - T - P - A$	a_i and a_j write the same topics
$A - P \rightarrow P \rightarrow P - A$	a_i cites papers that cite a_j
$A - P \leftarrow P \leftarrow P - A$	a_i is cited by papers that are cited by a_j
$A - P \rightarrow P \leftarrow P - A$	a_i and a_j cite the same papers
$A - P \leftarrow P \rightarrow P - A$	a_i and a_j are cited by the same papers

Meta-paths between authors under length 4

The Power of PathPredict

- Explain the prediction power of each meta-path
  - Wald Test for logistic regression

Social relations play very important role?

Meta Path	p-value	significance level[1]
$A - P \rightarrow P - A$	0.0378	**
$A - P \leftarrow P - A$	0.0077	***
$A - P - V - P - A$	1.2974e-174	****
$A - P - A - P - A$	1.1484e-126	****
$A - P - T - P - A$	3.4867e-51	****
$A - P \rightarrow P \rightarrow P - A$	0.7459	
$A - P \leftarrow P \leftarrow P - A$	0.0647	*
$A - P \rightarrow P \leftarrow P - A$	9.7641e-11	****
$A - P \leftarrow P \rightarrow P - A$	0.0966	*

[1] *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$, ****: $p < 0.001$

- Higher prediction accuracy than using projected homogeneous network
  - **11%** higher in prediction accuracy

Rank	Hybrid heterogeneous features	# Shared authors
1	**Philip S. Yu**	**Philip S. Yu**
2	**Raymond T. Ng**	Ming-Syan Chen
3	Osmar R. Zaïane	Divesh Srivastava
4	**Ling Feng**	Kotagiri Ramamohanarao
5	**David Wai-Lok Cheung**	**Jeffrey Xu Yu**

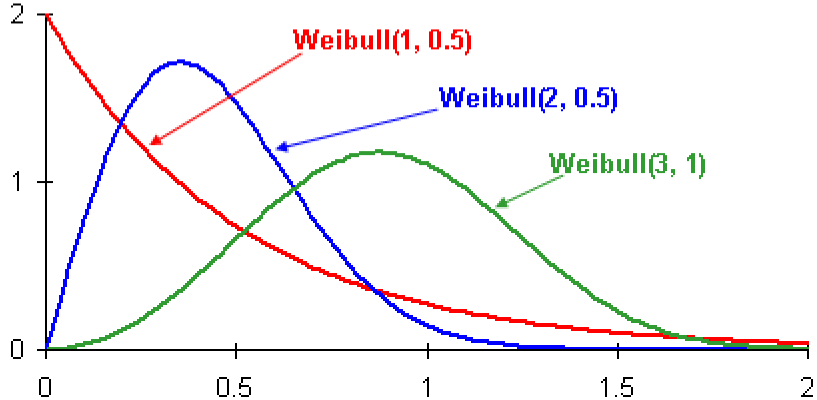
Co-author prediction for Jian Pei: Only 42 among 4809 candidates are true first-time co-authors!
(Feature collected in [1996, 2002]; Test period in [2003,2009])

When Will It Happen? [Sun, WSDM'12]

- From "whether" to "when"
  - "Whether": Will *Jim* rent the movie *"Avatar"* in Netflix?

Output: P(X=1)=?

  - "When": When will *Jim* rent *"Avatar"*?



Output: A distribution of time!

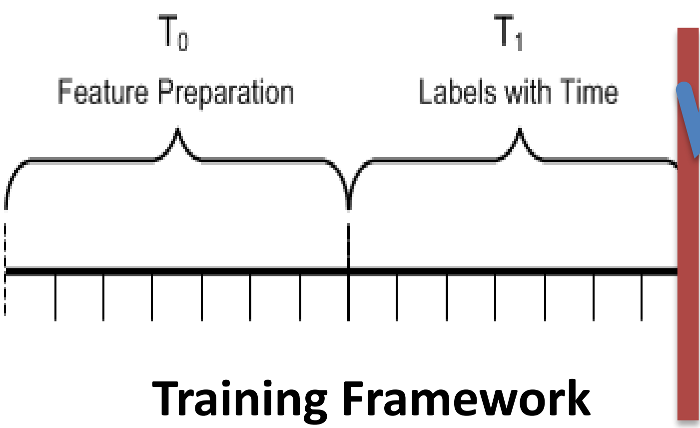
    - What is the probability Jim will rent "Avatar" ***within 2 months***?
      - $P(Y \leq 2)$
    - ***By when*** Jim will rent "Avatar" with 90% probability?
      - $t: P(Y \leq t) = 0.9$
    - What is the ***expected time*** it will take for Jim to rent "Avatar"?
      - $E(Y)$

May provide useful information to supply chain management

The Relationship Building Time Prediction Model

- Solution
  - Directly **model relationship building time**: P(Y=t)
    - Geometric distribution, Exponential distribution, Weibull distribution
  - Use **generalized linear model**
    - Deal with censoring (relationship builds beyond the observed time interval)

***T*: Right Censoring**



Training Framework

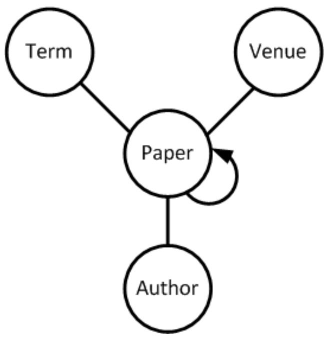
$$\log L = \sum_{i=1}^{n} (f_Y(y_i|\theta_i, \lambda) I_{\{y_i<T\}} + P(y_i \geq T|\theta_i, \lambda) I_{\{y_i \geq T\}})$$

Generalized Linear Model
under Weibull Distribution Assumption

$$LL_W(\boldsymbol{\beta}, \lambda) = \sum_{i=1}^{n} I_{\{y_i<T\}} \log \frac{\lambda y_i^{\lambda-1}}{e^{-\lambda \mathbf{X}_i \beta}} - \sum_{i=1}^{n} (\frac{y_i}{e^{-\mathbf{X}_i \beta}})^{\lambda}$$

Author Citation Time Prediction in DBLP

- Top-4 meta-paths for author citation time prediction



$$A - P - T - P - A$$
Study the same topic

$$A - P \leftarrow P \rightarrow P - A$$
Co-cited by the same paper

$$A - P - A - P \rightarrow P - A$$
Follow co-authors' citation

$$A - P - T - P - A - P \rightarrow P - A$$
Follow the citations of authors who study the same topic

Social relations are less important in author citation prediction than in co-author prediction.

- Predict when Philip S. Yu will cite a new author

a_i	a_j	Ground Truth	Median	Mean	25% quantile	75% quantile
Philip S. Yu	Ling Liu	1	2.2386	3.4511	0.8549	4.7370
Philip S. Yu	Christian S. Jensen	3	2.7840	4.2919	1.0757	5.8911
Philip S. Yu	C. Lee Giles	0	8.3985	12.9474	3.2450	17.7717
Philip S. Yu	Stefano Ceri	0	0.5729	0.8833	0.2214	1.2124
Philip S. Yu	David Maier	9+	2.5675	3.9581	0.9920	5.4329
Philip S. Yu	Tong Zhang	9+	9.5371	14.7028	3.6849	20.1811
Philip S. Yu	Rudi Studer	9+	9.7752	15.0698	3.7769	20.6849

Under Weibull distribution assumption

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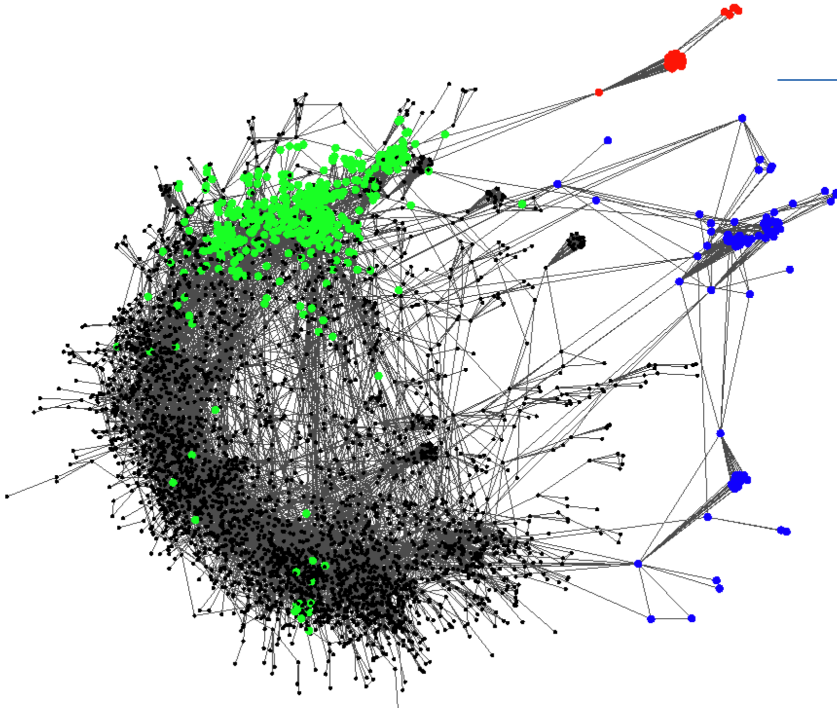
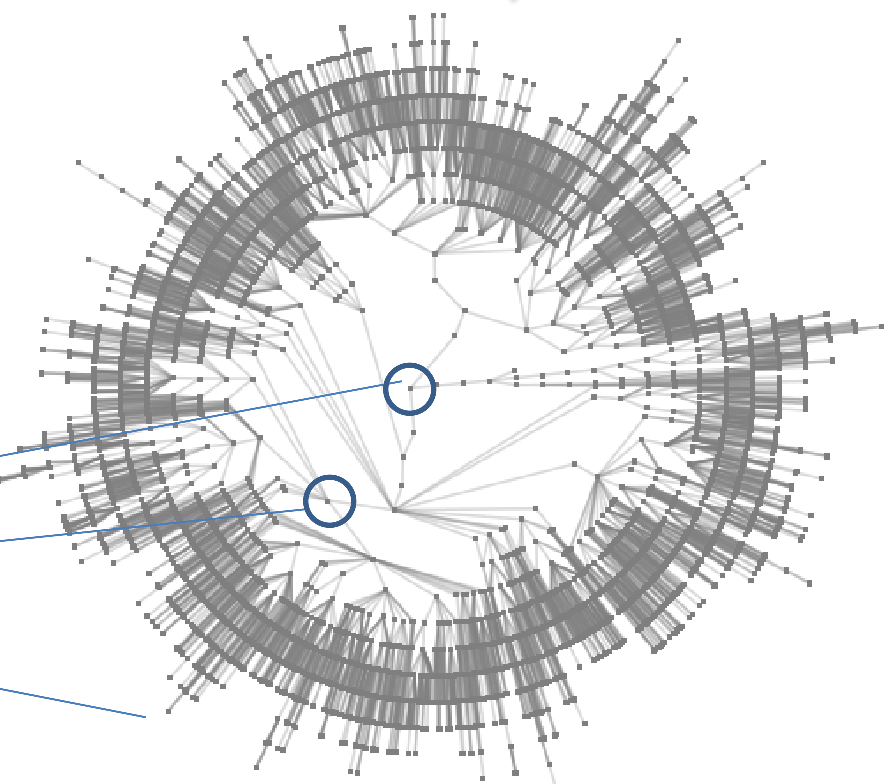
Role Discovery in Network: Why It Matters?



Army communication network (imaginary)



Automatically infer

Commander

Captain

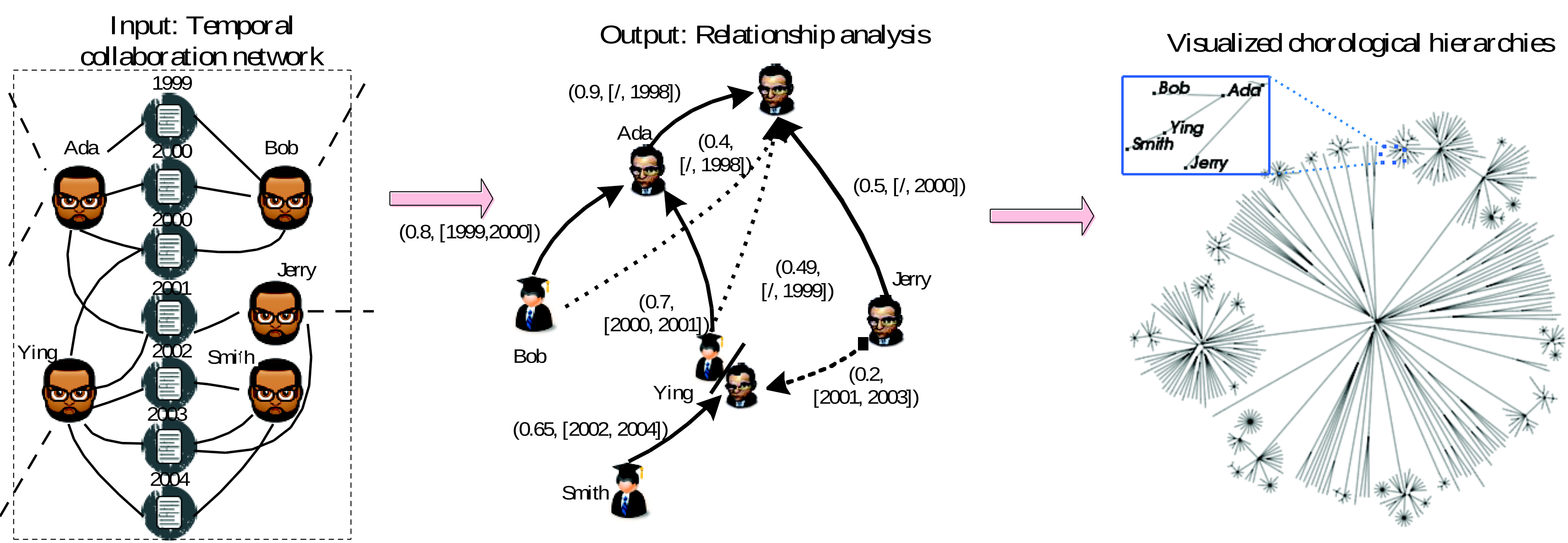
Solider

Role Discovery: Extraction Semantic Information from Links

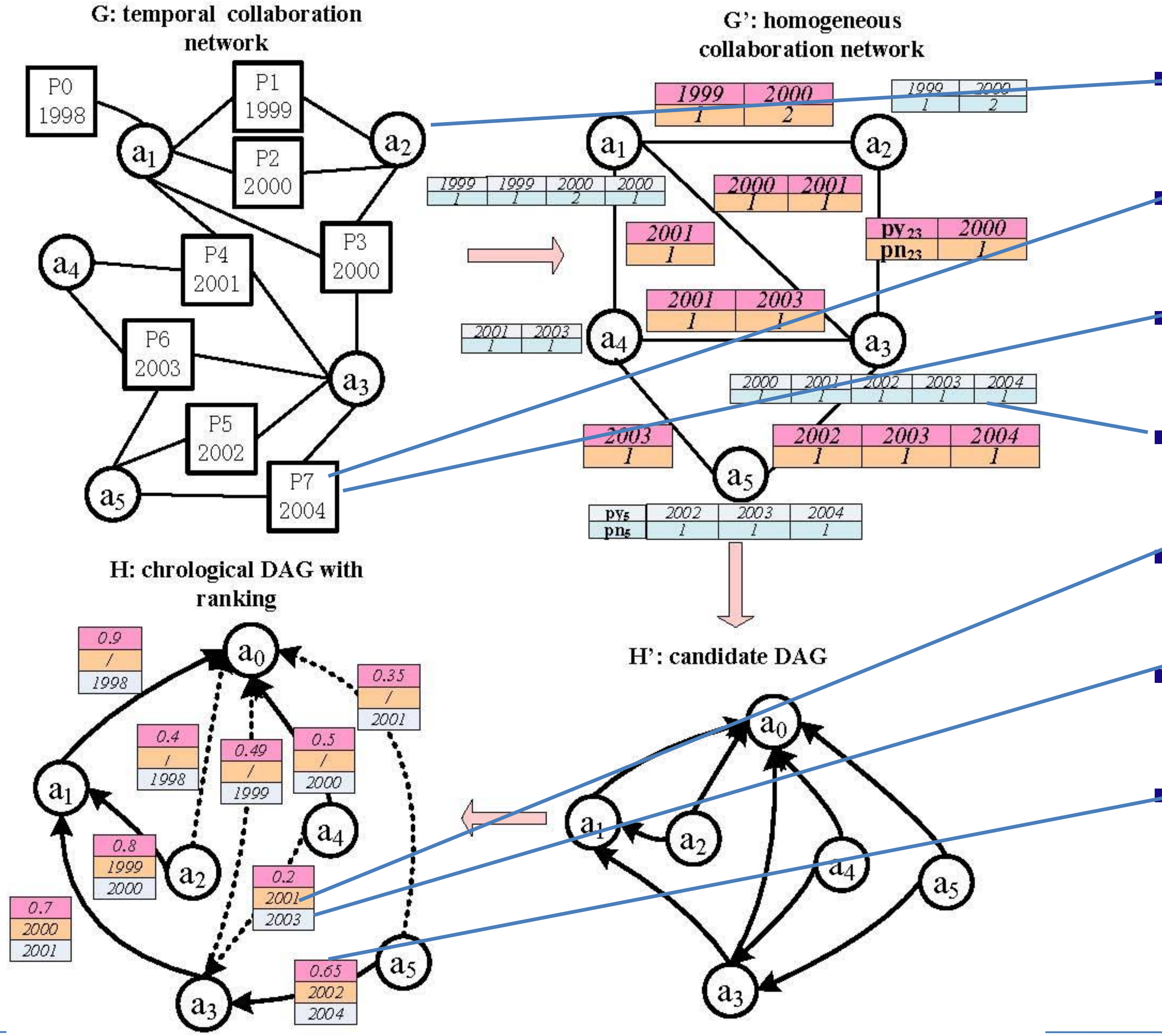
- Objective: Extract semantic meaning from plain links to finely model and better organize information networks
- Challenges
  - Latent semantic knowledge
  - Interdependency
  - Scalability
- Opportunity
  - Human intuition
  - Realistic constraint
  - Crosscheck with collective intelligence
- Methodology: propagate simple intuitive rules and constraints over the whole network

Discovery of Advisor-Advisee Relationships in DBLP Network [Wang, KDD'10]

- Input: DBLP research publication network
- Output: Potential advising relationship and its ranking (r, [st, ed])
- Ref. C. Wang, J. Han, et al., *"Mining Advisor-Advisee Relationships from Research Publication Networks"*, SIGKDD 2010

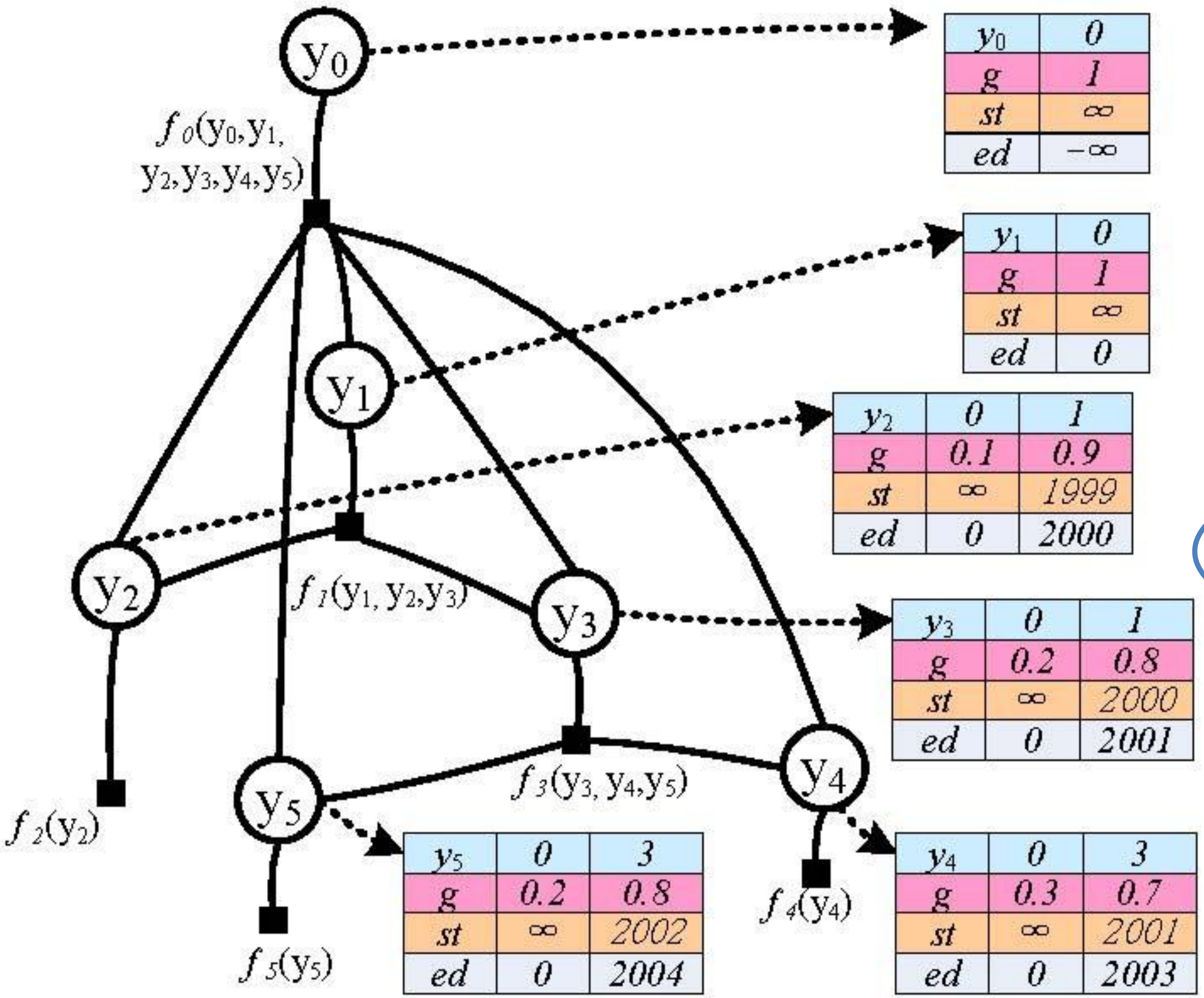


Overall Framework



- a_i: author i
- p_j: paper j
- py: paper year
- pn: paper#
- $st_{i,yi}$: starting time
- $ed_{i,yi}$: ending time
- $r_{i,yi}$: ranking score

Time-Constrained Probabilistic Factor Graph (TPFG)



y_0	0
g	1
st	∞
ed	−∞

y_1	0
g	1
st	∞
ed	0

y_2	0	1
g	0.1	0.9
st	∞	1999
ed	0	2000

y_3	0	1
g	0.2	0.8
st	∞	2000
ed	0	2001

y_5	0	3
g	0.2	0.8
st	∞	2002
ed	0	2004

y_4	0	3
g	0.3	0.7
st	∞	2001
ed	0	2003

- y_x: a_x's advisor
- $st_{x,yx}$: starting time
  $ed_{x,yx}$: ending time
- $g(y_x, st_x, ed_x)$ is predefined local feature
- $f_x(y_x,Z_x) = \max g(y_x, st_x, ed_x)$ *under time constraint*
- Objective function $P(\{y_x\}) = \prod_x f_x(y_x, Z)$
- $Z = \{z \mid x \in Y_z\}$
- Y_x: set of potential advisors of a_x

Experiment Results

- DBLP data: 654, 628 authors, 1076,946 publications, years provided
- Labeled data: Math Genealogy Project; AI Genealogy Project; Homepage

Datasets	RULE	SVM	IndMAX		TPFG	
TEST1	69.9%	73.4%	75.2%	78.9%	80.2%	**84.4%**
TEST2	69.8%	74.6%	74.6%	79.0%	81.5%	**84.3%**
TEST3	80.6%	86.7%	83.1%	90.9%	88.8%	**91.3%**

heuristics

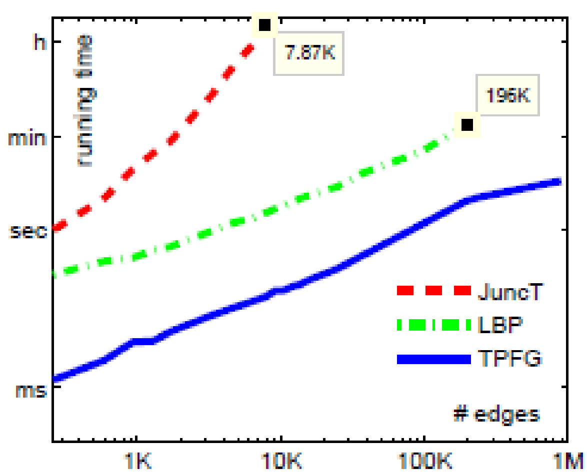
Supervised learning

Empirical parameter

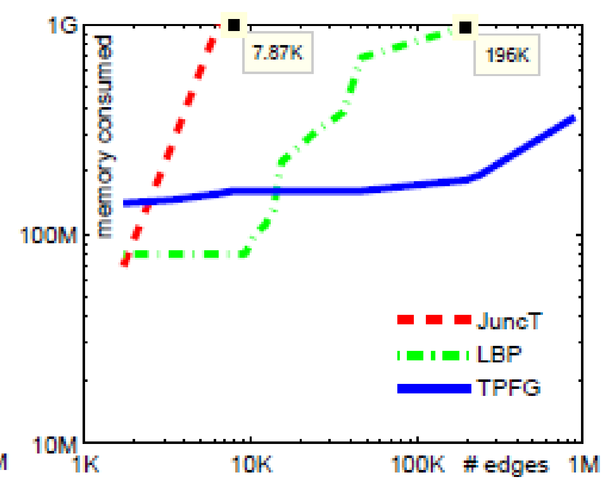
optimized parameter

Case Study & Scalability

Advisee	Top Ranked Advisor	Time	Note
David M. Blei	1. Michael I. Jordan	01-03	PhD advisor, 2004 grad
	2. John D. Lafferty	05-06	Postdoc, 2006
Hong Cheng	1. Qiang Yang	02-03	MS advisor, 2003
	2. Jiawei Han	04-08	PhD advisor, 2008
Sergey Brin	1. Rajeev Motawani	97-98	"Unofficial advisor"



(a) Time



(b) Space

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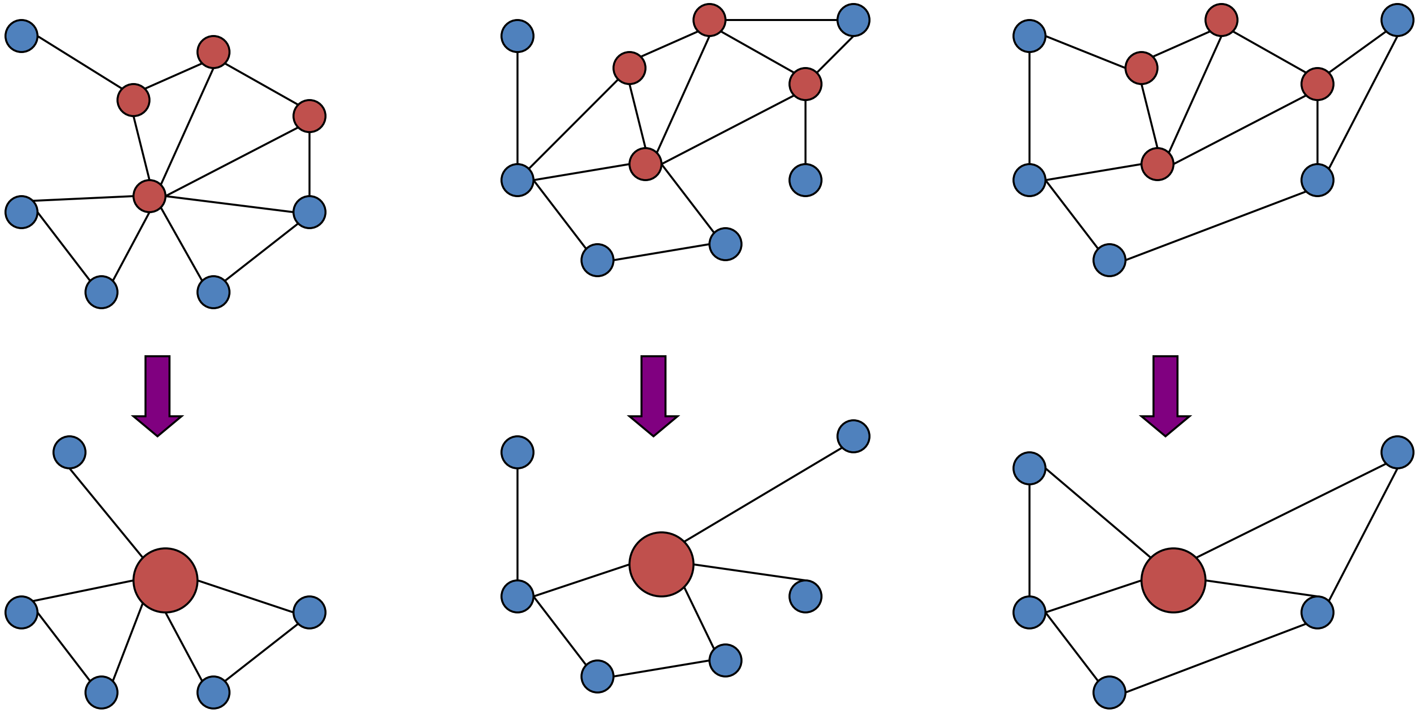
Graph/Network Summarization: Graph Compression

- Extract common subgraphs and simplify graphs by condensing these subgraphs into nodes

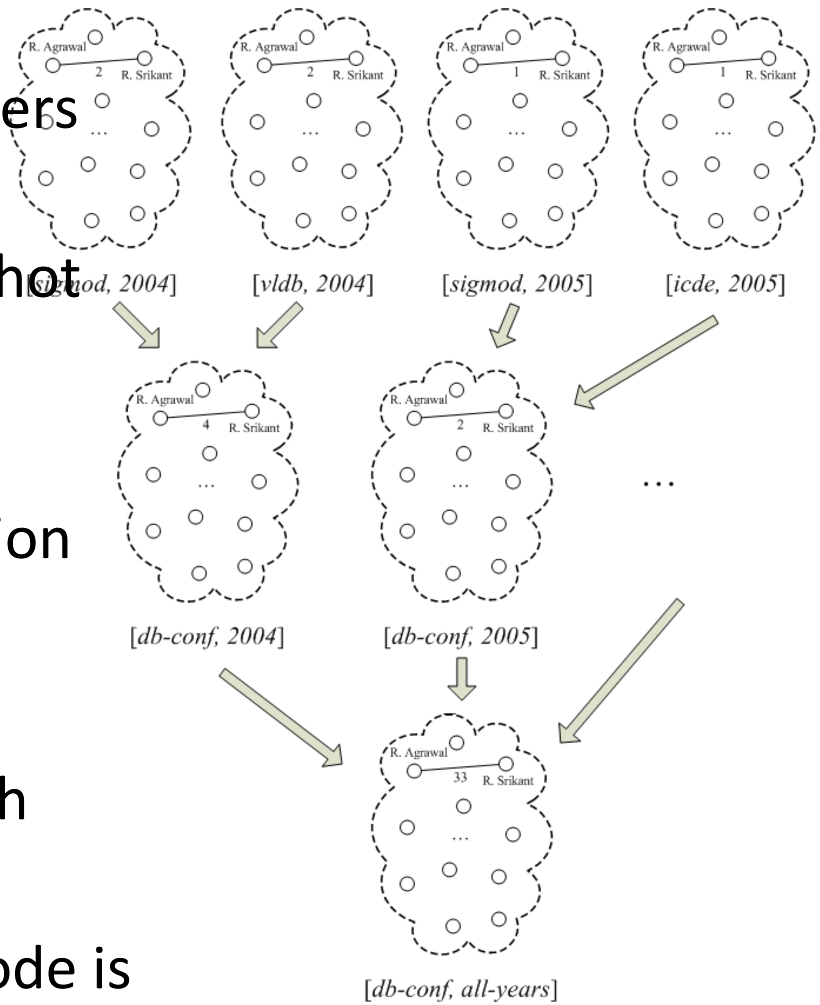


OLAP on Information Networks [Chen, ICDM'08]

- Why OLAP information networks?
- Advantages of OLAP: Interactive exploration of multi-dimensional and multi-level space in a data cube Infonet
  - Multi-dimensional: Different perspectives
  - Multi-level: Different granularities
- InfoNet OLAP: Roll-up/drill-down and slice/dice on information network data
  - Traditional OLAP cannot handle this, because they ignore links among data objects
- Handling two kinds of InfoNet OLAP
  - Informational OLAP
  - Topological OLAP

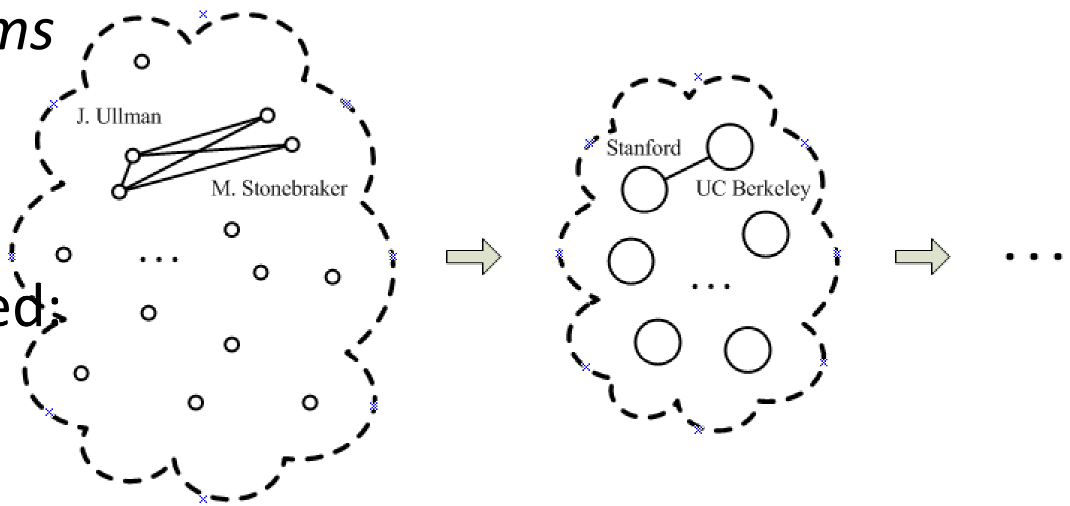
Informational OLAP

- In the DBLP network, study the collaboration patterns among researchers
- Dimensions come from informational attributes attached at the whole snapshot level, so-called *Info-Dims*
- I-OLAP Characteristics:
  - Overlay multiple pieces of information
  - No change on the objects whose interactions are being examined
    - In the underlying snapshots, each node is a researcher
    - In the summarized view, each node is still a researcher



Topological OLAP

- Dimensions come from the node/edge attributes inside individual networks, so-called *Topo-Dims*
- T-OLAP Characteristics
  - Zoom in/Zoom out
  - Network topology changed: “generalized” nodes and “generalized” edges
    - In the underlying network, each node is a researcher
    - In the summarized view, each node becomes an institute that comprises multiple researchers



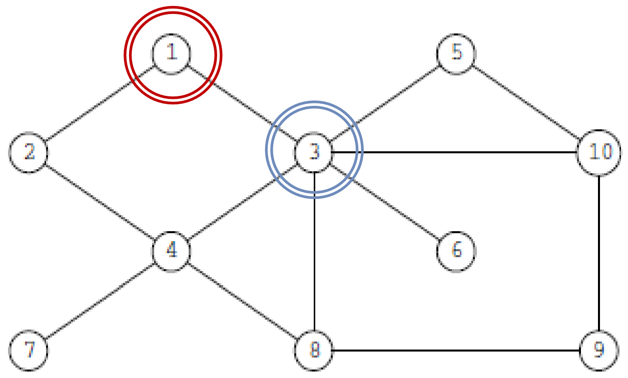
InfoNet OLAP: Operations & Framework

	InfoNet I-OLAP	InfoNet T-OLAP
Roll-up	Overlay multiple snapshots to form a higher-level summary via I-aggregated network	Shrink the topology & obtain a T-aggregated network that represents a compressed view, with topological elements (i.e., nodes and/or edges) merged and replaced by corresp. higher-level ones
Drill-down	Return to the set of lower-level snapshots from the higher-level overlaid (aggregated) network	A reverse operation of roll-up
Slice/dice	Select a subset of qualifying snapshots based on Info-Dims	Select a subnetwork based on Topo-Dims

- Measure is an aggregated graph & other measures like node count, average degree, etc. can be treated as derived
- Graph plays a dual role: (1) data source, and (2) aggregate measure
- Measures could be complex, e.g., maximum flow, shortest path, centrality
- It is possible to combine I-OLAP and T-OLAP into a hybrid case

Graph Cube: Online analytical processing in multidimensional information networks (Zhao, SIGMOD'11)

A Multidimensional Information Network



(a) Graph

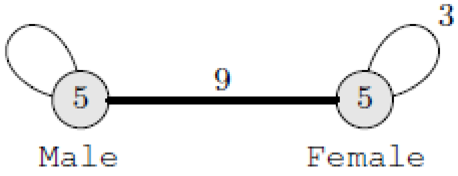
ID	Gender	Location	Profession	Income
1	Male	CA	Teacher	$70,000
2	Female	WA	Teacher	$65,000
3	Female	CA	Engineer	$80,000
4	Female	NY	Teacher	$90,000
5	Male	IL	Lawyer	$80,000
6	Female	WA	Teacher	$90,000
7	Male	NY	Lawyer	$100,000
8	Male	IL	Engineer	$75,000
9	Female	CA	Lawyer	$120,000
10	Male	IL	Engineer	$95,000

(b) Vertex Attribute Table

Figure: A Multidimensional Network Comprising a Graph Structure and a Multidimensional Vertex Attribute Table

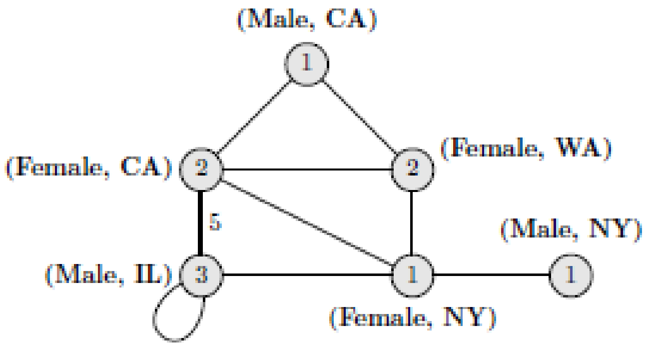
Conventional Group-by v.s. Network Summarization

Gender	COUNT(*)
Male	5
Female	5



Group by "Gender"

Gender	Location	COUNT(*)
Male	CA	1
Female	CA	2
Female	WA	2
Male	IL	3
Male	NY	1
Female	NY	1



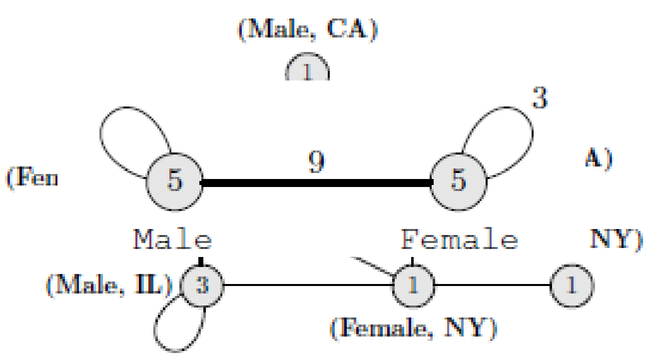
Group by "Gender" and "Location"

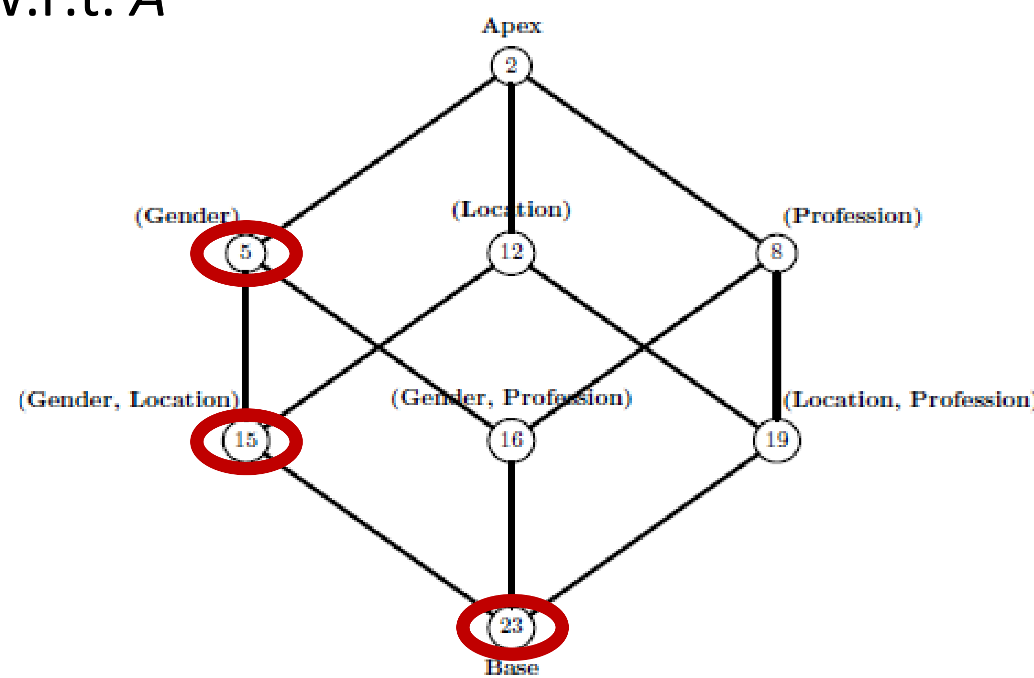
The Graph Cube Model

- Multidimensional network $N = (V, E; A)$
  - $A = \{A_1, A_2, \ldots\ldots, A_n\}$, the **dimension** of the network N, is a set of n vertex-specific attributes
    - Some (or all) dimension A_i could be *(ALL), representing a super-aggregation along A_i
    - there exist $\boldsymbol{2^n}$ multidimensional spaces (aggregations)
  - The **measure** within each possible space is no longer a simple numeric value, but an **aggregate network!**

The Graph Cube Model

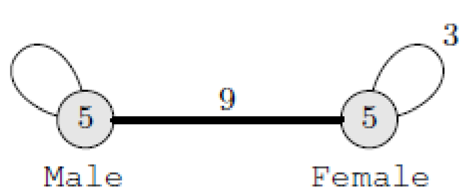
- Graph Cube
  - Restructure the network in **all possible multidimensional spaces (cuboids)** defined on *A*
  - For each multidimensional space *A'*, the measure is an **aggregate network** w.r.t. *A'*

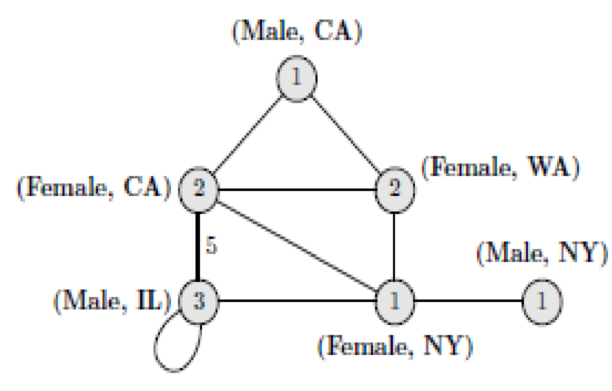




OLAP on Graph Cube

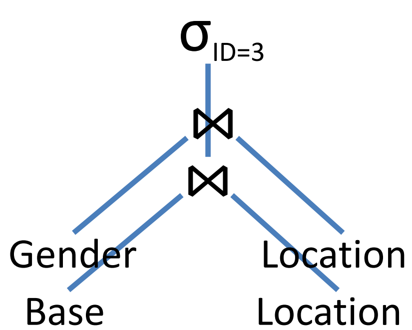
- Cuboid query
  - Return as output the aggregate network corresponding to a specific multidimensional space (**cuboid**)
    - *What is the aggregate network between various genders?*
    - *What is the aggregate network between various gender and location combinations?*

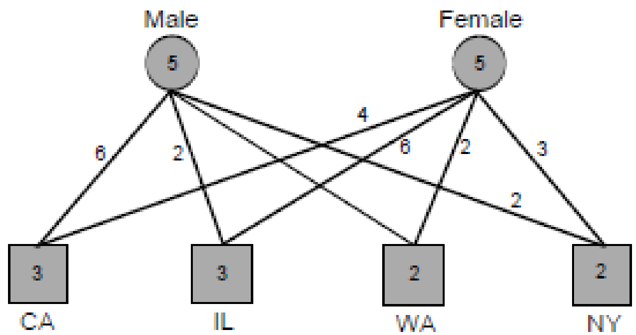




OLAP on Graph Cube

- Cuboid query
  - Within a single multidimensional space
- Crossboid query (⋈)
  - Crosses multiple multidimensional spaces of the network
    - *What is the network structure between user 3 and various locations?*
    - *What is the network structure between users grouped by gender v.s. users grouped by location?*





Outline

- **Motivation:** Why Mining Information Networks?
- **Part I:** Clustering, Ranking and Classification
  - Clustering and Ranking in Information Networks
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- **Part II:** Meta-Path Based Exploration of Information Networks
  - Similarity Search in Information Networks
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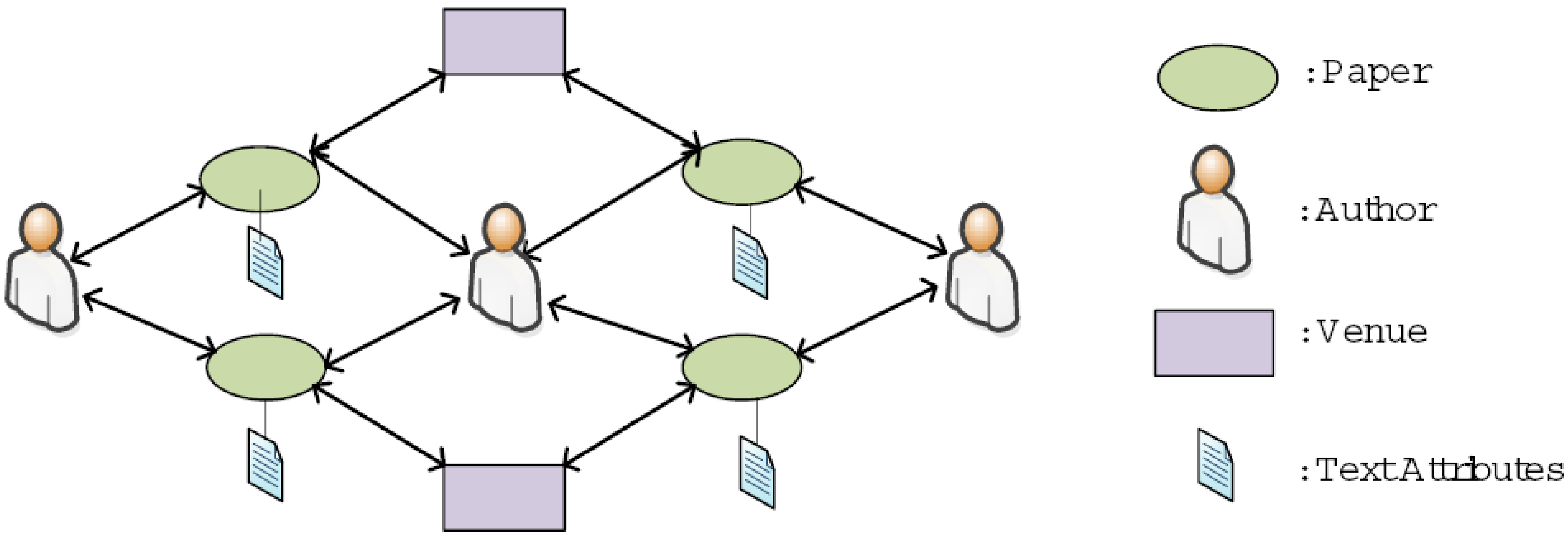
  - Relation Strength Learning in Information Networks
  - Mining Evolution and Dynamics of Information Networks
- **Conclusions**

Relation Strength-Aware Clustering of Heterogeneous InfoNet with Incomplete Attributes [Sun, VLDB'12]

- Content-Rich Heterogeneous information networks become increasingly popular
  - Heterogeneous links + (incomplete) attributes
  - Examples
    - Social media
    - E-Commerce
    - Cyber-physical system
- Soft clustering objects using both link information and attribute information
  - E-Commerce: customers, products, comments, …
  - Social websites: people, groups, books, posts, …
- Understanding the strengths for different relations in determining object's cluster

Example 1: Bibliographic Information Network



Link type:

- **Paper-Author, Paper-Venue, (Paper->Paper)**

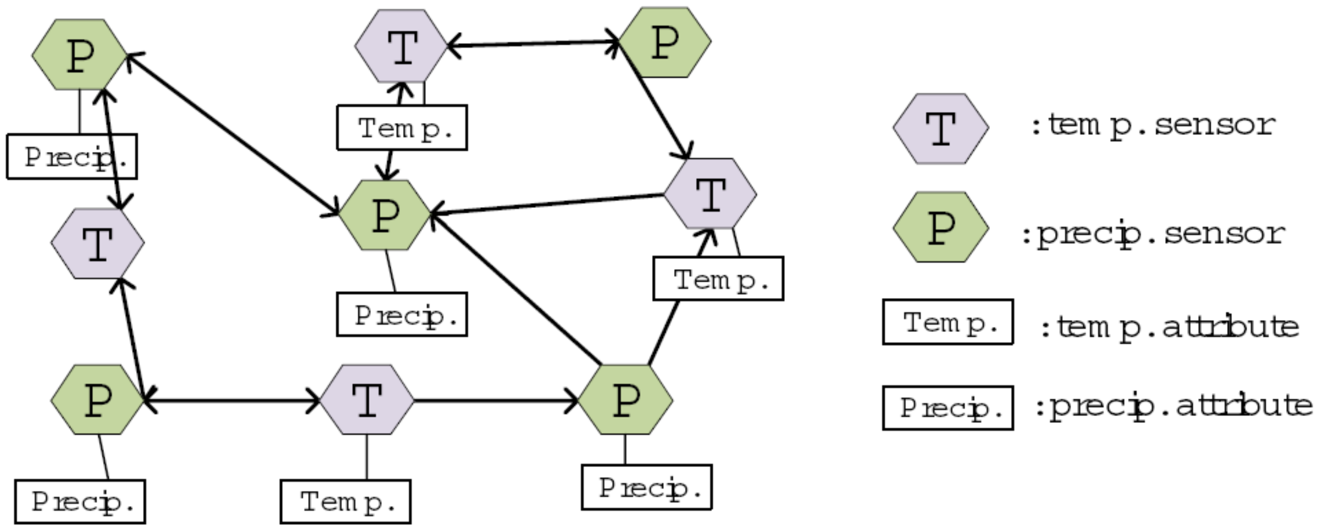
Attribute type:

- **Text attribute for Paper type**

Goal:

- **Clustering authors, venues, papers into different research areas**

Example 2: Weather Sensor Information Network



Link type:

- **T->P, T->T, P->P, P->T (According to KNN relationships)**

Attribute type:

- **Temperature attribute for T-typed sensors, Precipitation attribute for P-typed sensors**

Goal:

- **Clustering both types of sensors into different regional weather patterns**

Challenges

- Attributes are **incomplete** for objects
  - Not every type of objects contained the user specified attributes
    - E.g., Temperature typed sensors are only associated with temperature attributes
  - Missing value
    - E.g., some sensor may contain no observations due to malfunctioning
- Links are **heterogeneous**
  - Different types of links carry different importance in enhancing the quality of attribute-based clustering results
    - E.g., which type of links are more trustable to determine a person's political interest: friendship or person-like-book relationship?

Solution Overview

- Modeling attribute generation and structural consistency in a unified framework

$$p(\{\{v[X]\}_{v\in V_X}\}_{X\in\mathcal{X}}, \Theta|G, \boldsymbol{\gamma}, \boldsymbol{\beta}) = \prod_{X\in\mathcal{X}} p(\{v[X]\}_{v\in V_X}|\Theta, \boldsymbol{\beta})p(\Theta|G, \boldsymbol{\gamma})$$

  - Attribute generation as a mixture model
    - $p(\{v[X]\}_{v\in V_X}|\Theta, \boldsymbol{\beta}) = \prod_{v\in V_X}\prod_{x\in v[X]}\sum_{k=1}^{K}\theta_{v,k}p(x|\boldsymbol{\beta}_k)$
    - *v[X]: observed values for Attribute X on Object v*
    - *Θ: soft clustering membership matrix*
    - *$\boldsymbol{\beta}$: parameters associated with each mixture model component*
  - Structural consistency as a log-linear model
    - $p(\Theta|G, \boldsymbol{\gamma}) = \frac{1}{Z(\boldsymbol{\gamma})}\exp\{\sum_{e=\langle v_i, v_j\rangle\in E} f(\boldsymbol{\theta}_i, \boldsymbol{\theta}_j, e, \boldsymbol{\gamma})\}$
    - *$\boldsymbol{\gamma}$: relation strength vector*

The Objective Function and the Algorithm Overview

$$g(\Theta, \boldsymbol{\beta}, \boldsymbol{\gamma}) = \boxed{\log \sum_{X \in \mathcal{X}} p(\{v[X]\}_{v \in V_X} | \Theta, \boldsymbol{\beta})} + \boxed{\log p(\Theta | G, \boldsymbol{\gamma})} - \boxed{\frac{||\boldsymbol{\gamma}||^2}{2\sigma^2}}$$

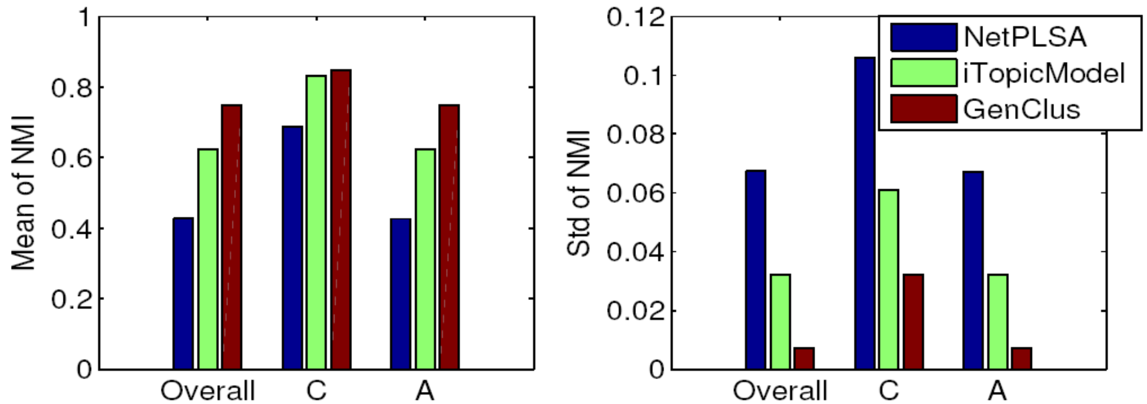
Attribute Generation

Structural Consistency

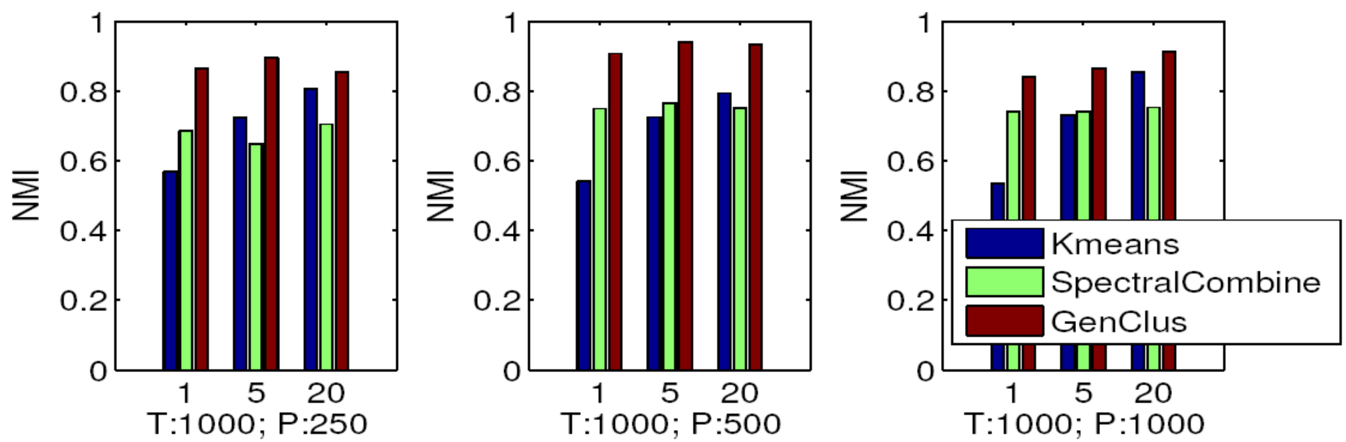
Regularization Term

- The clustering algorithm
  - Iterative algorithm
    - Step 1: Fix the relation strength and optimize the clustering result
      - Cluster optimization
    - Step 2: Fix the clustering result and optimize the relation strength
      - Relation strength learning

Higher Accuracy and More Stable Clustering Results

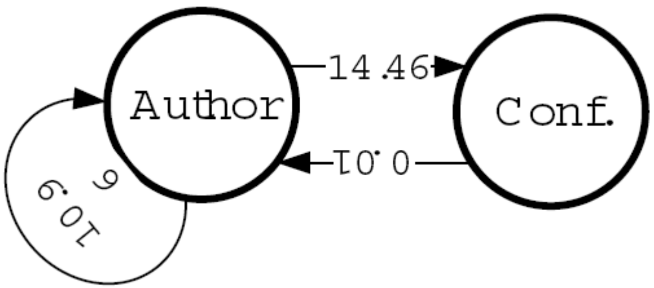


Clustering Accuracy Comparisons for AC

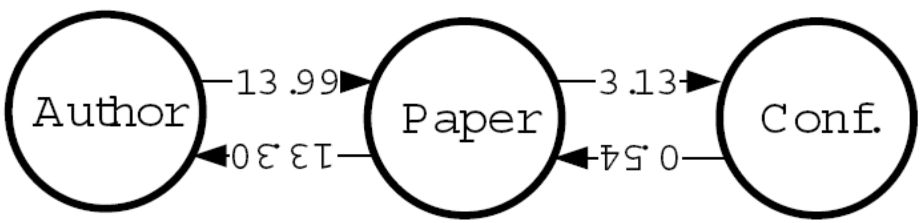


Clustering Accuracy Comparisons for Weather Sensor Network

Intuitive relation strength weights



(a) AC Network



(b) ACP Network

An author's research area is more determined by their attended venues than their co-authors (14.46 vs. 10.69)

A paper's research area is more determined by its authors than its venue (13.30 vs. 3.13)

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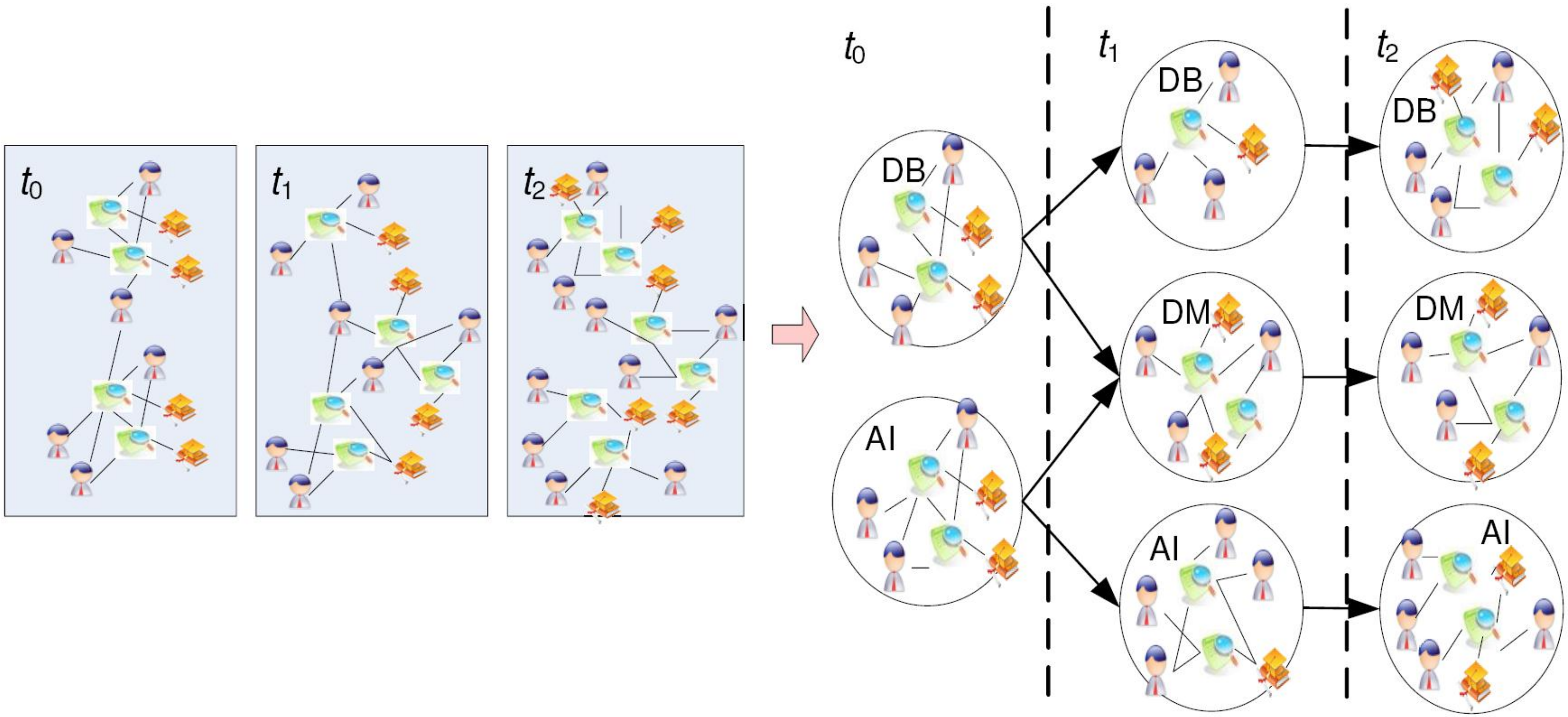
Mining Evolution and Dynamics of InfoNet [Sun, MLG'10]

- Many networks are with time information
  - E.g., according to paper publication year, DBLP networks can form network sequences
- Motivation: Model evolution of communities in heterogeneous network
  - Automatically detect the best number of communities in each timestamp
  - Model the smoothness between communities of adjacent timestamps
  - Model the evolution structure explicitly
    - Birth, death, split

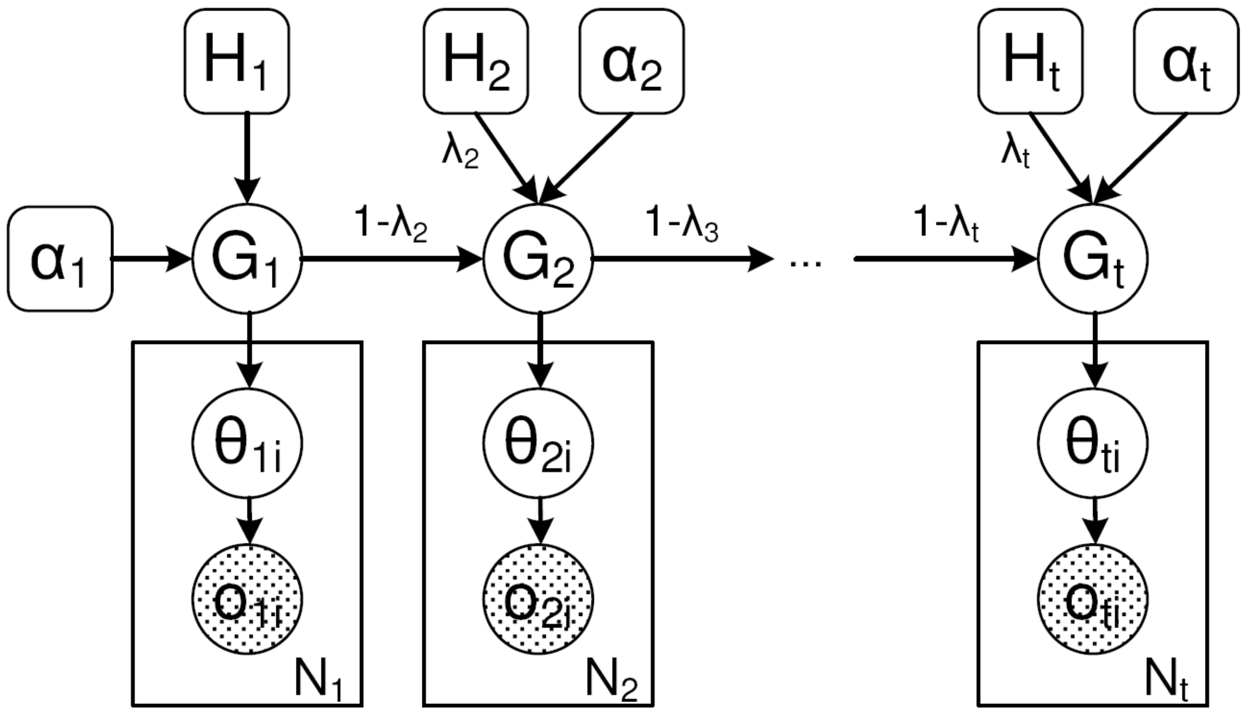
Evolution: Idea Illustration

- **From network sequences to evolutionary communities**



Graphical Model: A Generative Model

- **Dirichlet Process Mixture Model-based generative model**
  - At each timestamp, a community is dependent on historical communities and background community distribution



Generative Model & Model Inference

- To generate a new paper o_i
  - Decide whether to join an existing community or a new one
    - Join an existing community k with prob. $n_k/(i-1+\alpha)$
    - Join a new community k with prob. $\alpha/(i-1+\alpha)$: Decide its prior, either from a background distribution (λ) or historical communities ($(1-\lambda)\pi_k$), with different probabilities, draw the attribute distribution from the prior
  - Generate o_i according to the attribute distribution

$$\begin{aligned} p(o_{i,t}|z_{i,t}=k,\mathbf{\Theta}_t) &= p(o_{i,t}|\theta_{k,t}) \\ &= p(\mathbf{a}_{i,t}|\theta^A_{k,t})p(\mathbf{c}_{i,t}|\theta^C_{k,t})p(\mathbf{d}_{i,t}|\theta^D_{k,t}) \\ &= \prod_{j=1}^{|A|}\theta^A_{k,t}(j)^{a_{ij,t}}\prod_{j=1}^{|C|}\theta^C_{k,t}(j)^{c_{ij,t}}\prod_{j=1}^{|D|}\theta^D_{k,t}(j)^{d_{ij,t}} \end{aligned}$$

- Greedy inference for each timestamp: Collapse Gibbs sampling, which is trying to sample cluster label for each target object (e.g., paper)

Accuracy Study

- The more types of objects used, the better accuracy
- Historical prior results in better accuracy

Year	Training Type	Testing Type	Test Size 10% (cluster number K)	Test Size 20% (cluster number K)
1992	Term	Term	1.600 (4)	1.390 (4)
1992	Term+Author	Term+Author	2.205 (8)	1.697 (6)
1992	Term+Author+Conf.	Term+Author	2.434 (8)	2.095 (8)
1992|1991	Term+Author+Conf.	Term+Author	**2.8365** (8)	**2.671** (8)

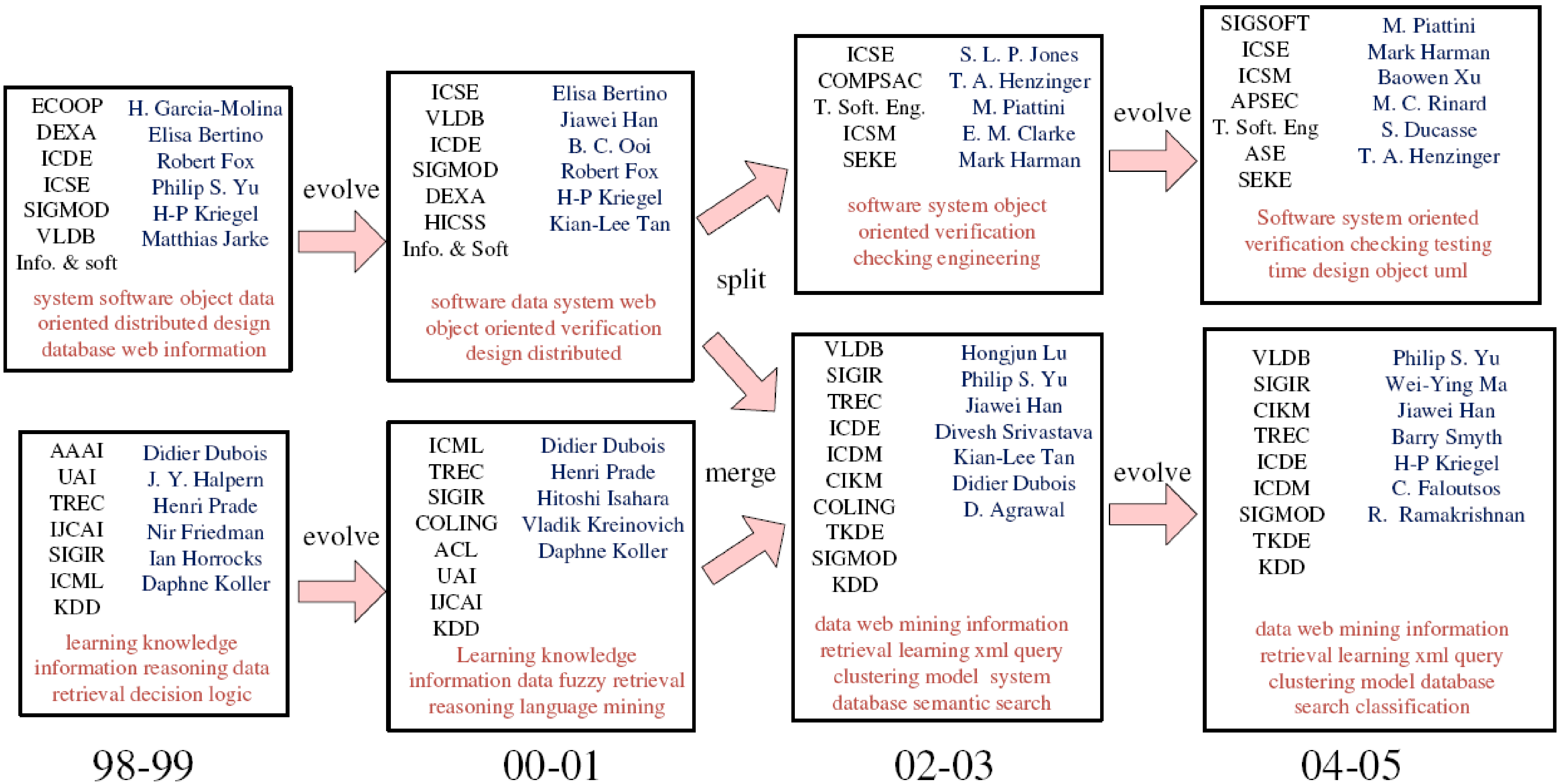
Table 1: Conference Compactness of Different Models on Test Dataset

Year	Training Type	Testing Type	Test Size 10%	Test Size 20%
1992	Term+Author+Conf.	Term+Author+Conf.	3.493×10^{18}	4.673×10^{18}
1992|1991	Term+Author+Conf.	Term+Author+Conf.	$\mathbf{6.384 \times 10^{17}}$	$\mathbf{7.106 \times 10^{17}}$

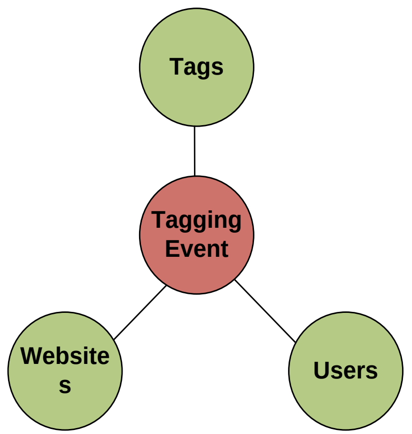
Table 2: Perplexity Comparison between Models with/without Historical Prior

Case Study on DBLP

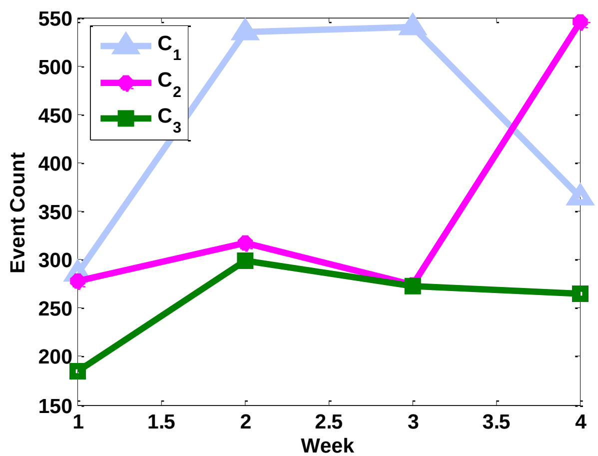
- Tracking database and information system community evolution



Case Study on Delicious.com



Delicious Schema



	Jan. 1 - Jan. 7	Jan. 8 – Jan. 14	Jan. 15 – Jan. 21	Jan. 22 – Jan. 28
C_1:	Security	Google	Security	Google
	Terrorism	China	Google	Security
	Politics	Security	China	China
	Travel	Internet	Internet	Internet
	Usa	Privacy	Microsoft	Privacy
	Airport	Politics	Privacy	Digg
	Israel	Censorship	Censorship	Politics
	Obama	Facebook	Politics	Datenschutz
	CIA	Business	Browser	Facebook
	Afghanistan	Terrorism	USA	USA
C_2:	Mac	Iphone	Iphone	Ipad
	Apple	Apple	Apple	Apple
	Iphone	Twitter	Mac	Iphone
	Windows	Mac	Mobile	Technology
	Tablet	Mobile	Twitter	Tablet
	Ipod	Apps	Software	Mac
	Tips	Ratio	Apps	Mobile
	Macbook	Blog	Business	Newspapers
	Tutorial	Newspapers	Osx	Kindle
	Drm	Technology	Radio	Media
C_3:	Health	Weather	Haiti	Haiti
	Depression	UK	Photography	BBC
	Sleep	Photography	BBC	Photography
	Teenagers	Photo	Earthquake	Animals
	Dubai	Haiti	Photos	Earthquake
	Tallest	Photos	UK	2010
	BBC	2010	2010	Photos
	Building	BBC	Disaster	Nature
	Architecture	Snow	Travel	Funny
	Mentalhealth	Earthquake	Wildlife	Theonion

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Conclusions

- Rich knowledge can be mined from information networks
- What is the magic?
  - ***Heterogeneous*, semi-structured *information networks***!
- Clustering, ranking and classification: Integrated clustering, ranking and classification: RankClus, NetClus, GNetMine, …
- Meta-Path based similarity search and relationship prediction
- Role discovery, OLAP, relation strength learning, and evolutionary analysis
- Knowledge is power, but knowledge is hidden in massive links!
- ***Mining heterogeneous information networks***: Much more to be explored!!

Future Research

- Discovering ontology and structure in information networks
- Discovering and mining hidden information networks
- Mining information networks formed by structured data linking with unstructured data (text, multimedia and Web)
- Mining cyber-physical networks (networks formed by dynamic sensors, image/video cameras, with information networks)
- Enhancing the power of knowledge discovery by transforming massive unstructured data: Incremental information extraction, role discovery, … ⇒ multi-dimensional structured info-net
- Mining noisy, uncertain, un-trustable massive datasets by information network analysis approach
- Turning Wikipedia and/or Web into structured or semi-structured databases by heterogeneous information network analysis

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