

PERSONALIZED TAG RECOMMENDATION

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Booming of Social Tagging Applications

- Del.icio.us (Web page)

Tags for a webpage →

Popular Bookmarks | Explore Tags

The most popular bookmarks on Delicious right now

See more Popular bookmarks →

New bookmarks saved in the last minute 3 1 4

Popular Tags

- design
- blog
- video
- software
- tools
- music
- programming
- webdesign
- reference
- tutorial
- art
- web
- howto
- javascript
- free
- linux
- web2.0
- development
- google

Bookmark 1: Flavour Extended: The Ultimate Icon Set For Web Designers | Freebies | Smashing Magazine (260) [SAVE](#)
tags: icons, icon, resources, graphics, free

Bookmark 2: Teach Yourself Graphic Design: A Self-Study Course Outline - Psdtuts+ (243) [SAVE](#)
tags: design, resources, graphics, tutorials, graphic

Bookmark 3: 5 Ways to Share Images on Twitter (119) [SAVE](#)
tags: twitter, photography, images, photos, web2.0

Bookmark 4: How To Backup Your Twitter Archive (141) [SAVE](#)
tags: twitter, backup, tools, howto, archive

Bookmark 5: raspberry buttermilk cake | smitten kitchen (159) [SAVE](#)
tags: food, recipes, cake, recipe, baking

Booming of Social Tagging Applications

- Flickr (Photos & Image)



22072008658

Tags for an image

A screenshot of the Flickr image page for the photo shown in the previous image. It displays the upload date (July 22, 2008) and the user (ralf.schenkel). Below this is a link to the user's photostream. A section titled "Tags" contains a list of tags: sigir, 2008, sigir2008, banquet, singapore, and sentosa. A green rounded rectangle highlights this list, and a black arrow points from the text "Tags for an image" to the top of the list. Below the tags is an "Additional Information" section with copyright and privacy settings.

Uploaded on July 22, 2008
by [ralf.schenkel](#)

[+ ralf.schenkel's photostream](#)

Tags

- sigir
- 2008
- sigir2008
- banquet
- singapore
- sentosa

Additional Information

© All rights reserved

Anyone can see this photo

Booming of Social Tagging Applications

- CiteULike (Research publications)

The screenshot shows the CiteULike website interface. At the top, there is a search bar and navigation links. The main content area is titled "My library [2 articles]" and lists two articles. The first article is "Personalized, interactive tag recommendation for flickr" with tags "social_tagging" and "recommender". The second article is "Towards effective browsing of large scale social annotations" with tags "social_tagging" and "clustering". A sidebar on the right shows "welbyhebei's tags" including "clustering recommender" and "social_tagging". A red box highlights the "social_tagging" tag in the first article, and an arrow points from it to the text "Two tags for a paper" below the screenshot.

My library [2 articles]

Recent papers added to My library.

[Hide details](#)

- [Personalized, interactive tag recommendation for flickr](#) [My Copy]
In RecSys '08: Proceedings of the 2008 ACM conference on Recommender systems (2008), pp. 67-74.
by [Nikhil Garg](#), [Ingmar Weber](#)
posted to **social_tagging recommender** by [welbyhebei](#) on 2009-05-18 08:56:30 as ★★ [along with 2 people](#)
- [Towards effective browsing of large scale social annotations](#) [My Copy]
In WWW '07: Proceedings of the 16th international conference on World Wide Web (2007), pp. 943-952.
by [Rui Li](#), [Shenghua Bao](#), [Yong Yu](#), [Ben Fei](#), [Zhong Su](#)
posted to [social_tagging](#) [clustering](#) by [welbyhebei](#) on 2009-03-15 04:49:57 as ✓ [along with 11 people and 1 group](#)

Note: You may cite this page as: <http://www.citeulike.org/user/welbyhebei>

welbyhebei's tags
All tags in welbyhebei's library
Filter:

clustering recommender
social_tagging

Two tags for a paper

Booming of Social Tagging Applications

- Last.fm (Music)

last.fm Music Videos Radio Events Charts Music Search welbyhebei Log out | Inbox | Paint it Black | Help | English

Artist

Carpenters

2,777,350 plays (280,306 listeners)

Listening now: valgorgurth
248 shouts

+ Add to my Library

Share

Los Angeles

With their light, airy melodies and meticulously crafted, clean arrangements, the Carpenters stood in direct contrast with the excessive, gaudy pop/rock of the '70s; yet they became one of the most popular artists of the decade, scoring 12 Top Ten hits, including three number one singles.

Play Carpenters Radio

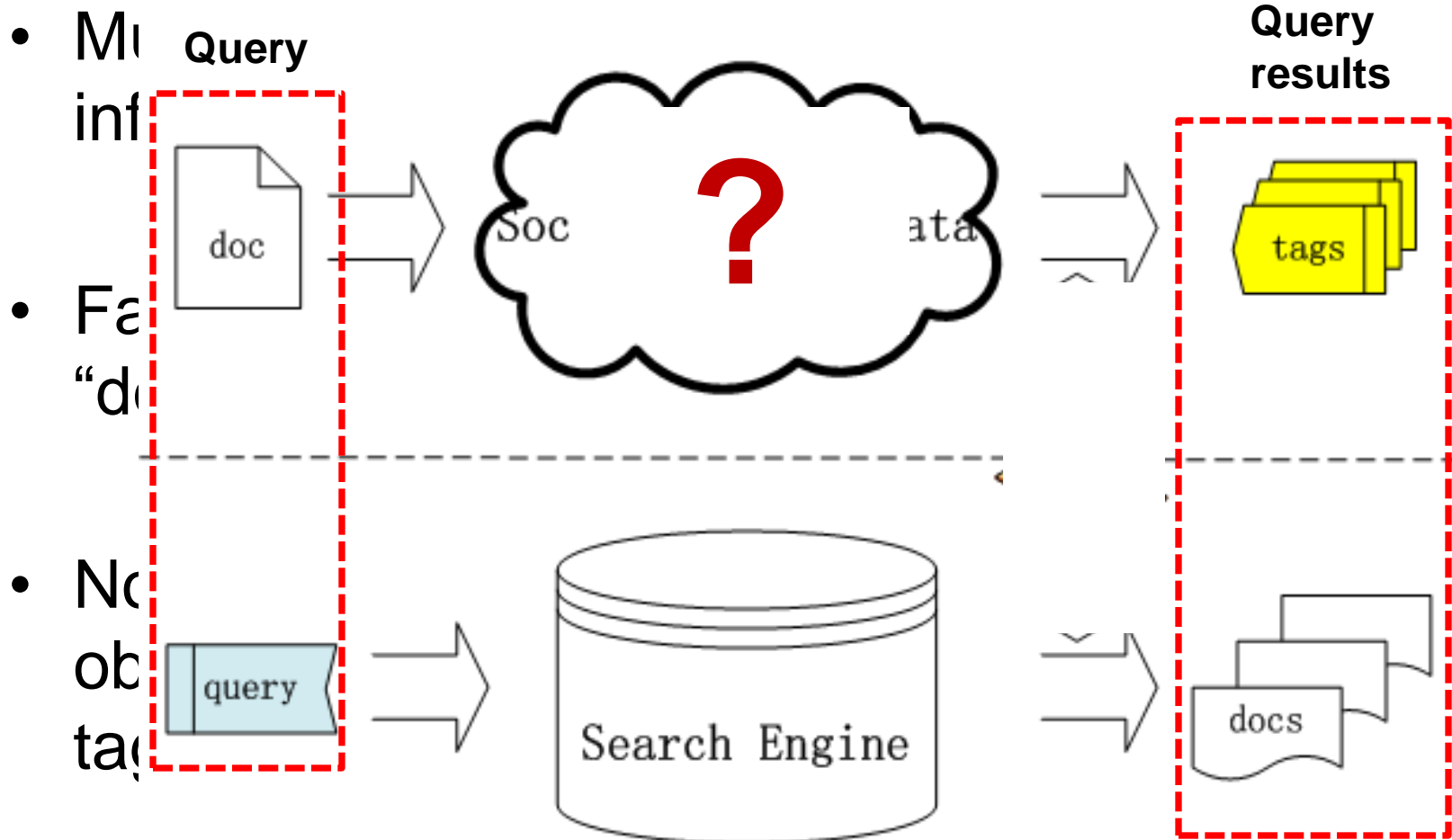
Karen Carpenter's calm, often somber voice was the most distinctive element of their music, settling in perfectly amidst the precise, lush arrangements provided by her brother Richard.

Read more... Edit

Tagged as:
pop, 70s, female vocalists, oldies, easy listening
See more...

Tags for an artist

Compared to Web Search



Tag Recommendation in Real Applications

- Last.fm (Music)
 - Suggested tags: tags for the artist, selected by other users
 - Your tags: historical tags of the user
- Delicious (Web page)
 - “Popular” tags: tags selected by other users
 - “Recommended” tags: “Popular” U “Your tags”

Artist to annotate

URL

TITLE

NOTES

TAGS

Do Not Share

Recommendation section

Tags People

▼ Recommended
media news newspaper

▼ Popular
bbc tv uk radio sport english television

▶ All my tags

Recommendation section

Personalization is Important

- Different users' bookmarks for the home page of ESPN: <http://www.espn.com>

Scores ▶ NBA Full Scoreboard » NHL MLB Customize » Playoffs: May 19, 2009 Auto Update: On

Final
DEN 103
LAL 105

ESPN TV RADIO MAGAZINE INSIDER SHOP ESPN360 SC En Español Register Now myESPN (Sign In)

ALL SPORTS COLUMNISTS PAGE 2 FANTASY GAMES VIDEO SPORTSNATION THE LIFE SEARCH

NFL MLB NBA Soccer College Football IPL MASCAR TOPICS: NFL Playoffs NHL Playoffs NCAA: Spring Tourneys

TERMINATOR SALVATION
JOIN THE RESISTANCE THURSDAY MAY 21 WE FIGHT BACK PG-13

TOP STORIES TOP VIDEOS: Featuring Kobe Talks About Lakers' Game 1 Win

HEADLINES MY HEADLINES RSS

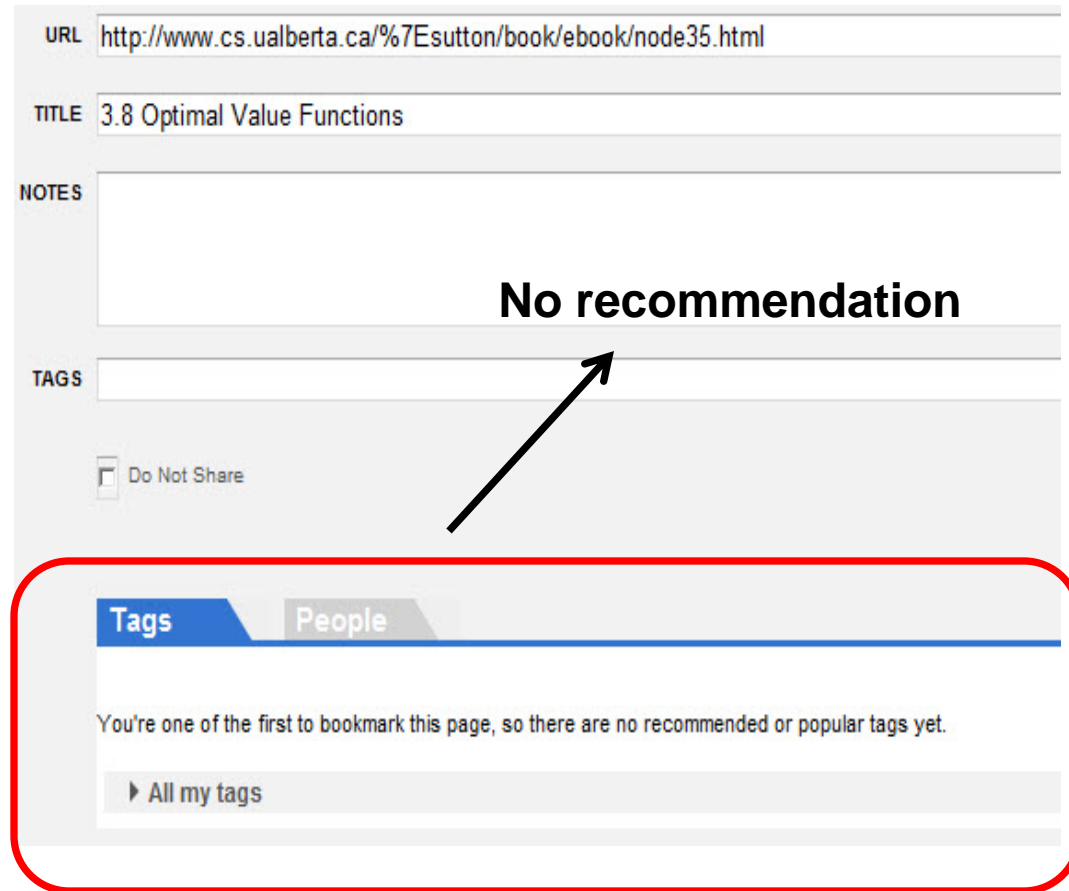
Vick released from prison, evades media
Kobe bests Melo; Lakers win Game 1 | Dime
Clippers win lottery | Griffin set for L.A.
Wings lead 2-0 as Hawks slip in OT | LeBrun
New Orleans gets '13 Super Bowl | Pasquarelli
Woman busted at Nowitzki house: I'm pregnant
French court rejects Ferrari's bid to halt F1 cap
Wall picks Kentucky, wants 'new beginning'
Tennessee plans to self-report another violation
Rumors: Kurt Rambis, Showtime to Sac-Town

He's Going Home
ESPN.com Illustration
Michael Vick has mostly paid his legal debt to society, reportedly leaving prison Wednesday for home confinement. But life's tough on ex-cons. [Howard Bryant](#) » [Vick released](#) » [Munson: Tough road](#)

TERMINATOR SALVATION THURSDAY MAY 21

Challenges

- Lots of web objects have few tags;
- Lots of users have few/no tags;
- Hard to combine “popular tags” and “your tags”;
- Collaborative, robust recommendation algorithms needed



Our Work v.s. Previous Work

- Most previous work focused on recommending tags for resources, ignoring the user factor.
 - Collaborative filtering based on documents (“users”) and tags (“movies”);
- Combine with user preference in an ad hoc way.
- We address personalized tag recommendation.
- An optimization framework with a unified objective function.

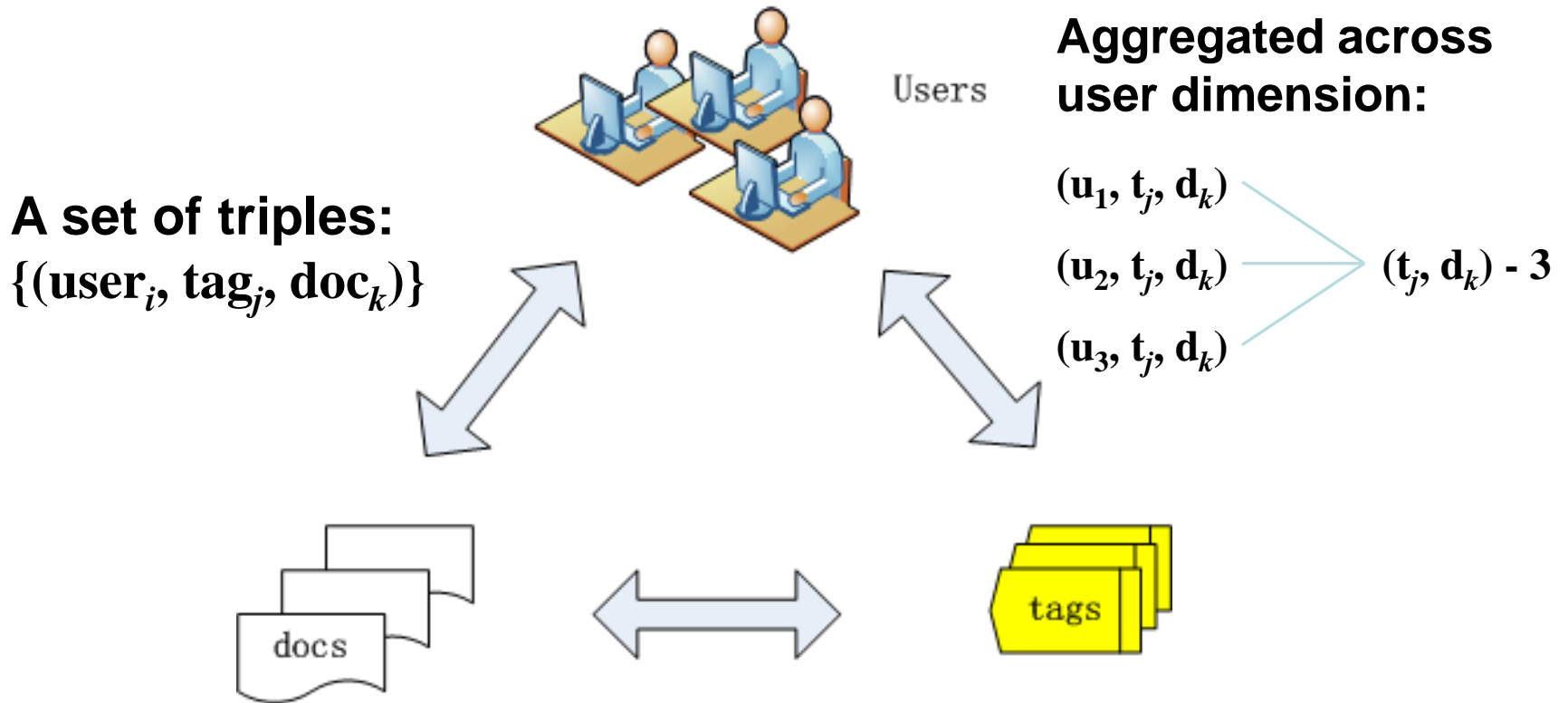
General idea of Our Approach



**Graph-based
Ranking of
Multi-type
interrelated
Objects**

**Ranked
list of
tags**

Representation of Tagging Data



- Tagging data involves three interrelated types of objects: users, docs and tags

Highlights of Our Approach

- “Query” = document + user
- Exploit the affinity relation between documents; annotation relation between documents and tags; preference relation between users and tags.
- Model the problem as a graph-based ranking problem; developed a novel algorithm named Graph-based Ranking of Multi-type interrelated Objects (**GROMO**)

Graph-based Regularization

- Given data graph $G = (V, E, W)$, to learn a function $f : V \rightarrow \mathbb{R}$ from the data (e.g. for ranking or semi-supervised learning)
- A graph-based regularizer makes f smooth over the graph, i.e. similar data points should have similar function values (Zhou et al. NIPS04):

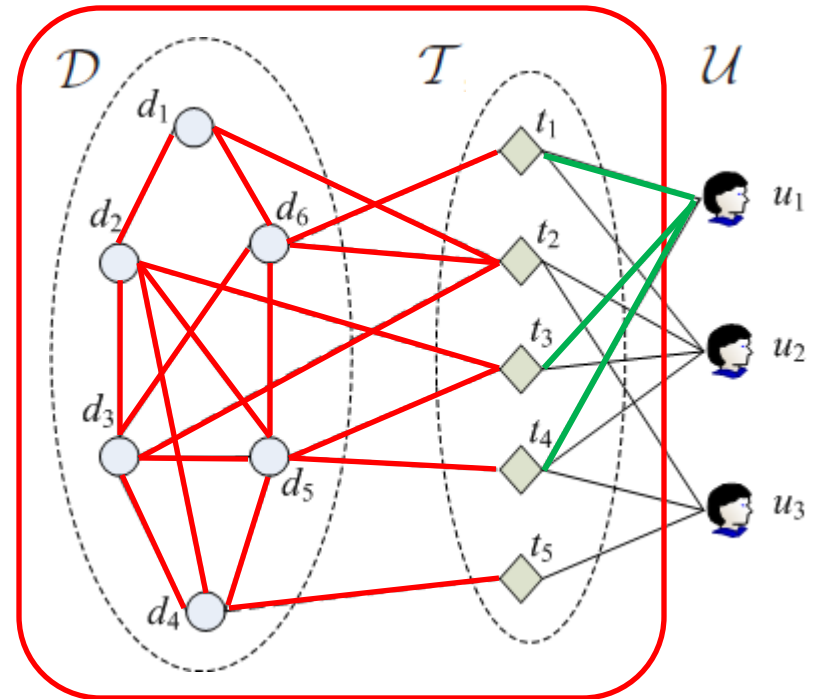
$$\frac{1}{2} \sum_{i,j} W_{ij} \left(\frac{1}{\sqrt{D_{ii}}} f_i - \frac{1}{\sqrt{D_{jj}}} f_j \right)^2 = \mathbf{f}^T \mathbf{L} \mathbf{f}$$

D: diagonal matrix, $D_{ii} = \sum_j W_{ij}$

Problem Formulation (Personalized Tag Recommendation)

■ Notations

- \mathcal{D} – the set of documents
- \mathcal{T} – the set of tags
- \mathcal{U} – the set of users
- G_D – **affinity graph** of \mathcal{D}
- $H_{D,T}$ – **bipartite graph** describing annotation relationships between \mathcal{D} and \mathcal{T}
- $H_{U,T}$ – **bipartite graph** describing users' historical usage of tags



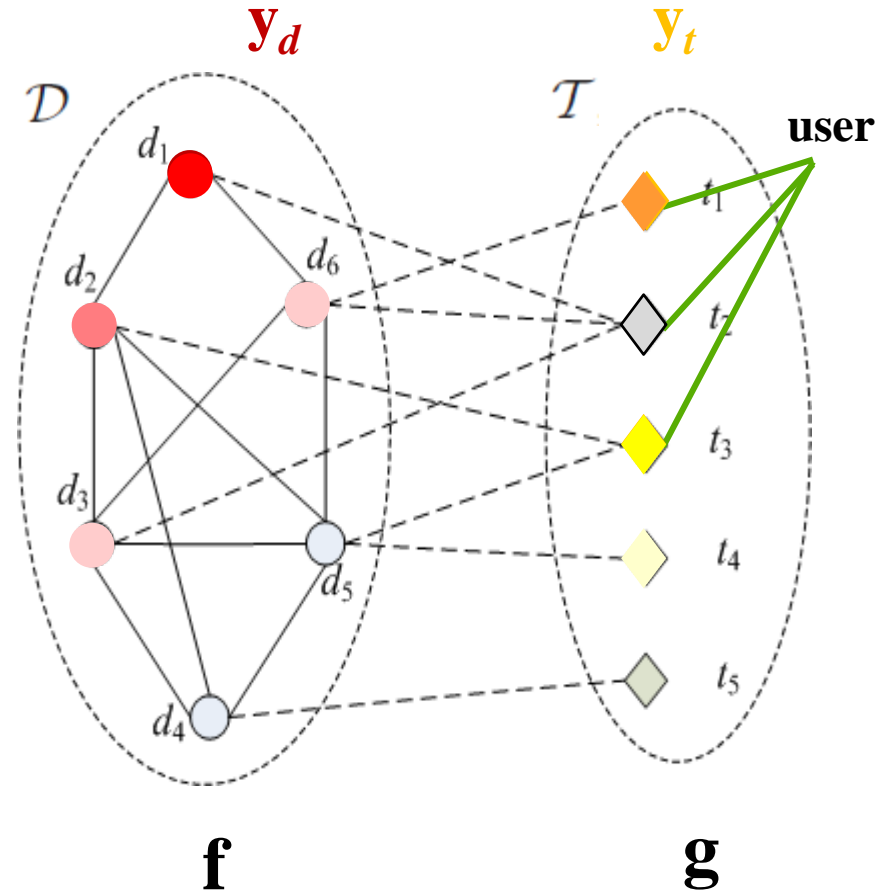
- **Exploit the affinity and document relationships between documents and tags**
 - **We use a user's tag usage history to represent a user (profile of tag preferences)**

Problem Formulation (GRoMO)

- Notations

- \mathbf{W} – adjacency matrix of G_D
- \mathbf{R} – adjacency matrix of $H_{D,T}$
- $\mathbf{y}_d, \mathbf{y}_t$ – query vectors of documents and user-preferred tags
- \mathbf{f}, \mathbf{g} – ranking vectors of documents and tags

- Problem: given $\mathbf{W}, \mathbf{R}, \mathbf{y}_d$ and \mathbf{y}_t , to learn \mathbf{f} and \mathbf{g}



Optimization Framework of GRoMO

$$\begin{aligned}
 Q(\mathbf{f}, \mathbf{g}) = & \frac{1}{2}\mu \sum_{i,j=1}^{|\mathcal{D}|} W_{ij} \left(\frac{1}{\sqrt{D_{ii}}} f_i - \frac{1}{\sqrt{D_{jj}}} f_j \right)^2 \\
 & + \eta \sum_{i=1}^{|\mathcal{D}|} \sum_{j=1}^{|\mathcal{T}|} R_{ij} \left(\frac{1}{\sqrt{D_{ii}^d}} f_i - \frac{1}{\sqrt{D_{jj}^t}} g_j \right)^2 \\
 & + \alpha \sum_{i=1}^{|\mathcal{D}|} (f_i - y_{di})^2 + \beta \sum_{i=1}^{|\mathcal{T}|} (g_i - y_{ti})^2, \quad (1)
 \end{aligned}$$

Similar documents have similar scores

If a tag is often used for a document, they have similar scores

Keep fidelity to the targeted document (s)

Keep fidelity to user-preferred tags

$$\langle \mathbf{f}, \mathbf{g} \rangle = \arg \min_{\mathbf{f}, \mathbf{g}} Q(\mathbf{f}, \mathbf{g}).$$

Matrix-vector Form

- Define

$$\mathbf{S}_W = \mathbf{D}^{(-1/2)} \mathbf{W} \mathbf{D}^{(-1/2)}, \quad \mathbf{S}_R = \mathbf{D}_d^{(-1/2)} \mathbf{R} \mathbf{D}_t^{(-1/2)}.$$

- The cost function can be written as

$$Q(\mathbf{f}, \mathbf{g}) = \mu \mathbf{f}^T (\mathbf{I} - \mathbf{S}_W) \mathbf{f} + \eta (\mathbf{f}^T \mathbf{f} + \mathbf{g}^T \mathbf{g} - 2 \mathbf{f}^T \mathbf{S}_R \mathbf{g}) \\ + \alpha (\mathbf{f} - \mathbf{y}_d)^T (\mathbf{f} - \mathbf{y}_d) + \beta (\mathbf{g} - \mathbf{y}_t)^T (\mathbf{g} - \mathbf{y}_t).$$

- Closed-form solution:

$$\mathbf{f}^* = \left[(1 - \beta) \mathbf{I} - \mu \mathbf{S}_W - \frac{\eta^2}{\beta + \eta} \mathbf{S}_R \mathbf{S}_R^T \right]^{-1} \times \left(\alpha \mathbf{y}_d + \frac{\beta \eta}{\beta + \eta} \mathbf{S}_R \mathbf{y}_t \right)$$

$$\mathbf{g}^* = \frac{\eta}{\beta + \eta} \mathbf{S}_R^T \mathbf{f}^* + \frac{\beta}{\beta + \eta} \mathbf{y}_t.$$

Iterative Solution of GRoMO

- Set $\mathbf{f}(0) = \mathbf{y}_d$, $\mathbf{g}(0) = \mathbf{y}_t$. In the t -th iteration, first use $\mathbf{f}(t)$ to compute $\mathbf{g}(t+1)$:

$$\mathbf{g}(t+1) = \frac{\eta}{\beta + \eta} \mathbf{S}_R^T \mathbf{f}(t) + \frac{\beta}{\beta + \eta} \mathbf{y}_t,$$

- Then, use $\mathbf{g}(t+1)$ and $\mathbf{f}(t)$ to compute $\mathbf{f}(t+1)$:

$$\mathbf{f}(t+1) = \frac{\mu}{1 - \beta} \mathbf{S}_W \mathbf{f}(t) + \frac{\eta}{1 - \beta} \mathbf{S}_R \mathbf{g}(t+1) + \frac{\alpha}{1 - \beta} \mathbf{y}_d.$$

- Another Iterative form involving \mathbf{f} only:

$$\begin{aligned} \mathbf{f}(t+1) &= \frac{1}{1 - \beta} \left(\mu \mathbf{S}_W + \frac{\eta^2}{\beta + \eta} \mathbf{S}_R \mathbf{S}_R^T \right) \mathbf{f}(t) \\ &\quad + \frac{\alpha}{1 - \beta} \mathbf{y}_d + \frac{\beta \eta}{(1 - \beta)(\beta + \eta)} \mathbf{S}_R \mathbf{y}_t. \end{aligned}$$

Graph Construction

- For \mathbf{W} we use cosine similarities between documents as edge weights.
- We set W_{ij} (document affinity) as

$$W_{ij} = \begin{cases} \text{cosine}(i, j) & \text{if } i \in \text{KNN}(j) \text{ or } j \in \text{KNN}(i) \\ 0 & \text{otherwise} \end{cases}$$

- We set R_{ij} (\mathcal{B} is the observed set of tagging data)

$$R_{ij} = | \{u_k \mid u_k \in \mathcal{U} \text{ and } (u_k, d_i, t_j) \in \mathcal{B}\} |$$

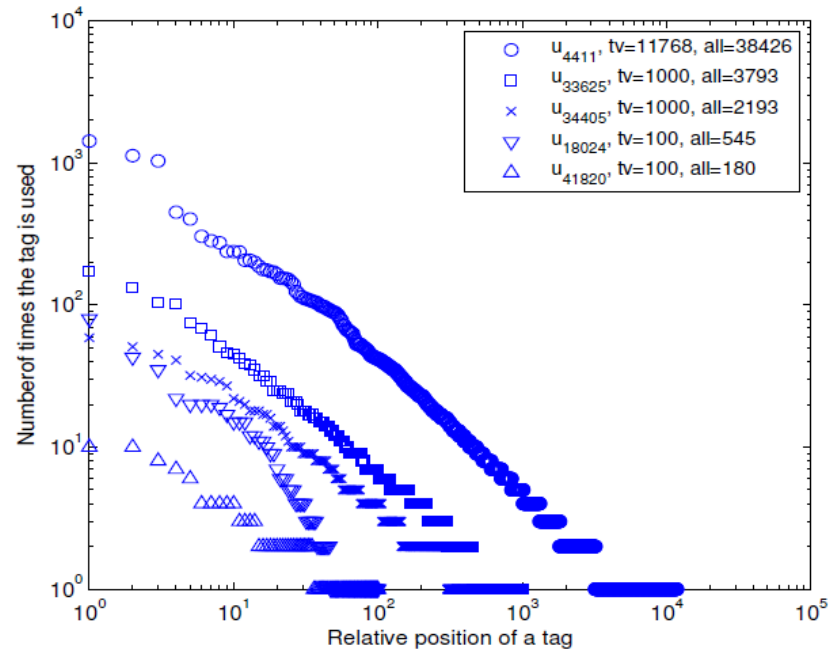
Setting Query Vectors

- Query vector \mathbf{y}_d is set as follows

$$y_{di} = \begin{cases} 1 & d_i = d \\ 0 & \text{otherwise} \end{cases} .$$

- Tag frequency of a user tends to follow power law, hence \mathbf{y}_t is set as

$$y_{ti} = \begin{cases} \frac{[\log(\text{frequency}_{u,t_i})+1]}{\sum_{t_j \in \mathcal{T}_u} [\log(\text{frequency}_{u,t_j})+1]} & t_i \in \mathcal{T}_u \\ 0 & \text{otherwise} \end{cases} ,$$



Frequency of tag v.s. relative position

Experiments

- Dataset
 - Our dataset contains 167,885 bookmarks.

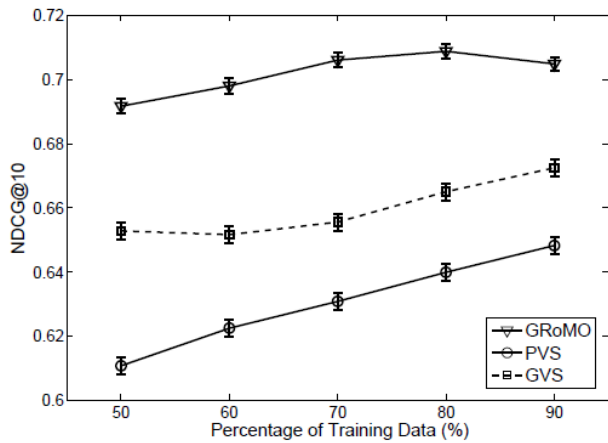


- Statistics: 300 users, 11,795 Web pages, 17,777 tags
- We use 10% bookmarks as test data
 - Web page + user as “queries”; tags as gold standard.
- Evaluate with NDCG, average precision, average recall.

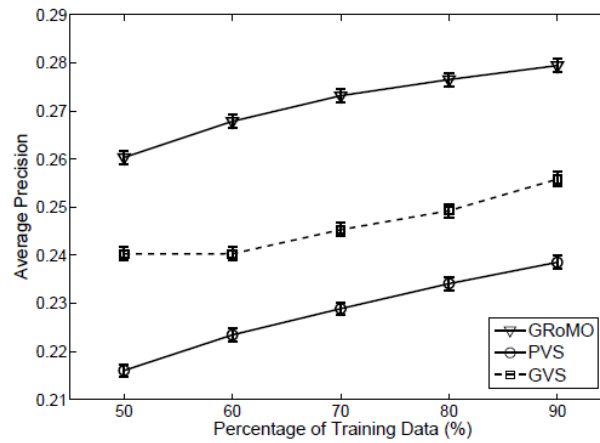
Baseline

- Global Vector Similarity (GVS): independent to the user, only dependent on the docs & tags.
 - Item-based collaborative filtering using documents and tags;
- Personal Vector Similarity (PVS): recommend the tags used by the user.
 - Using documents (and tags) tagged by the particular user

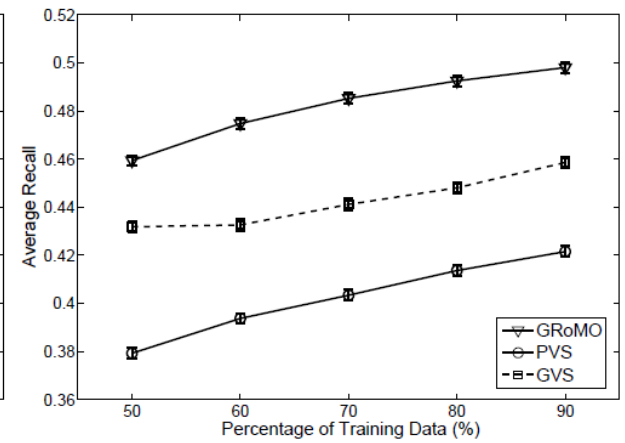
Experimental Results – Performance Comparison



(a) NDCG@10



(b) Avg. Precision



(c) Avg. Recall

GRoMO > GVS > PVS

Experimental Results – Performance Comparison

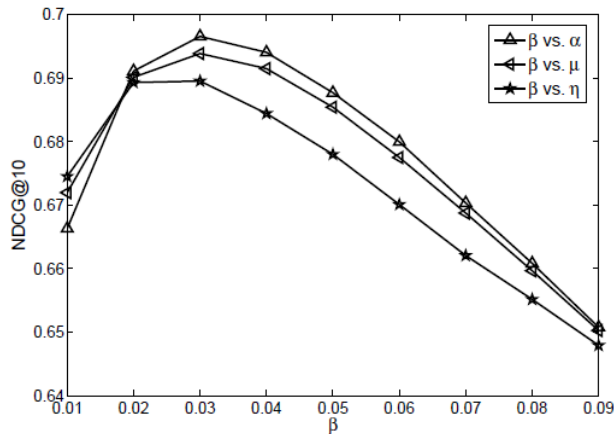
| Training Data (%) | NDCG@1 | | | NDCG@3 | | | NDCG@5 | | |
|-------------------|-----------------|--------|--------|-----------------|--------|--------|-----------------|--------|--------|
| | GRoMO | PVS | GVS | GRoMO | PVS | GVS | GRoMO | PVS | GVS |
| 50 | 0.5422** | 0.4518 | 0.5136 | 0.5357** | 0.4617 | 0.5209 | 0.5863** | 0.5127 | 0.5593 |
| 60 | 0.5434** | 0.4645 | 0.5202 | 0.5381** | 0.4726 | 0.5122 | 0.5897** | 0.5234 | 0.5542 |
| 70 | 0.5558** | 0.4759 | 0.5301 | 0.5474** | 0.4825 | 0.5179 | 0.5982** | 0.5314 | 0.5593 |
| 80 | 0.5534 | 0.4873 | 0.5478 | 0.5483* | 0.4907 | 0.5322 | 0.5990** | 0.5398 | 0.5706 |

NDCG@1, NDCG@3, and NDCG@5.

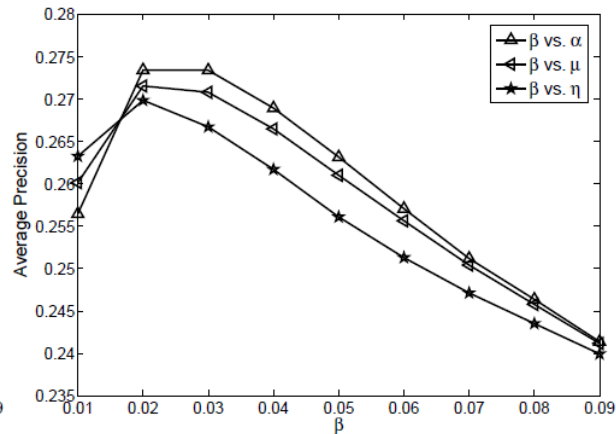
GRoMO > GVS > PVS

GRoMO works especially better when smaller training data is observed

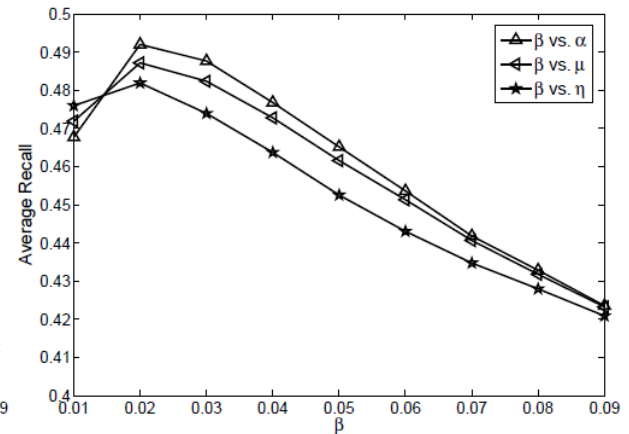
Experimental Results – Parameter Setting



(a) NDCG@10



(b) Precision



(c) Recall

β versus each of the other parameters α , μ , η
(fix the other two)

Observation: β need to be kept small

Optimal: $\mu = 0.3$; $\eta = 0.17$; $\alpha = 0.5$; $\beta = 0.03$

Experimental Results

Tag Recommendation Example

| URL: http://www.brand-name-coupons.com/how-to-search-amazon-for-deals/ | | |
|--|---|--|
| UserID | Ground Truth | GROMO Recommended |
| 8414 | amazon, bargains, Coupons, deals, discount, howto, shopping | amazon, deals, bargains, shopping , discounts, coupons, bargain, s3, search, discount |
| 37982 | amazon, cheap, coupons, sales, shopping | amazon , deals, shopping , bargains, coupons , discounts, s3, search, cheap , discount |
| 5472 | blog, howto, shopping, tips, tools | shopping, tools , free, web, design, reference, software, howto, tips , amazon |

- **Three Users' annotations in the last 10% testing data for the URL "http://www.brand-name-coupons.com/how-to-searchamazon-for-deals.html".**
- **Tags with bold font indicate matches with the tags actually used by the user.**

Summary

- Personalized tag recommendation
- Graph-based ranking of multi-type interrelated objects
 - Doc-doc; doc-tag; and user-tag relations
- A solution by optimizing a unified objective function
- Future work
 - Explore doc-user, user-user relations
 - Parameter tuning
 - Efficient (e.g., distributed) solution for large scale data;

Thank You !

Derivation of Optimal Solution

- Differentiate Q with respect to \mathbf{f} and \mathbf{g} , we obtain

$$\frac{\partial Q}{\partial \mathbf{f}} = [(1 - \beta)\mathbf{I} - \mu\mathbf{S}_W]\mathbf{f} - \eta\mathbf{S}_R\mathbf{g} - \alpha\mathbf{y}_d = 0.$$

$$\frac{\partial Q}{\partial \mathbf{g}} = (\beta + \eta)\mathbf{g} - \eta\mathbf{S}_R^T\mathbf{f} - \beta\mathbf{y}_t = 0.$$

$$\mathbf{f}^* = \left[(1 - \beta)\mathbf{I} - \mu\mathbf{S}_W - \frac{\eta^2}{\beta + \eta}\mathbf{S}_R\mathbf{S}_R^T \right]^{-1} \times \left(\alpha\mathbf{y}_d + \frac{\beta\eta}{\beta + \eta}\mathbf{S}_R\mathbf{y}_t \right)$$

$$\mathbf{g}^* = \frac{\eta}{\beta + \eta}\mathbf{S}_R^T\mathbf{f}^* + \frac{\beta}{\beta + \eta}\mathbf{y}_t.$$