

Leveraging Publication Metadata and Social Data into FolkRank for Scientific Publication Recommendation

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¹Knowledge and Data Engineering Group, University of Kassel

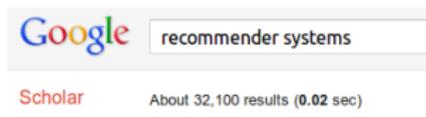
²L3S Research Center, Hannover

³Data Mining and Information Retrieval Group, University of Würzburg

RSWeb: 9th September 2012



Publication Overload



- # papers doubles every 10 years
- # journals doubles every 15 years
- → information overload

typical approach: scientific article recommender
e.g., in collaborative tagging systems



1 Item Recommendations in Folksonomies

2 Datasets and Experiments

- Datasets
- Experiments

3 Recommendation Results

- Including New Dimensions
- Modifying the Preference Vector

4 Conclusion and Future Work



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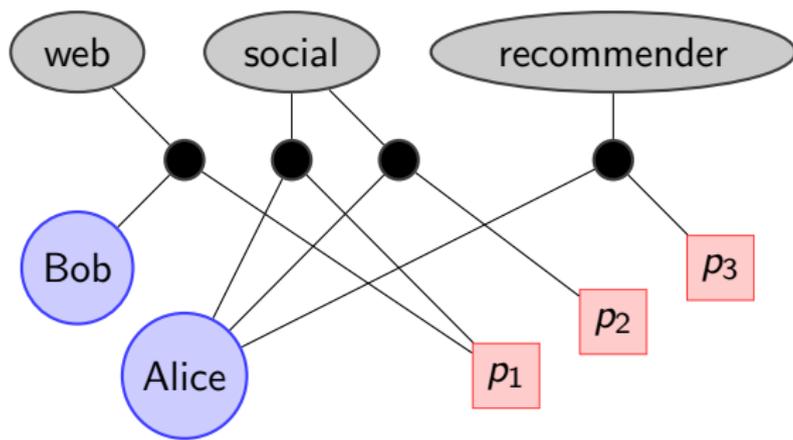
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Item Recommendations in Folksonomies

Folksonomy

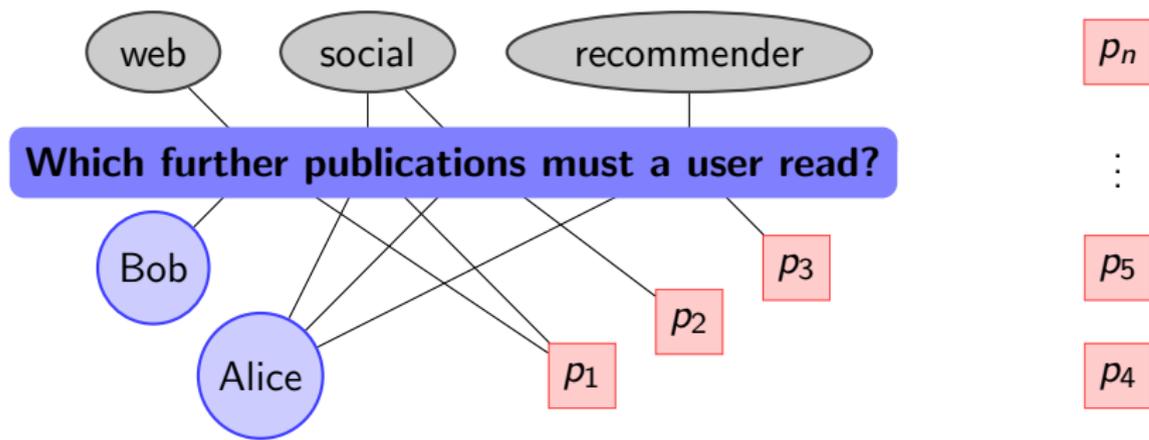
A *folksonomy* is a quadruple $\mathbb{F} := (U, T, R, Y)$, where U , T , and R are finite sets, whose elements are called *users*, *tags* and *resources*, resp., and Y is a ternary relation between them, i.e., $Y \subseteq U \times T \times R$, whose elements are called *tag assignments*.



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BOOKMARKS



Recommender Systems – Introduction and Handb...

Supporting website for the text books 'Recommender Systems An Introduc...'
3 days and 16 hours ago by holtho

handbook introduction material recommender slides...

★★★★★ (1)

RecSys 2012 Workshop on Recommender System...

<http://lib13-www.cs.uni-dortmund.de/homepage/rswb2012/index.shtml>
3 months and 3 days ago by holtho

2012 chair myown recommender systems workshop

★★★★★ (0)

Scientometrics 2.0 Toward new metrics of scholar...

<http://www.uic.edu/hbin/cgiwrap/biv/ogs/index.php/fm/article/view/2874/2570>
6 months and a day ago by sdo

scientometrics index quality item recommender toRe...

★★★★★ (0)

ACM Recommender Systems 2012

<http://recsys.acm.org/2012/>
6 months and a day ago by holtho

2012 acm conference pc recommender systems web

★★★★★ (0)



PUBLICATIONS



Eigentaste: A constant time collaborative filtering ...

K. Goldberg, T. Roeder, D. Gupta, and C. Perkins *Information Retrieval 4*...
9 hours and 42 minutes ago by folkie

cf collaborative evaluation filtering recommender syst...

★★★★★ (0)

Leveraging Publication Metadata and Social Data i...

Stephan Doerfel, Robert Jäschke, Andreas Holtho, and Gerd Stumme *Pro...*
12 hours and 16 minutes ago by jaeschke

2012 bookmarking collaborative folkrank myown reco...

★★★★★ (0)

A spatio-temporal approach to collaborative filtering

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12 hours and 18 minutes ago by jaeschke

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★★★★★ (1)



browse

related tags

tags

(alpha | freq) (cloud | list) (minfreq 1 | 2 | 5 | 10 | 50)

2.0 2005 2006 2007 2008 2009
2010 2011 2012 10m admin ag1
algorithm analysis android api
begriffsanalyse bibliography BibSonomy
bibsonomy bibsonomynews bibtex
blog book bookmark bookmarking
boomerang challenge citation
citedBy:doerfel2012publication classification
clustering code collaborative collective
community comparison computing
concept conceptual conference css
darmstadt data database dataset
design detection Development
diploma_thesis discovery diy dm
documentation download eclipse ecml
engine eswc european evaluation
everywhere example extraction fba
FCA fca folkrank folksonomies
folksonomy formal formale



BibSonomy group :: kde :: search (Knowledge and Data Engineering Group) EN DE

THE BLUE SOCIAL BOOKMARK AND PUBLICATION SHARING SYSTEM.

home myBibSonomy add post groups popular logged in as sdo logout

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related tags
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2.0 2005 2006 2007 2008 2009
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algorithm analysis android api
begriffsanalyse bibliography BibSonomy
bibsonomy bibsonomynews bibtex
blog book bookmark bookmarking
boomerang challenge citation
citedBy:doerfel2012publication classification
clustering code collaborative collective
community comparison computing
concept conceptual conference css
darmstadt data database dataset
design detection Development
diploma_thesis discovery diy dm
documentation download eclipse ecml
engine eswc european evaluation
everywhere example extraction fba
FCA fca folkrank folksonomies
folksonomy formal formale

- users, tags, publications
- authors, years, journals, ...
- user groups

FolkRank

$$\mathbb{F} = (U, T, R, Y) \rightarrow \text{undirected graph } G_{\mathbb{F}} = (U \cup T \cup R, E)$$
$$(u, t, r) \in Y \rightarrow \{u, t\}, \{u, r\}, \{t, r\} \in E$$

$$\text{Adapted PageRank (APR) } \vec{w}^d : \vec{w}_{i+1}^d \leftarrow dA^T \vec{w}_i^d + (1-d)\vec{p}$$

$$\text{FolkRank} : \vec{w}^d - \vec{w}^1$$

A = the row-stochastic adjacency matrix of $G_{\mathbb{F}}$

\vec{p} = preference vector

$d \in [0, 1]$ = parameter for the influence of \vec{p}



Adding new Dimensions to the Graph

$\mathbb{F} + M := (U, T, R, M, Y')$ extends the folksonomy \mathbb{F} where

- Y' is a relation $Y' \subseteq U \times T \times R \times M$ and
- each triple of Y is extended with those elements of M that one of the elements of the triple is associated with.

Modifications to the Preference Vector

Select certain users, resources or tags and assign them some weight in \vec{p} .



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Four Datasets

Publication posts of BibSonomy¹

D_{08} challenge dataset from 2008

D_{12} recent dataset from 2012

D_R each publication in ≥ 2 posts

D_{UR} each publications in ≥ 2 posts, each user ≥ 20 posts

dataset	users	publications
$D_{12,R}$	2,886	29,921
$D_{12,UR}$	541	25,072
$D_{08,R}$	729	13,001
$D_{08,UR}$	150	11,689

¹<http://www.kde.cs.uni-kassel.de/bibsonomy/dumps/>



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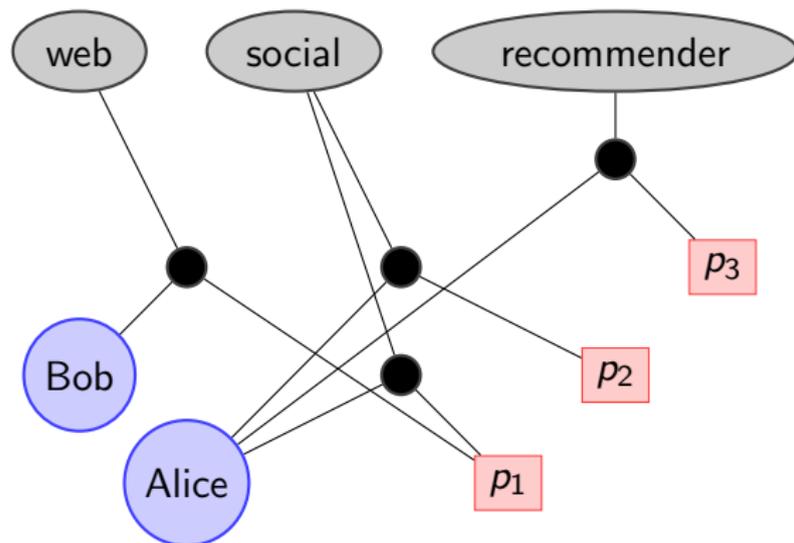
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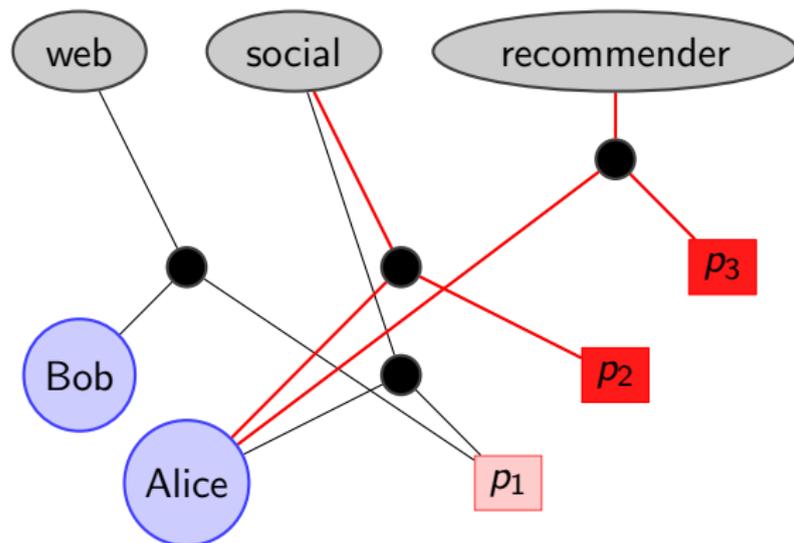
Experimental Methodology



LeaveNPostsOut



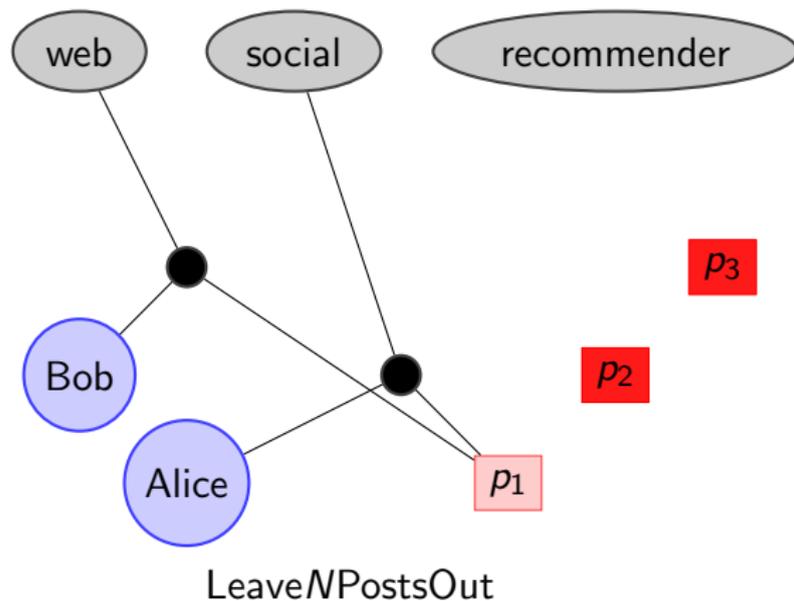
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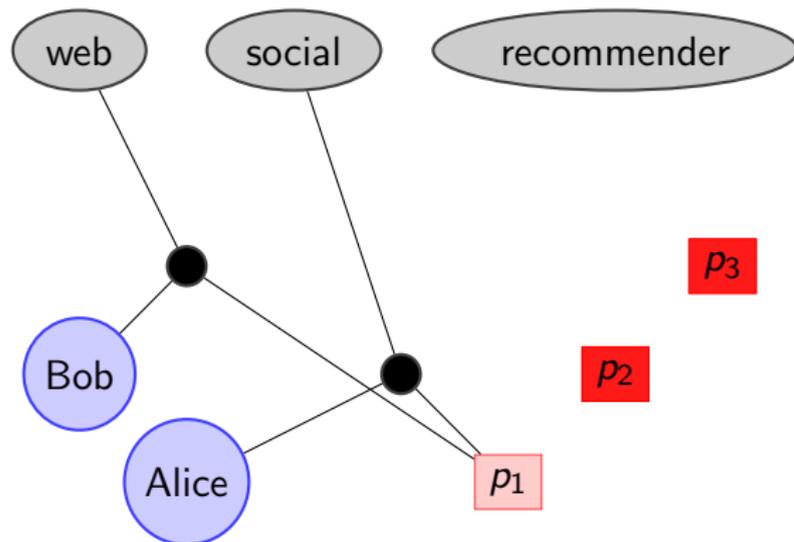
LeaveNPostsOut



Experimental Methodology



Experimental Methodology



LeaveNPostsOut

1. p_2

2. p_{10}

3. p_7

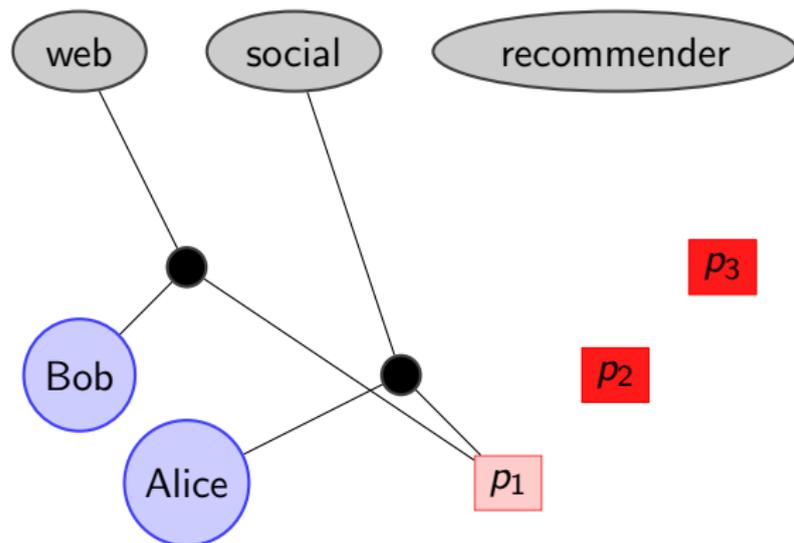
4. p_3

5. p_8

⋮



Experimental Methodology



LeaveNPostsOut

MAP = Mean Average Precision

1. p_2

2. p_{10}
3. p_7
4. p_3

5. p_8
- ⋮



Most Popular

- global ranking
- suggesting the most often bookmarked publications to a user

User-Based Collaborative Filtering

- users are represented as vectors in
 - the tag vector space $\rightarrow CF_T$
 - or the resource vector space $\rightarrow CF_R$
- using a similarity function, one determines a set of similar users and recommends publications that are popular among them



Experiment: Who has the publications to recommend?

How many similar users does it take, to find the 10 left-out resources? –
The average coverage of the withheld resources in differently sized neighborhoods of similar users:

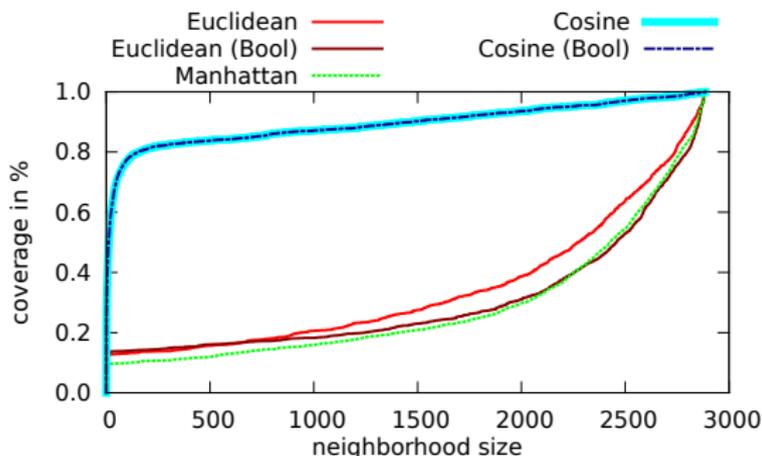


Figure: $D_{12,R}$ as resource vector space.

→ Winner: Cosine similarity in the resource vector space



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Baselines and plain FolkRank and APR

MAP scores	$D_{12,R}$	$D_{08,R}$	$D_{12,UR}$	$D_{08,UR}$
CF_R $k = 10$	0.109	0.141	0.120	0.152
FolkRank	0.090	0.118	0.099	0.129
adapted PageRank (APR)	0.066	0.058	0.070	0.062
CF_T $k = 4$	0.062	0.081	0.060	0.088
most popular	0.006	0.013	0.007	0.013

$$CF_R > FolkRank > \begin{cases} APR \\ CF_T \end{cases} > \text{most popular}$$



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Including New Dimensions

MAP scores	$D_{12,R}$	$D_{08,R}$	$D_{12,UR}$	$D_{08,UR}$
(plain) FolkRank	0.090	0.118	0.099	0.129
\mathbb{F} + first authors	0.089	0.113	0.102	0.126
\mathbb{F} + last authors	0.086	0.108	0.097	0.120
\mathbb{F} + all authors	0.085	0.103	0.096	0.115
\mathbb{F} + group	0.085	0.117	0.093	0.128



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first authors > last authors > all authors



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comparable to plain FolkRank



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\mathbb{F} + posting year, publication year, tag clusters, venues, ...



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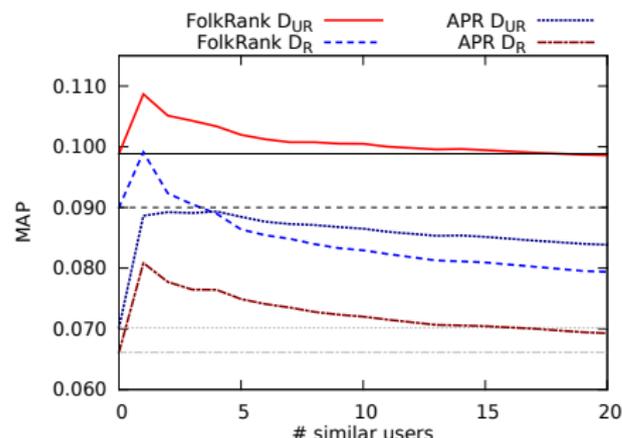
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Exploiting Similar Users

Motivation: Good results of CF_R .

For user u select the k most similar users, insert their similarity value to u into \vec{p} .



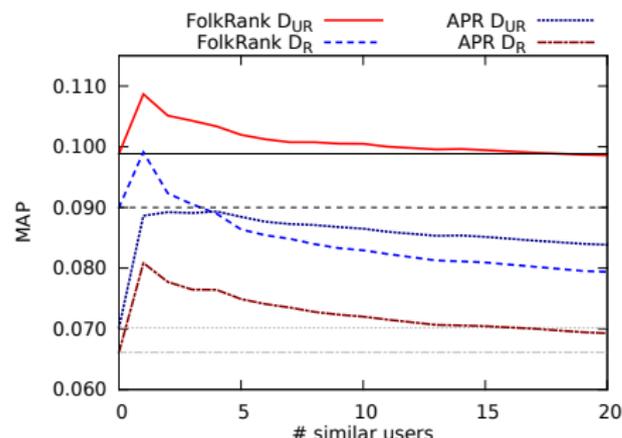
All scenarios profit from the *inclusion of* at least very small *user neighborhoods*.



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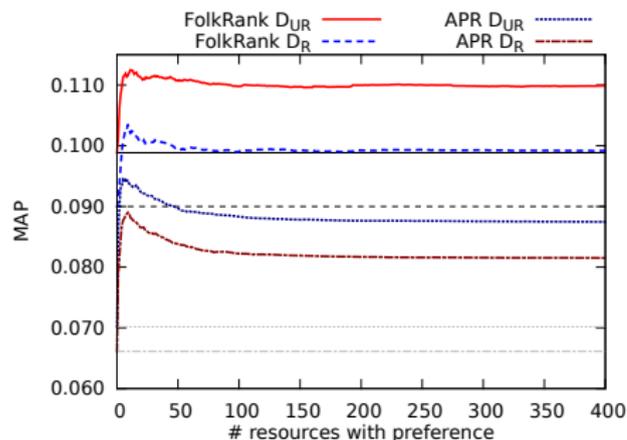
- **Best results:** only the single most similar user gets additional preference
- APR profits even more from the inclusion of similar users, also for larger neighborhoods
- Using the *Euclidean distance* decreases MAP.

All scenarios profit from the *inclusion of* at least very small *user neighborhoods*.



Exploiting Recent Resources

Motivation: User's interests vary during the use of the system.
For user u select the k most recently posted resources, assign the same weight to them in \vec{p} .

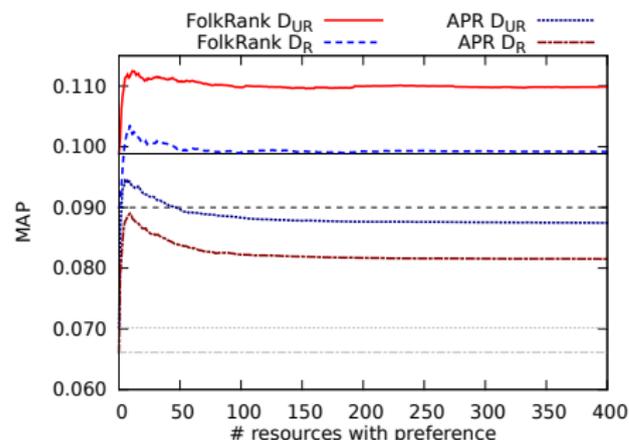


Comparable to the scores of CF_R .



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- *Significantly exceeds FolkRank* (for ≥ 3 resources on all datasets).
- Highest MAP scores for different number of recent resources.
- Constant MAP for larger numbers of recent resources.

Comparable to the scores of CF_R .



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Conclusions

- Cosine similarity is the measure of choice (CF_R or \vec{p} in FolkRank).
- Generally FolkRank below CF_R but better than CF_T .
- Using resources seems to be more beneficial than using tags.
- Authors or groups as additional dimension \rightarrow scores comparable to plain FolkRank.
- Small user neighborhoods can improve FolkRank recommendations.
- Recency of a post is a valuable indicator for the current interests of a user (best FolkRank results).



- Repeat the more successful experiments on further datasets.
- Investigate whether certain types of users can benefit more from the inclusion of certain data than others.
- Truly capture a recommender's performance: Online-Evaluation in BibSonomy
- Use different versions of FolkRank as candidates for hybrid-recommenders.

<http://www.kde.cs.uni-kassel.de/bibsonomy/dumps/>



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Thank you for your attention!



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