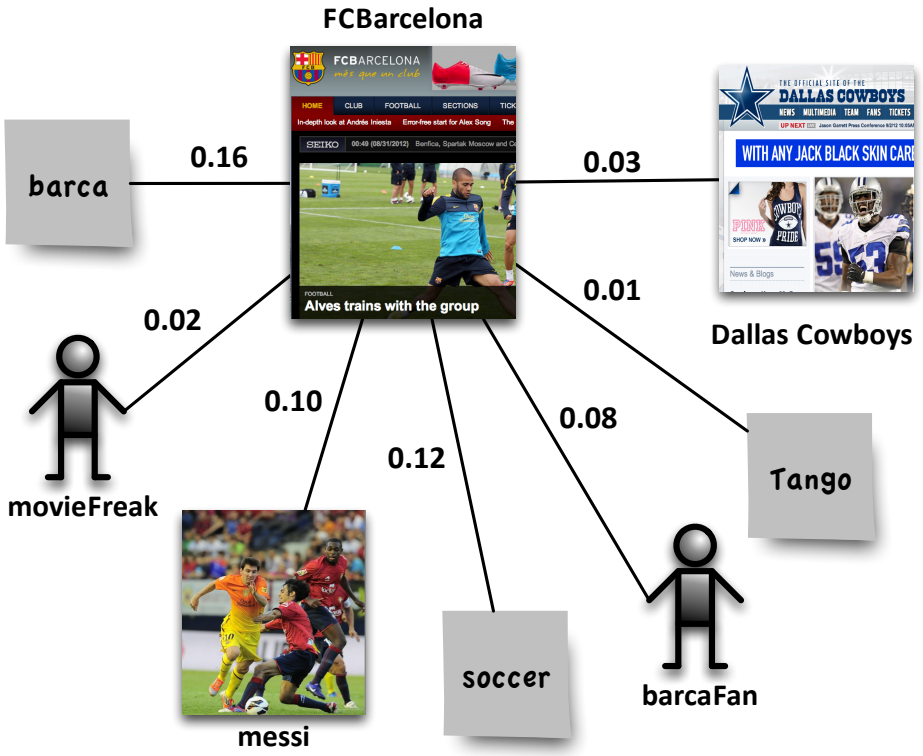
Context Determines Content

An Approach to Resource Recommendation in Folksonomies



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Overview

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- Motivation
- Context of an Entity in a Folksonomy
- VSScore Framework
- Evaluation Methodology and Metrics
- Results
- Conclusion & Future Work

Challenge: Concept Drift

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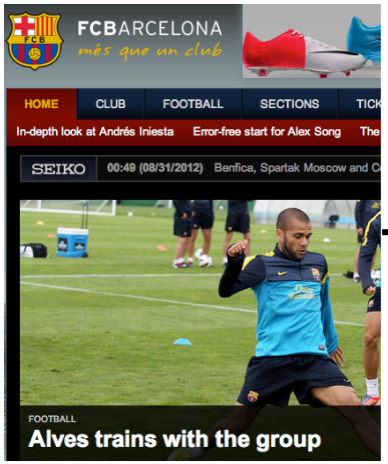
Concept drift is a challenge for graph-based ranking algorithms

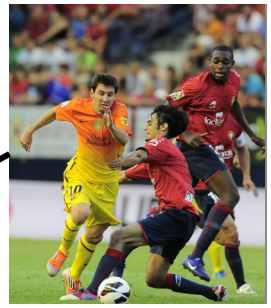
- e.g. Ambiguous tags can cause concept drift as a single tag might represent multiple semantic concepts



FC Barcelona Website

?

?



News about Messi

Dallas Cowboys' Website

Context of an Entity in a Folksonomy

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Assumption on the Context of an Entity

- The context of an entity in a folksonomy describes the entity well

Assumptions on a Folksonomy's Content and Structure

[adapted from Abel 2011]

- Tags of a resource describe the resource's content well
- Tags of a user describe the user's interests well
- Resources of a user describe the user's interests well
- Resources of a tag describe the tag's semantic well
- Users of a tag describe the tag's semantic well
- Users of a resource describe the resource's content well

Context of an Entity in a Folksonomy

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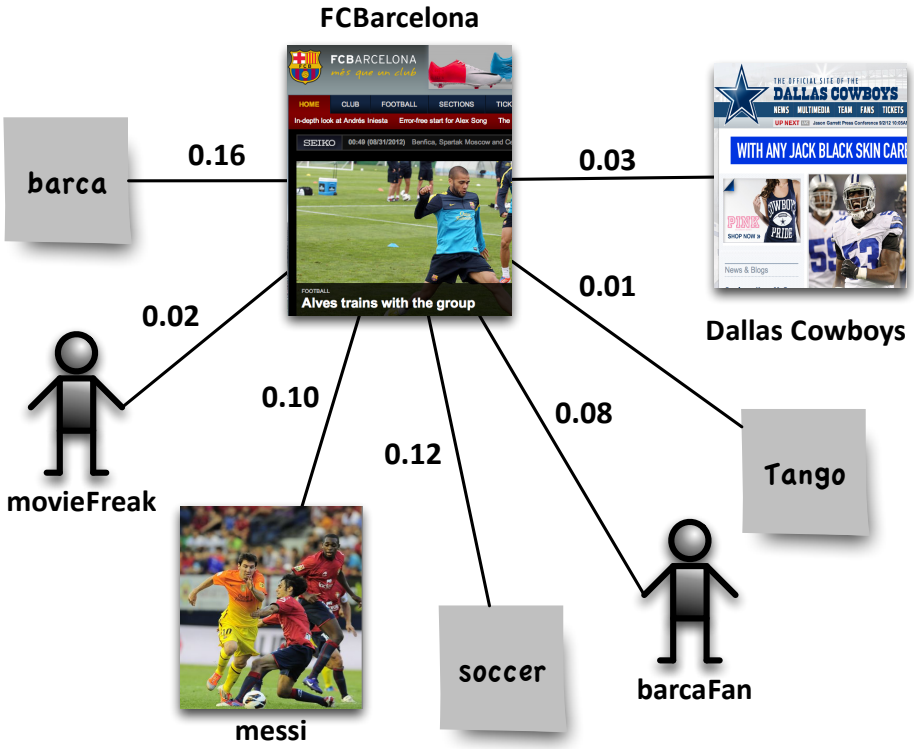
Assumption on the Context of an Entity *e* in a Folksonomy

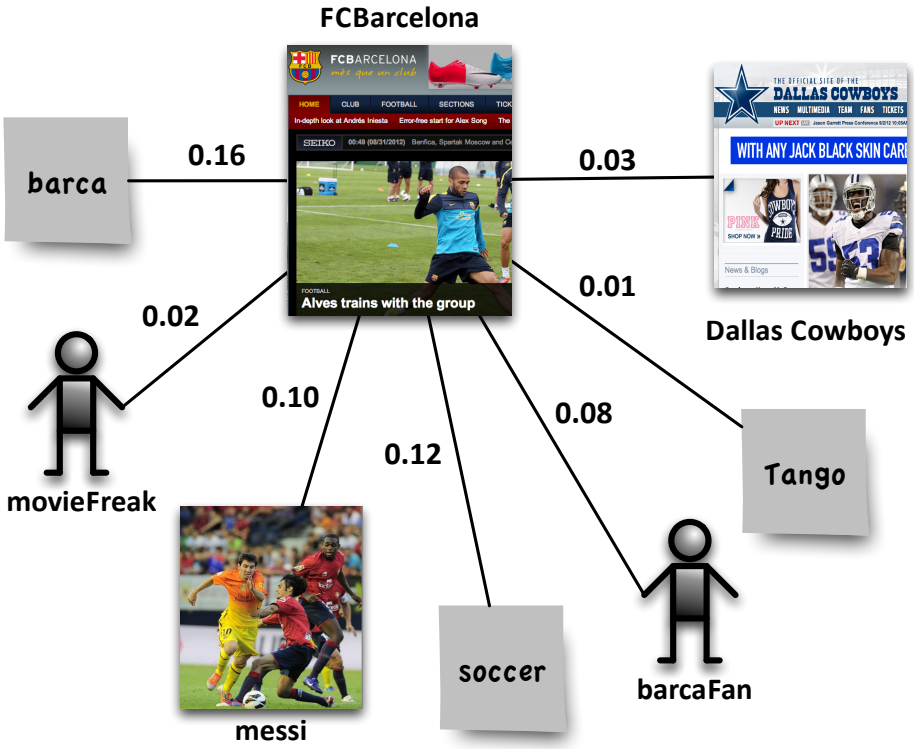
- The context of an entity *e* is given by the strength of relations between *e* and other entities in the folksonomy



Context of an Entity in a Folksonomy

Assumption on the Context of an Entity *e* in a Folksonomy

- A vector $\vec{s}_e$ created with a ranking algorithm (e.g. FolkRank) for a single query entity *e*, describes the relationship between *e* and other entities in the folksonomy well



$$\vec{s}_{\text{FCBarcelona}} = \begin{pmatrix} 0.16 \\ 0.02 \\ 0.10 \\ 0.12 \\ 0.08 \\ 0.01 \\ 0.03 \\ \dots \end{pmatrix} \begin{matrix} \text{barca} \\ \text{movieFreak} \\ \text{messi} \\ \text{soccer} \\ \text{barcaFan} \\ \text{Tango} \\ \text{Dallas Cowboys} \\ \dots \end{matrix}$$

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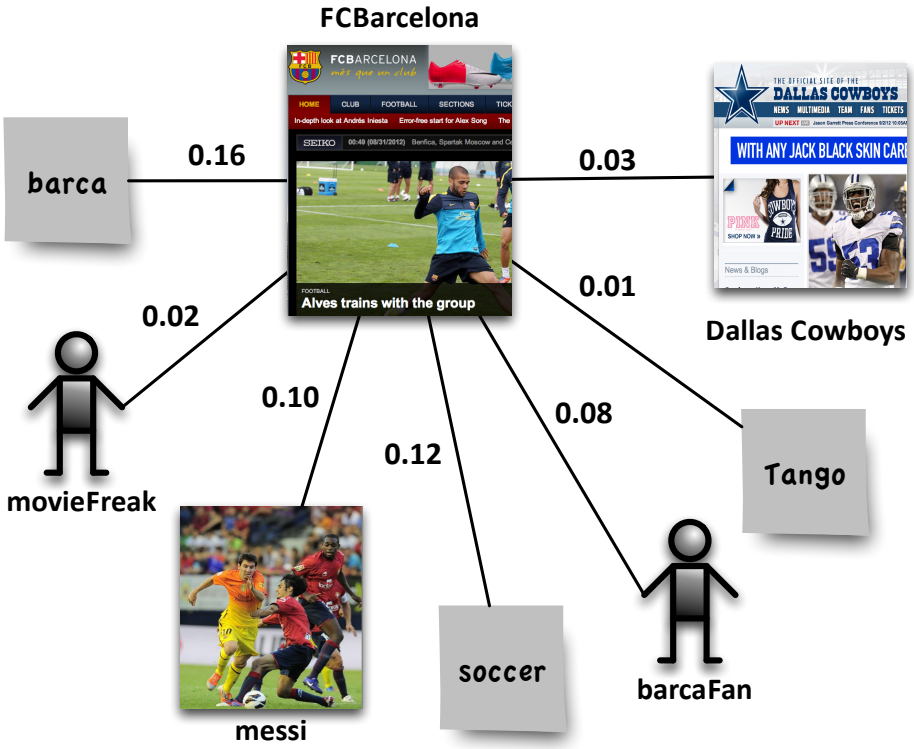

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- Entities in a folksonomy represent semantic concepts
- Any entity (e.g. a query entity) can be represented by it's context

Vector Space Score (VSScore)

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VSScore is a flexible framework which incorporates context-specific information into the recommendation process

- Based on the vector space model

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- Creates a vector representation of semantic concepts for each entity in the folksonomy using a ranking algorithm e.g. FolkRank [Hotho et al. 2006]

Vector Space Score (VSScore)

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VSScore is a flexible framework which incorporates context-specific information into the recommendation process

- Based on the vector space model
- Creates a vector representation of semantic concepts for each entity in the folksonomy using a ranking algorithm e.g. FolkRank [Hotho et al. 2006]
- Applies the cosine similarity to calculate the distance between these vectors

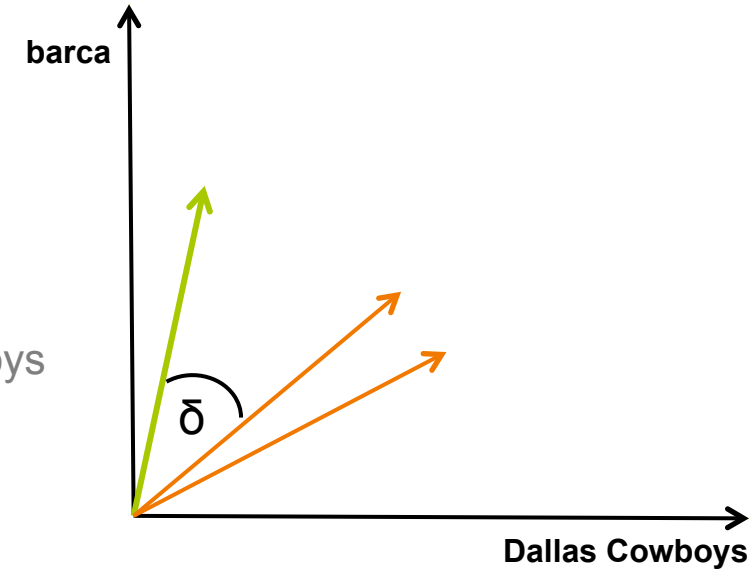
query-entity's context

$$\begin{bmatrix} 0.8 \\ \dots \\ 0.1 \end{bmatrix}$$

resources' contexts

$$\begin{bmatrix} 0.4 \\ \dots \\ 0.6 \end{bmatrix} \quad \begin{bmatrix} 0.3 \\ \dots \\ 0.7 \end{bmatrix}$$

barca
…
Dallas Cowboys



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Evaluation Ranking Tasks

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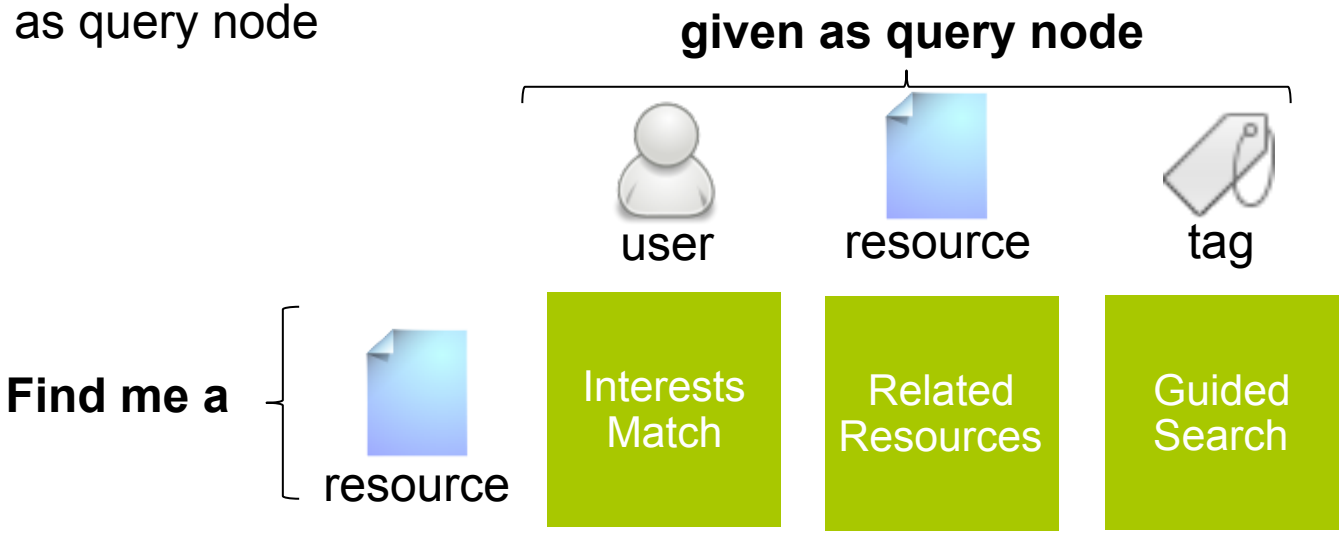
Interests Match

- User as query node

Guided Search

- Tag as query node



[adapted from Bogers 2009]

Evaluation Methodology: LeavePostOut

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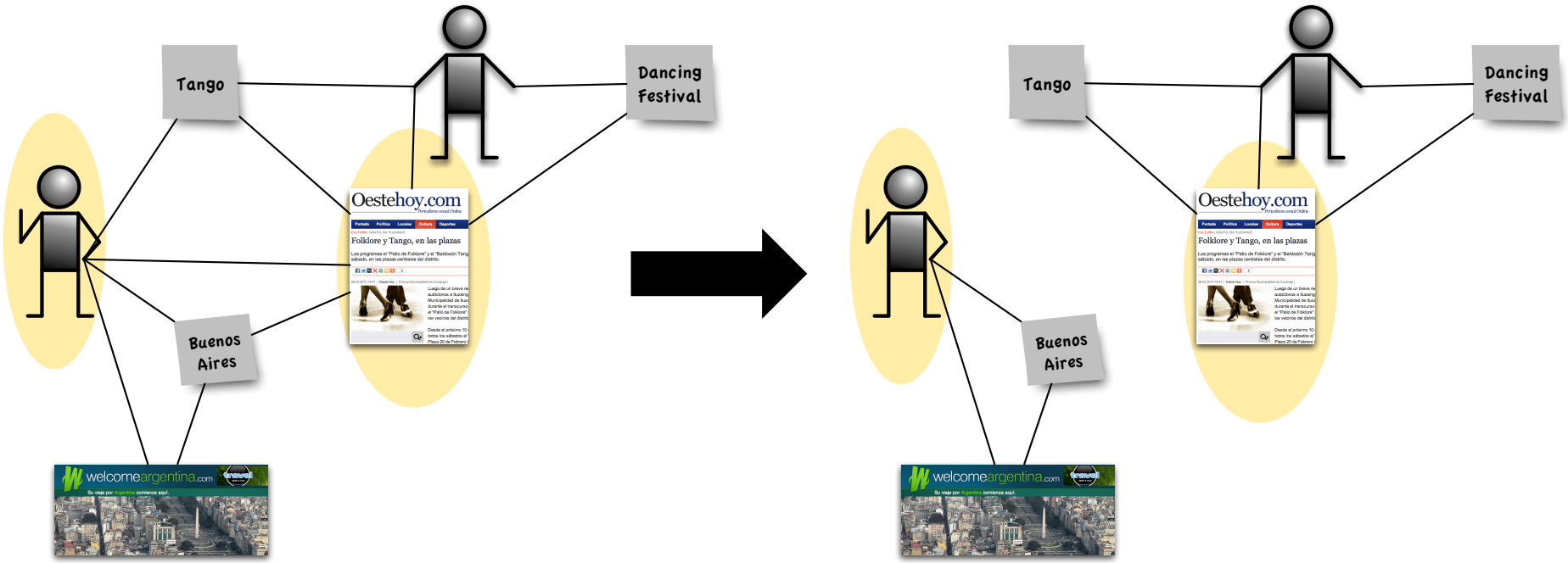
A post is a $P_{u,r}$= {(u,r,t)|(u,r,t) ∈ Y}

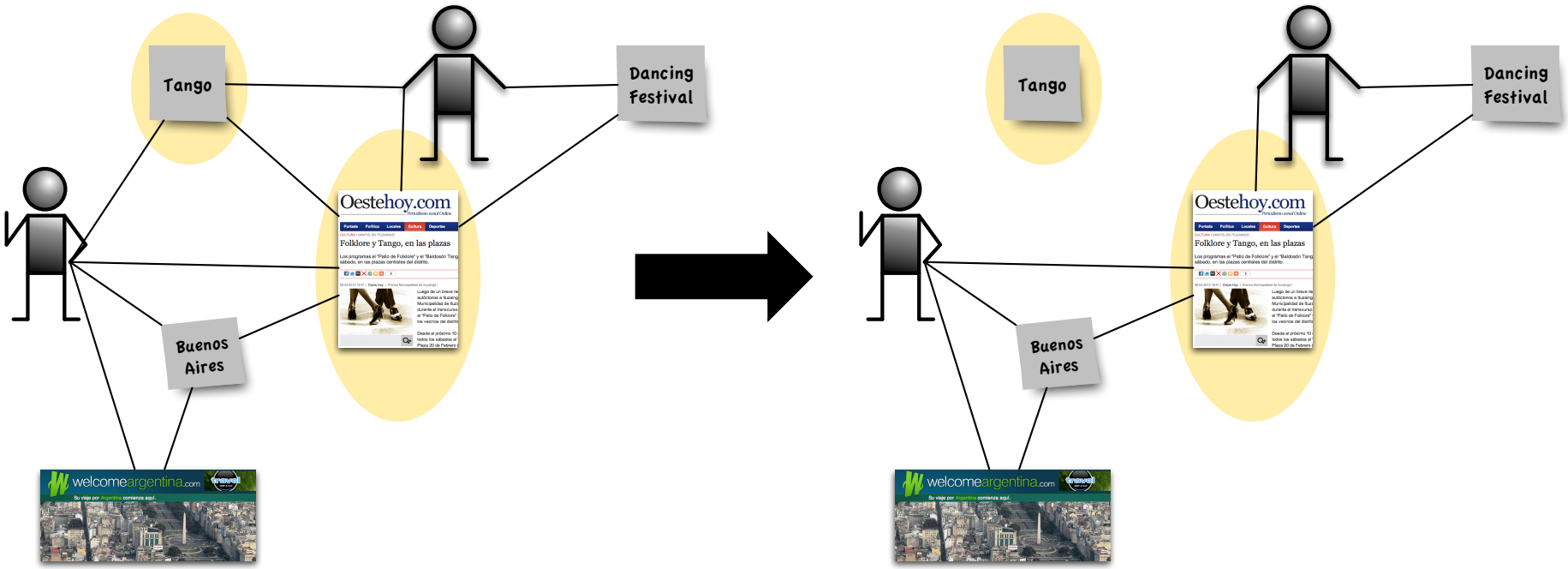


For LeavePostOut, the recommendation task with user as input is harder as with tag as input

[Jäschke et al. 2007]

Evaluation Methodology: LeaveRTOut

$RT_{r,t} = \{(u,r,t) | (u,r,t) \in Y\}$



For LeaveRTOut, the recommendation task with tag as input is harder as with user as input

Evaluation Metrics

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Mean Average Precision:

$$\mathrm{MAP}(\mathrm{Q}) = \frac{1}{|\mathrm{Q}|} \sum_{\mathrm{j}=1}^{|\mathrm{Q}|} \frac{1}{\mathrm{m_j}} \sum_{\mathrm{k}=1}^{\mathrm{m_j}} \mathrm{Precision}(\mathrm{R_{jk}})$$

The mean of the Average Precision over several queries Q

[Manning et al 2008]

Mean Normalized Precision:

$$\mathrm{MNP}(\mathrm{Q}, \mathrm{k}) = \frac{1}{|\mathrm{Q}|} \sum_{\mathrm{j}=1}^{|\mathrm{Q}|} \frac{\mathrm{Precision_j(k)}}{\mathrm{Precision_{max,j}(k)}}$$

The mean of the normalized Precision at k (with respect to the maximal achievable Precision at k) over several queries Q

e.g. for LeavePostOut with k = 10, $\mathrm{Precision}_{\mathrm{max}}(k) = 1/10$

Evaluation Corpus

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Bibsonomy corpus with p-core extraction at level 5 to reduce noise and to focus on the dense portion of the corpus

	Before	After
Users	7243	69
Bookmark resources	281550	9
Bibtex resources	469654	134
Tags	216094	179
Tag assignments	2740834	3269
Bookmark posts	330192	51
Bibtex posts	526691	959

FReSET – Domínguez García et al 2012
http://www.kom.tu-darmstadt.de/research-results/downloads/software/freset/

Visualization of Results with Violin Plots

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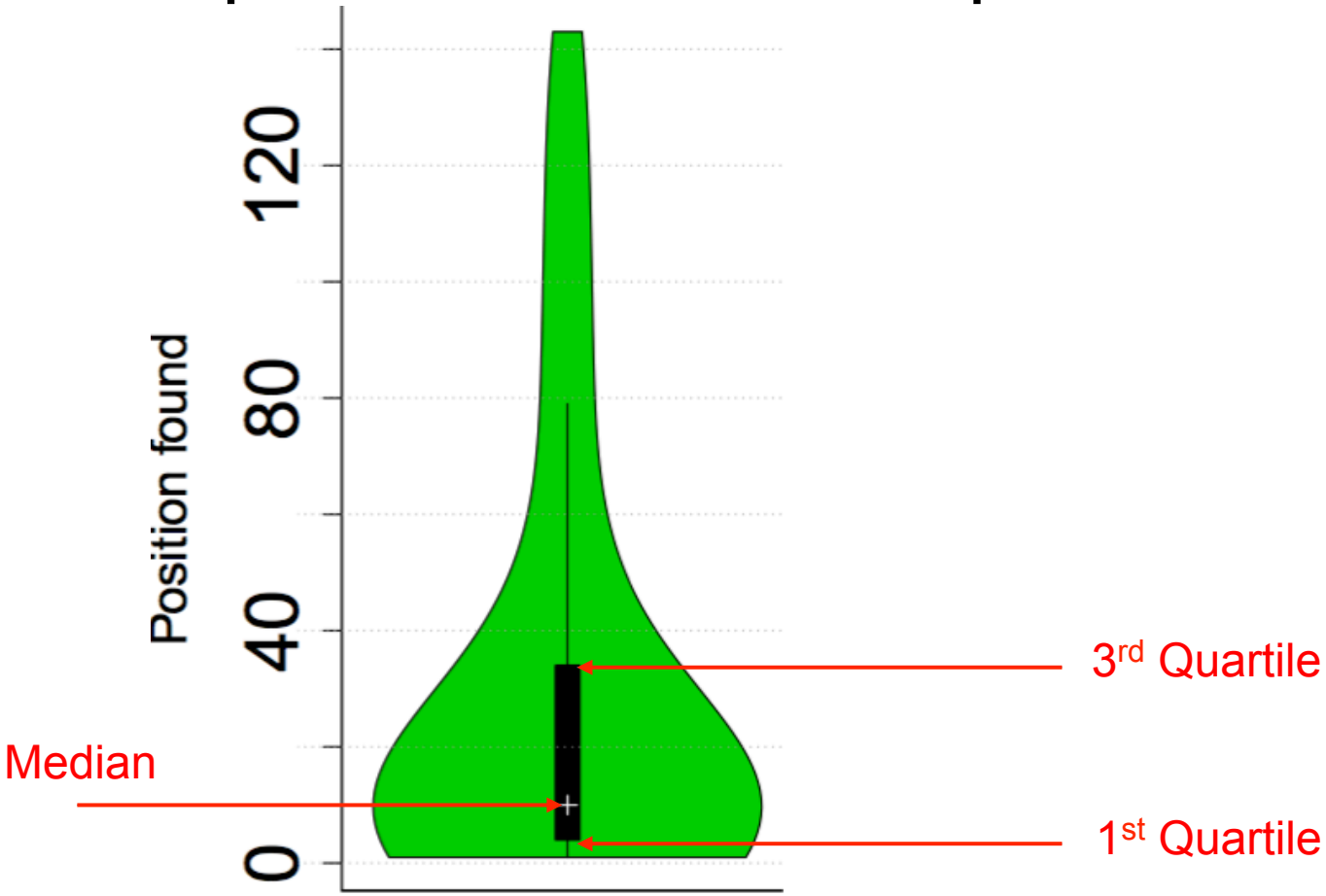
A violin plot is a combination of a box plot and a density trace



Evaluation Results for LeavePostOut

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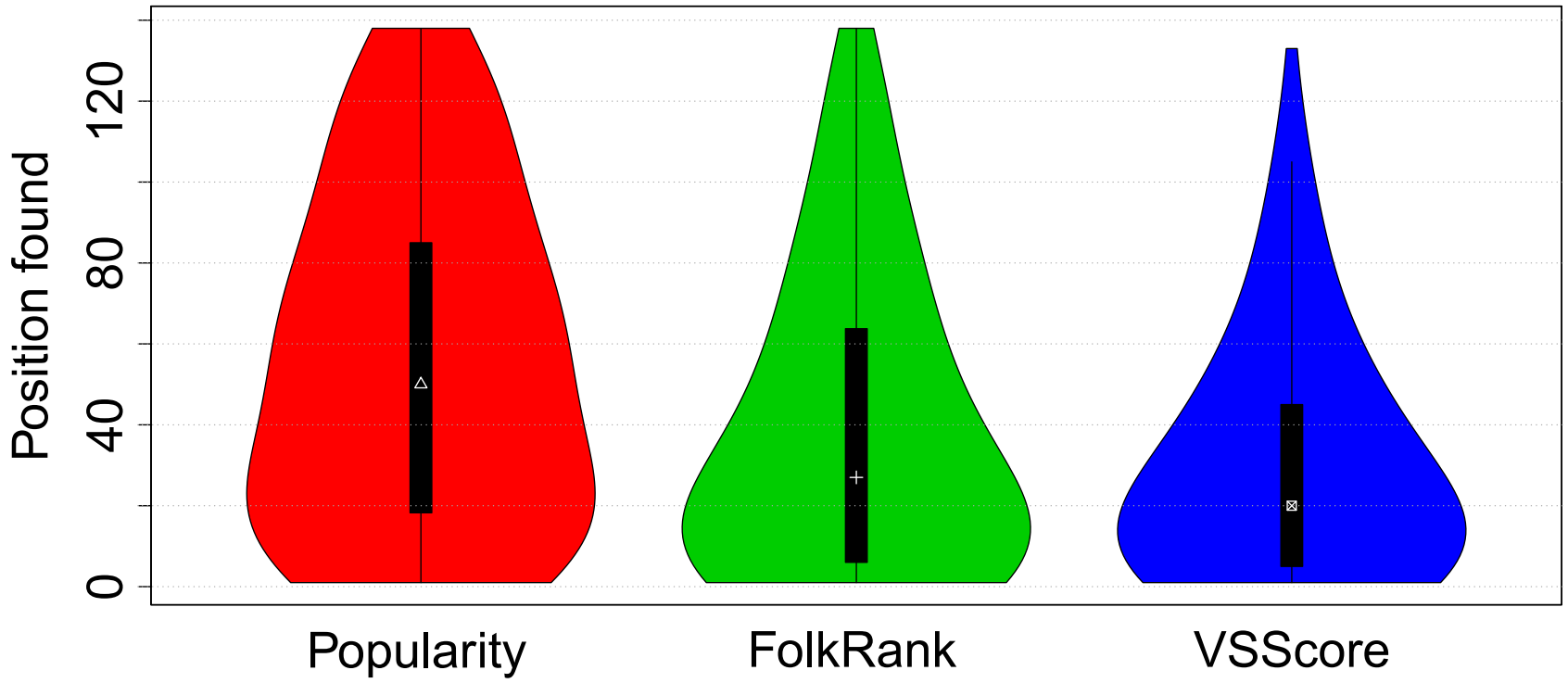
Evaluation results for recommendation task Interests Match



(Popularity of a resource is calculated as the sum of tags and users of a resource)

Evaluation Results for LeavePostOut

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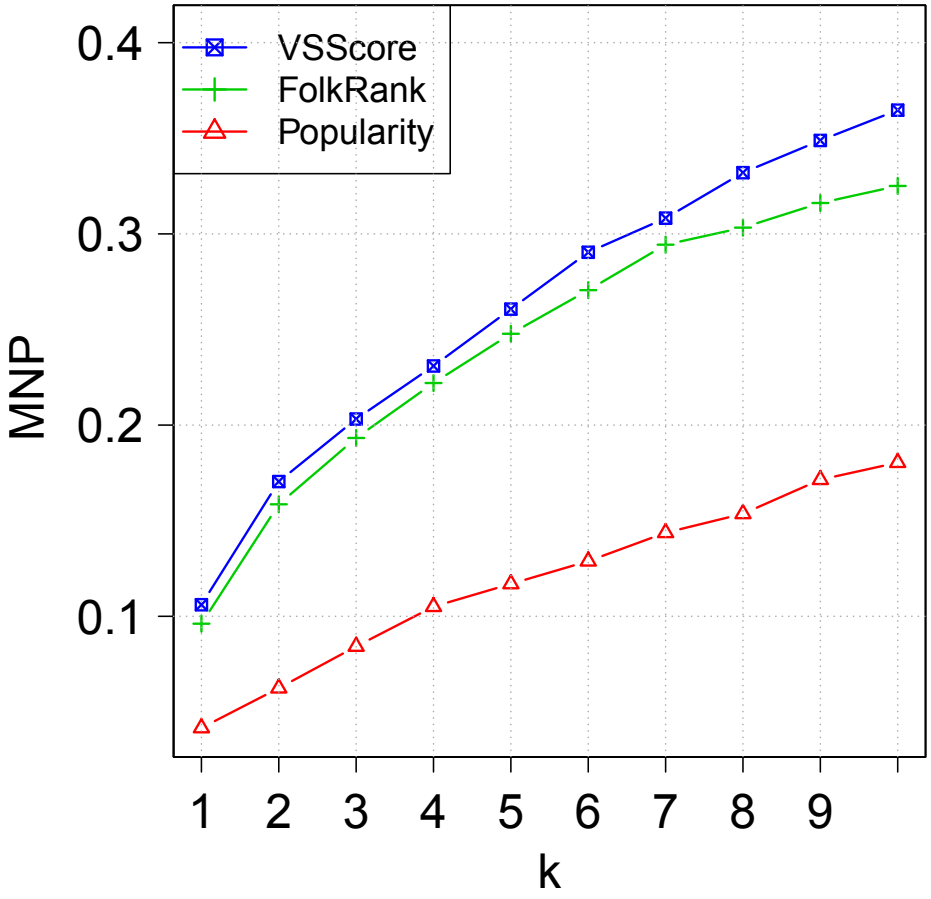

Approaches	MAP
VSScore	0.1972
FolkRank	0.1809
Popularity	0.0943

Evaluation Results for LeaveRTOut

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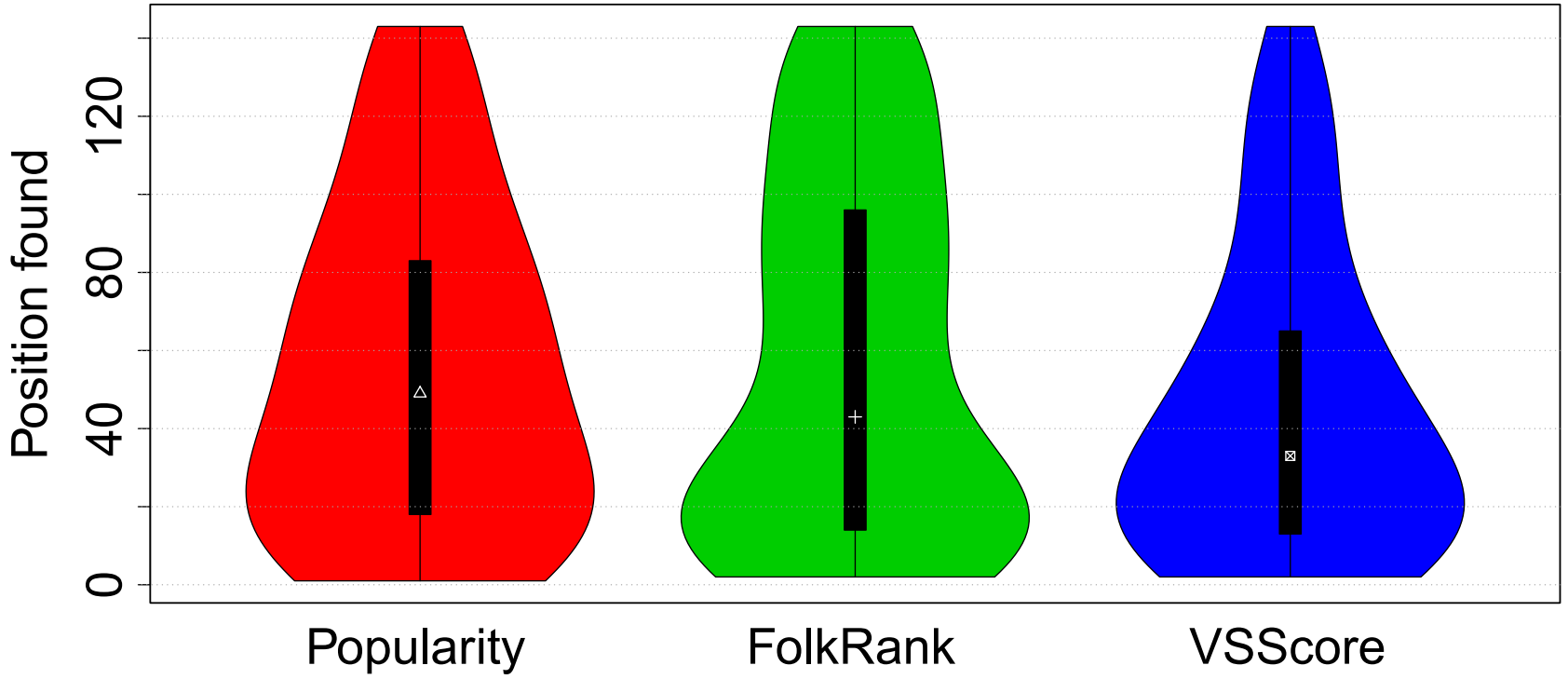
Evaluation results for recommendation task Guided Search



Evaluation Results for LeaveRTOut

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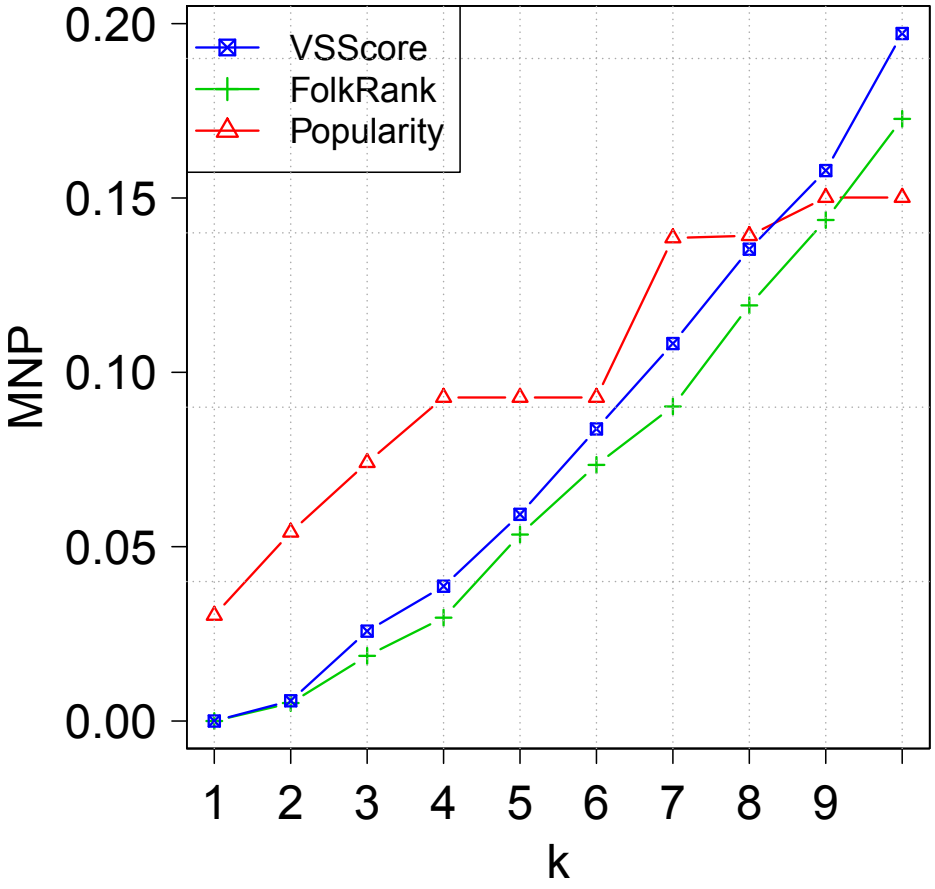

Approaches	MAP
Popularity	0.0834
VSScore	0.0592
FolkRank	0.0529

Results for Statistical Significance Tests

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Pairwise comparisons based on Average Precision with significance level of $p = 0.05$

- Scenario A: User-based resource recommendation
- Scenario B: Ranking of user‘s resources
- Scenario C: Tag-based resource recommendation

Methodology	Interests Match	Guided Search
LeavePostOut	VSScore^{A}	VSScore^{C}
LeaveNPostsOut	VSScore^{A}	FolkRank^{C}, VSScore^{C}
LeaveRTOut	FolkRank^{B}	VSScore^{C}
LeaveNRTsOut	FolkRank^{B}	VSScore^{C}

Wilcoxon signed-rank tests

Conclusion and Future Work

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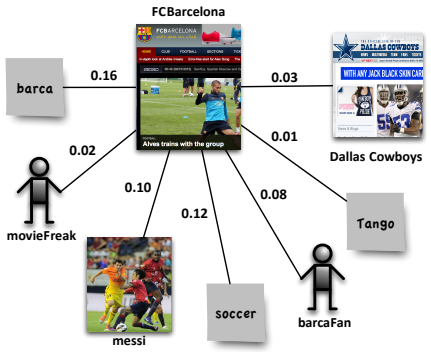
VSScore is a Framework leveraging context-specific information inherently found in a folksonomy for resource recommendation.



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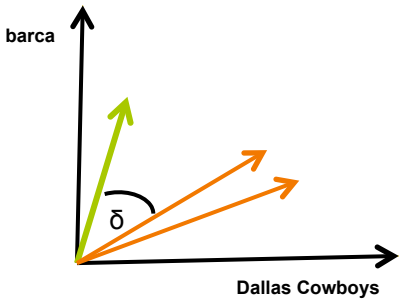

Limitations

- VSScore is computationally complex, therefore evaluations were performed on a limited corpus size

Future Work

- Reduce high-dimensional vector space to reduce computational complexity
- Evaluate on larger corpora from different domains
- Investigate further recommendation scenarios e.g. tag or user recommendation

Questions & Contact

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Department of Electrical Engineering
and Information Technology
Multimedia Communications Lab - KOM

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