Modeling Activation Processes in Human Memory to Improve Tag Recommendations

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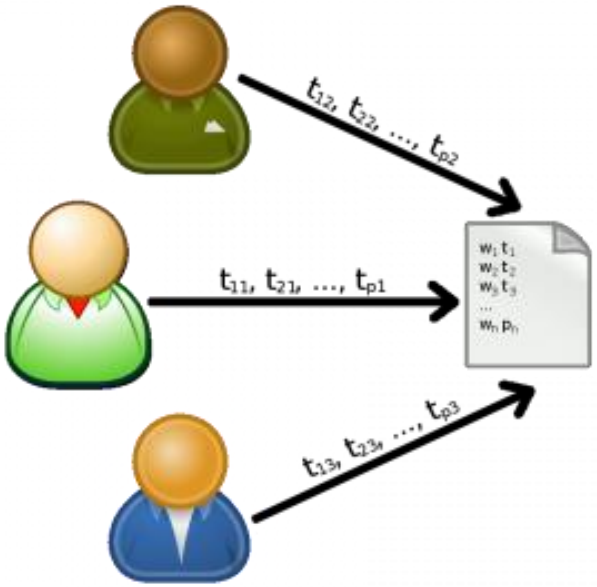
PhD defense, Graz (Austria), Tuesday October 10th 2017

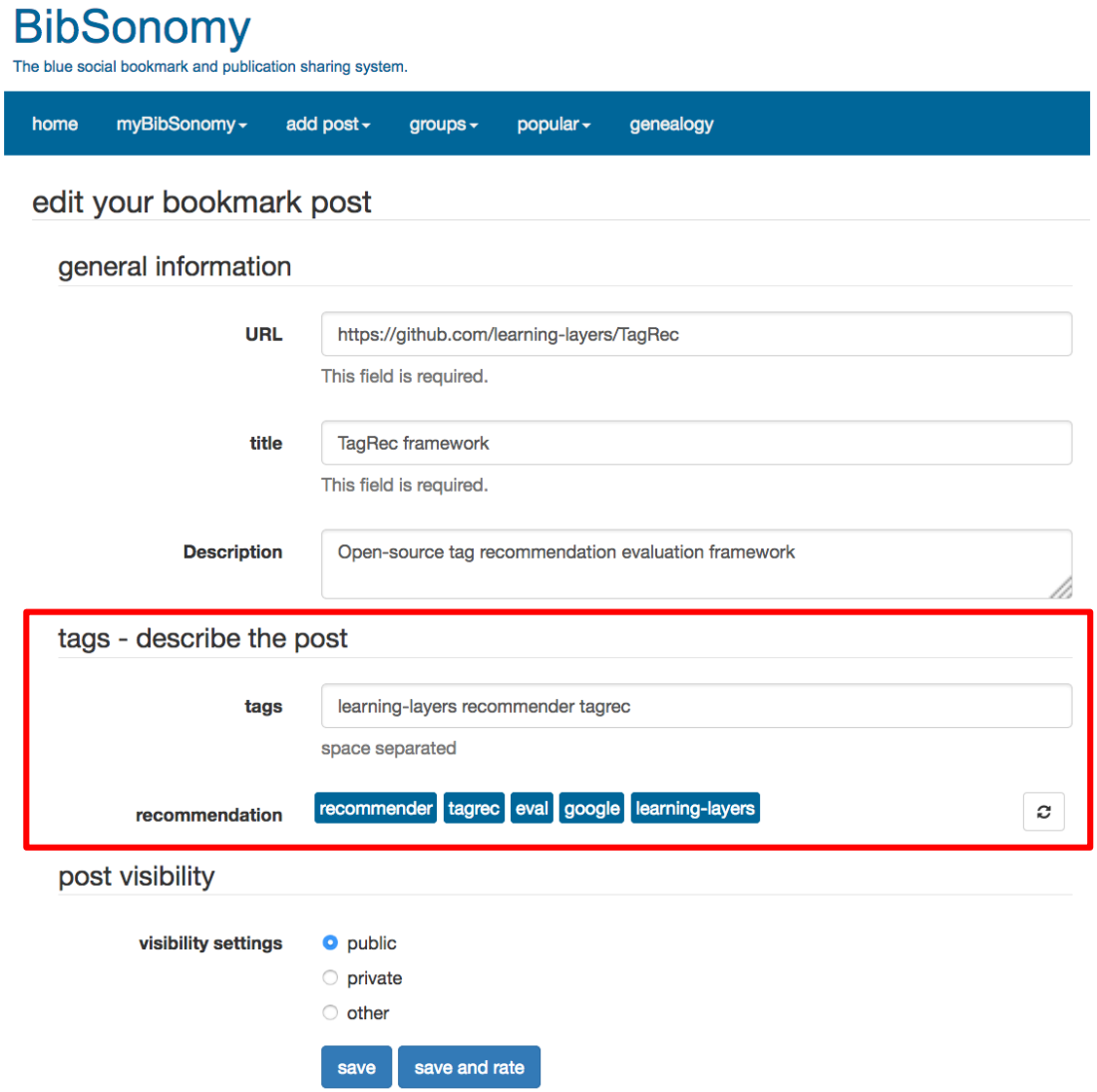
Social Tagging

- Social tagging is the process of **collaboratively annotating content** with keywords (i.e., *tags*)
- Essential instrument of Web 2.0 to **structure and search Web content**
- ***Issues***
  - Tags are **freely-chosen** keywords
    → no rules
  - Synonyms, spelling errors, etc.
  - Hard to come up with a **set of descriptive tags** by their own



[Zubiaga, 2009]

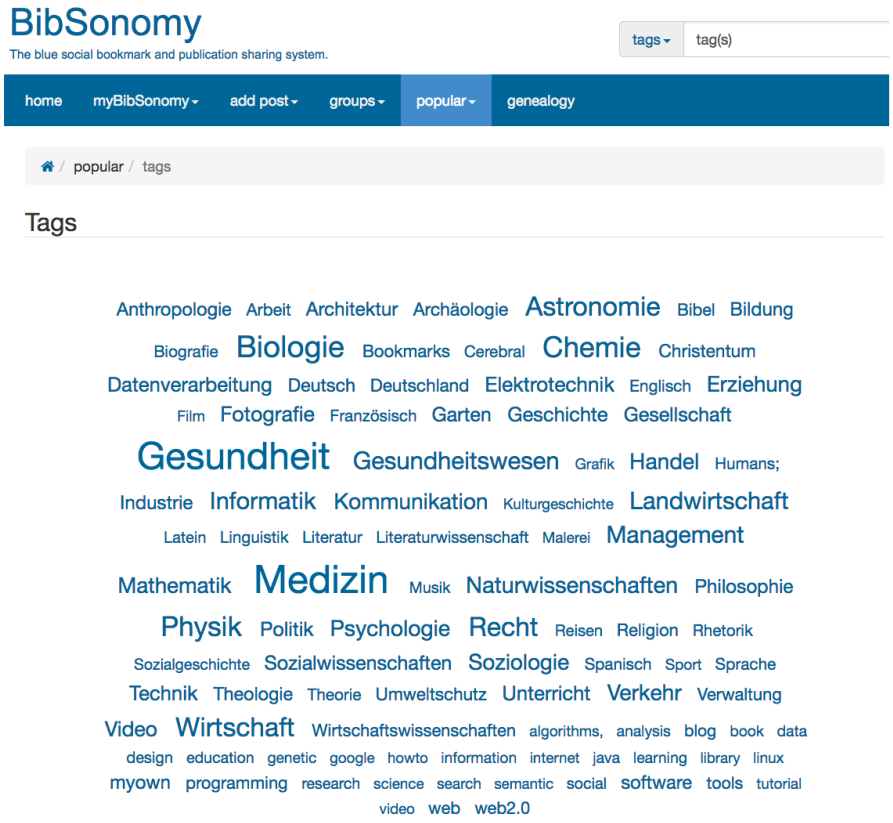
Tag Recommendations



[BibSonomy, 2017]

Tag Recommendations: Benefits

- Help the **individual** to find appropriate tags for annotating a resource [Wang et al., 2012]
- Increase the **indexing quality** of resources [Dellschaft & Staab, 2012]
- Support the **collective** in consolidating the **shared tag vocabulary** (semantic stability) [Wagner et al., 2014; Font et al., 2016]



[BibSonomy, 2017]

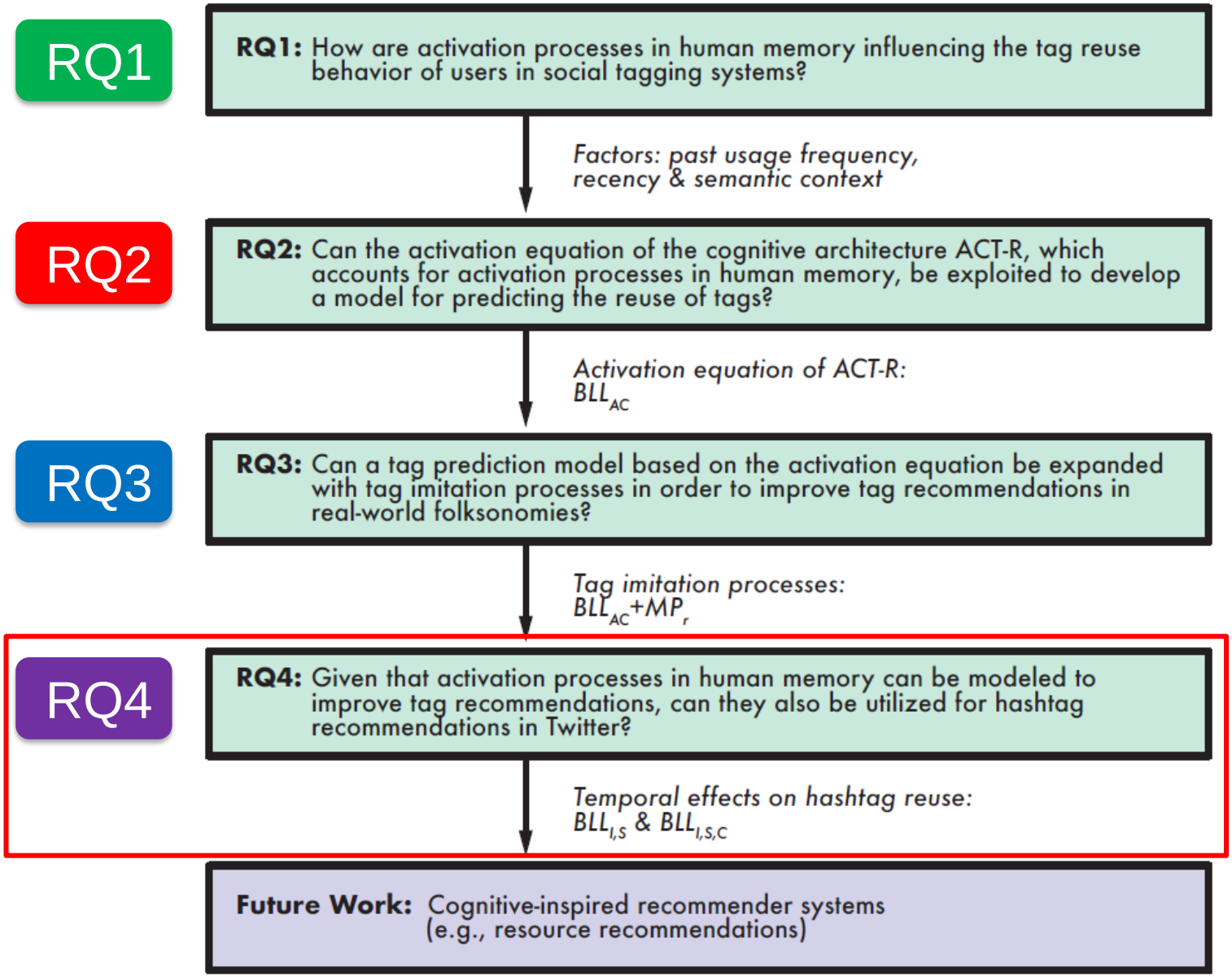
Research Gap

- The way users choose tags for their resources strongly corresponds to **processes in human memory** and its cognitive structures [Fu, 2008; Seitlinger & Ley, 2012]
  - **Activation processes** in human memory → **ACT-R** [Anderson et al., 2004]
  - **Activation equation** → usefulness of memory unit depends on **general usefulness** (i.e., frequency and recency) and usefulness in **current semantic context**
- Current tag recommendation algorithms are designed in a purely **data-driven** way
  - Tag popularity, user similarities, topic modeling, factorization of resource features, etc.
  - **Ignore** these insights from **cognitive science**

Problem Statement

*There is a lack of knowledge about (i) how **activation processes in human memory** can be modeled for the task of **predicting and recommending tags**, and (ii) if this could lead to **improvements in real-world tag recommendation** settings*

Kowald, D. (2015). Modeling cognitive processes in social tagging to improve tag recommendations. In *Proceedings of the 24th International Conference on World Wide Web, WWW '15 Companion*, ACM

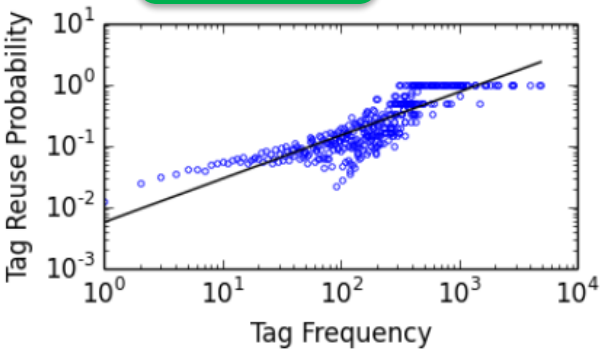

RQ1
RQ1: How are activation processes in human memory influencing the tag reuse behavior of users in social tagging systems?
Factors: past usage frequency, recency & semantic context
RQ2
RQ2: Can the activation equation of the cognitive architecture ACT-R, which accounts for activation processes in human memory, be exploited to develop a model for predicting the reuse of tags?
Activation equation of ACT-R: BLL_{AC}
RQ3
RQ3: Can a tag prediction model based on the activation equation be expanded with tag imitation processes in order to improve tag recommendations in real-world folksonomies?
Tag imitation processes: $BLL_{AC}+MP_r$
RQ4
RQ4: Given that activation processes in human memory can be modeled to improve tag recommendations, can they also be utilized for hashtag recommendations in Twitter?
Temporal effects on hashtag reuse: $BLL_{I,S}$ & $BLL_{I,S,C}$
Future Work: Cognitive-inspired recommender systems (e.g., resource recommendations)

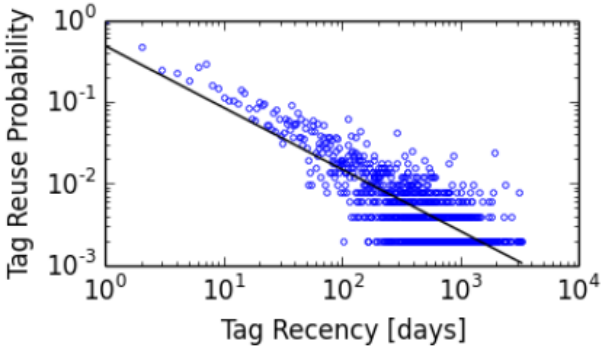
RQ1

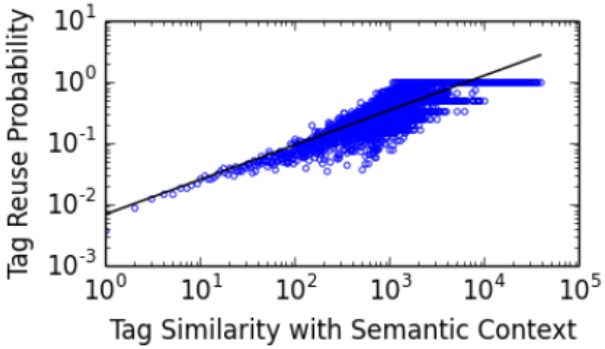
*How are **activation processes in human memory** influencing the **tag reuse behavior** of users in social tagging systems?*

Kowald, D. and Lex, E. (2016). The influence of frequency, recency and semantic context on the reuse of tags in social tagging systems. In *Proceedings of the 27th ACM Conference on Hypertext and Social Media, HT '16*, ACM.

RQ1 Results







[CiteULike, 2016]

- The **more frequently** a tag was used in the past **(k > 0)**, the higher its reuse probability is.
- The **more recently** a tag was used in the past **(k < 0)**, the higher its reuse probability is.
- The **more similar** a tag is to tags of the **current sem. context (k > 0)**, the higher its reuse probability is.

→ The **activation equation of ACT-R** models these factors

RQ2

*Can the **activation equation** of the cognitive architecture ACT-R, which accounts for activation processes in human memory, be exploited to develop a **model for predicting the reuse of tags**?*

Kowald, D., Seitlinger, P., Trattner, C., and Ley, T. (2014). Long time no see: The probability of reusing tags as a function of frequency and recency. In *Proceedings of the 23rd International Conference on World Wide Web, WWW '14 Companion*, ACM

Trattner, C., **Kowald, D.**, Seitlinger, P., Ley, T., and Kopeinik, S. (2016). Modeling activation processes in human memory to predict the use of tags in social bookmarking systems. *The Journal of Web Science*, 2(1).

RQ2 The Activation Equation of ACT-R

- Activation equation [Anderson et al., 2004]

$$A_i = B_i + \sum_j (W_j \cdot S_{j,i})$$

- Activation of memory unit *i* (e.g., a tag) = **base-level activation** of *i* (general usefulness) + **associative activation** of *i* (relevance to **context cues** *j*)

- Base-Level Learning (BLL) equation [Anderson & Schooler, 1991]
- Integrates past usage frequency and recency of i

$$B_i = ln(\sum_{j=1}^{n} t_j^{-d})$$

RQ2 Methodology

- **6 Datasets**
  - Flickr, CiteULike, BibSonomy, Delicious, MovieLens and LastFM
- Evaluation protocol
  - For each user, put **most recent bookmark into test set** → the rest is used for training
- Evaluation metrics
  - Precision, Recall, **F1-score**, MRR, nDCG, **MAP**
- Recommendation algorithms
  - MostPopular (MP_u), MostRecent (MR_u), GIRP [Zhang et al., 2012], FolkRank (FR) [Hotho et al., 2006], PITF [Rendle & Schmidt-Thieme, 2010] → **BLL_{AC}**

RQ2 Results

Dataset	Metric	MP_u	MP_r	GIRP	BLL_{AC}	FR	PITF
Flickr	F_1@5	.371	.000	.455	**.470**	.365	.350
	MAP@10	.509	.000	.647	**.680**	.501	.469
CiteULike	F_1@5	.231	.042	.243	**.259**	.250	.178
	MAP@10	.307	.054	.335	**.367**	.327	.233
BibSonomy	F_1@5	.253	.068	.262	**.280**	.279	.215
	MAP@10	.307	.073	.323	**.346**	.337	.257
Delicious	F_1@5	.173	.135	.190	**.243**	.196	.199
	MAP@10	.206	.153	.238	**.312**	.226	.229
LastFM	F_1@5	.193	.199	.198	.251	.270	**.276**
	MAP@10	.226	.226	.239	.312	.313	**.336**
MovieLens	F_1@5	.077	.135	.077	.086	.153	**.156**
	MAP@10	.159	.223	.160	.188	.253	**.275**

- **BLL_{AC}** outperforms related methods in Flickr, CiteULike, BibSonomy and Delicious (narrow folksonomies)

→ Algorithms that utilize **tag imitation** processes provide the best results in LastFM and MovieLens (broad folksonomies)

RQ3

Can a tag prediction model based on the activation equation be ***expanded with tag imitation processes*** *in order to improve* ***tag recommendations in real-world folksonomies****?*

Kowald, D. and Lex, E. (2015). Evaluating tag recommender algorithms in real-world folksonomies: A comparative study. In *Proceedings of the 9th ACM Conference on Recommender Systems, RecSys '15*, ACM

RQ3 Tag Imitation and Hybrid Approach

- Tag imitation is realized via the most popular tags assigned to the resource (**MPr**) [Floeck et al., 2010]

$$\widetilde{T}_k(u,r) = \arg\max_{t \in T_r}^{k}(|Y_{t,r}|)$$

- **BLLAC** and **MPr** are mixed using a linear combination

$$\widetilde{T}_k(u,r) = \arg\max_{t \in T_u \cup T_r}^{k}(\underbrace{\beta \underbrace{\sigma_{T_u}(A(t,u,r)}_{BLL_{AC}} + (1-\beta)\sigma_{T_r}(|Y_{t,r}|)}_{BLL_{AC}+MP_r})$$

- β can be used to assign weights to the components (currently set to 0.5)
- ϭ maps the components on a common range (0 – 1)

RQ3 Results

Dataset	Metric	MP_u	MP_r	GIRP	BLL_{AC}	FR	PITF	$BLL_{AC}+MP_r$
Flickr	F_1@5	.371	.000	.455	.470	.365	.350	**.470**
	MAP@10	.509	.000	.647	.680	.501	.469	**.680**
CiteULike	F_1@5	.231	.042	.243	.259	.250	.178	**.273**
	MAP@10	.307	.054	.335	.367	.327	.233	**.380**
BibSonomy	F_1@5	.253	.068	.262	.280	.279	.215	**.298**
	MAP@10	.307	.073	.323	.346	.337	.257	**.365**
Delicious	F_1@5	.173	.135	.190	.243	.196	.199	**.283**
	MAP@10	.206	.153	.238	.312	.226	.229	**.358**
LastFM	F_1@5	.193	.199	.198	.251	.270	.276	**.283**
	MAP@10	.226	.226	.239	.312	.313	.336	**.344**
MovieLens	F_1@5	.077	.135	.077	.086	.153	.156	**.160**
	MAP@10	.159	.223	.160	.188	.253	.275	**.276**

- This **hybrid approach** (**$BLL_{AC}+MP_r$**) outperforms all related algorithms in all datasets (narrow and broad)

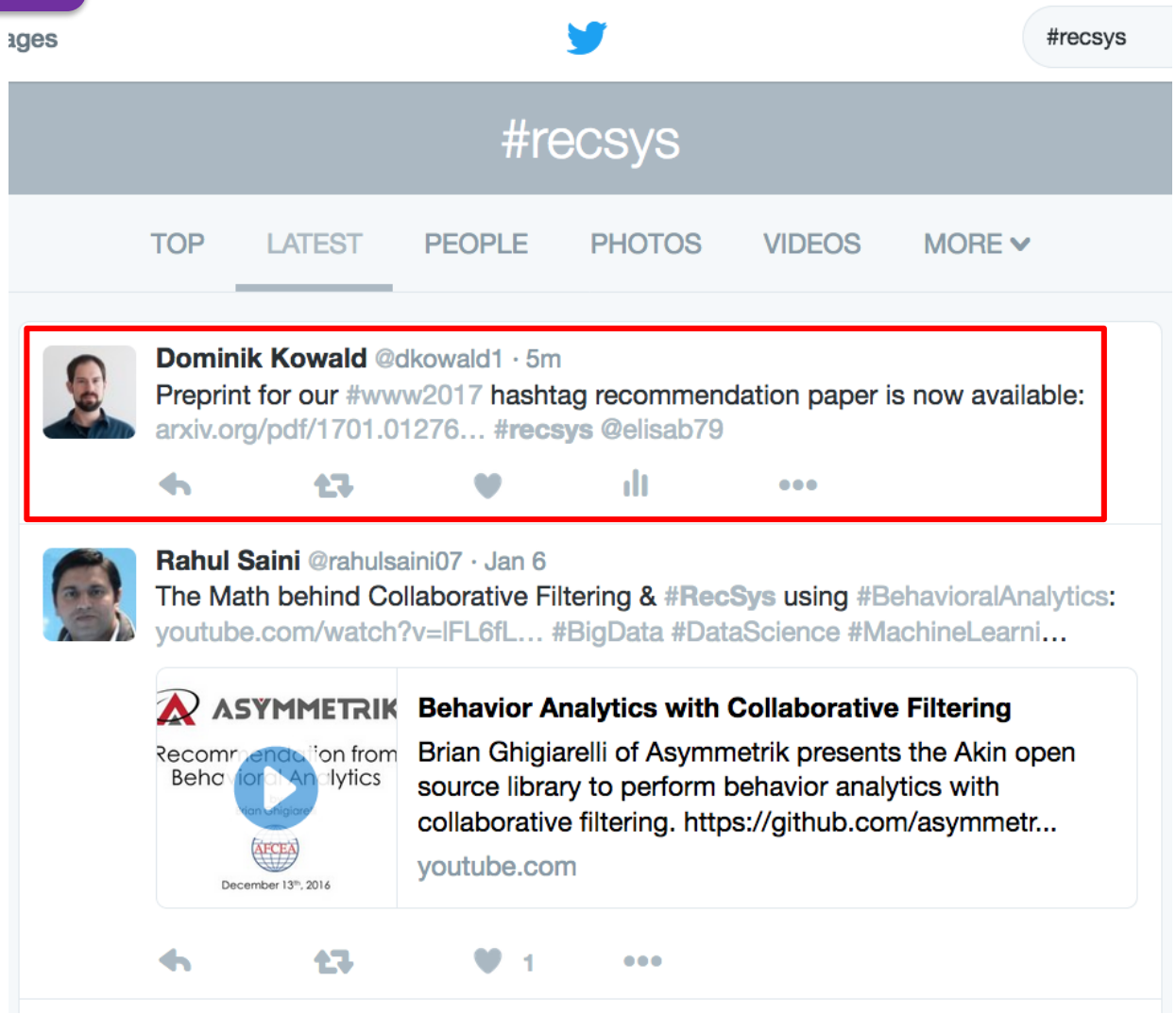
→ **BLL_{AC}** can be combined with **MP_r** to model tag imitation processes

RQ4

Given that activation processes in human memory can be modeled to improve tag recommendations, can they also be ***utilized for hashtag recommendations in Twitter****?*

Kowald, D., Pujari, S., and Lex, E. (2017). Temporal effects on hashtag reuse in Twitter: A cognitive-inspired hashtag recommendation approach. In *Proceedings of the 26th International Conference on World Wide Web, WWW'17*, ACM.

RQ4 Hashtags in Twitter



[Twitter, 2017]

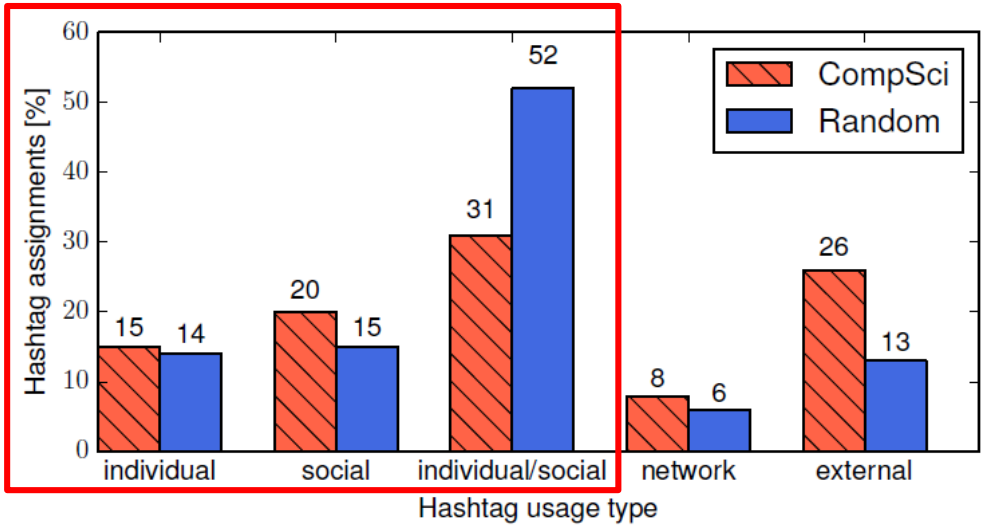
RQ4 Datasets

- 2 datasets: ***CompSci* and *Random***
- **Crawling strategy**
  - (i) Crawl seed users [Hadgu & Jäschke, 2014]
  - (ii) Crawl followees
  - (iii) Crawl tweets
  - (iv) Extract hashtag assignments

Dataset	$\|U_S\|$	$\|U\|$	$\|T\|$	$\|HT\|$	$\|HTAS\|$
CompSci	2,551	91,776	5,649,359	1,081,403	9,161,842
Random	3,466	127,112	8,157,702	1,507,773	13,628,750

RQ4 Hashtag Reuse Types

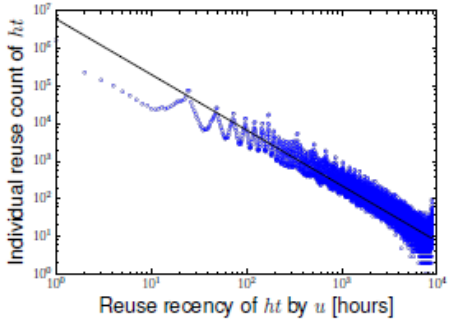
- *How are people **reusing hashtags** in Twitter?*



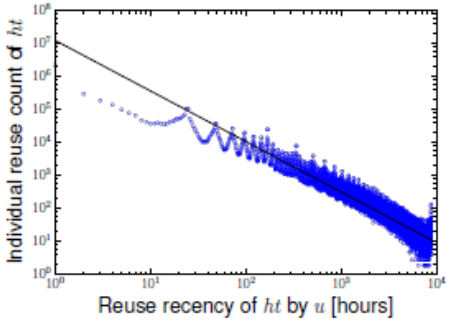
- 66% and 81% of hashtag assignments can be explained by **individual** or **social** hashtag reuse

RQ4 Temporal Effects on Hashtag Reuse

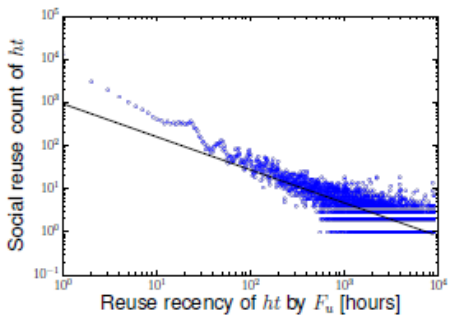
- *Do temporal effects have an **influence on individual and social hashtag reuse**?*



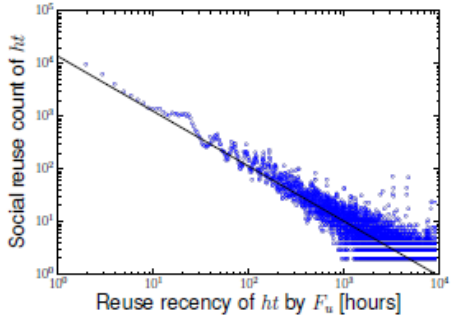
(a) Individual hashtag reuse *CompSci* dataset ($R^2 = .883$)



(b) Individual hashtag reuse *Random* dataset ($R^2 = .894$)



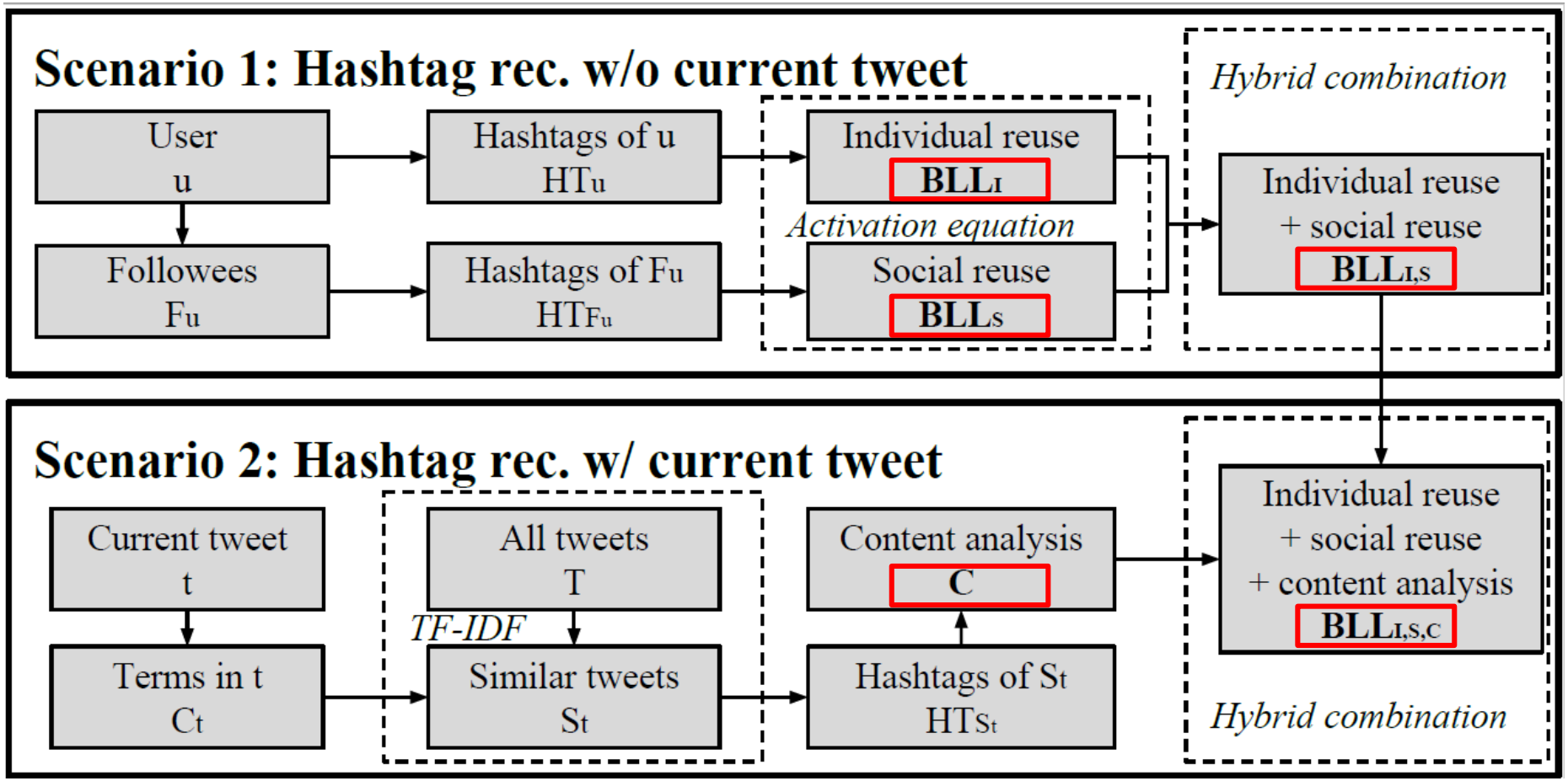
(c) Social hashtag reuse *CompSci* dataset ($R^2 = .689$)



(d) Social hashtag reuse *Random* dataset ($R^2 = .771$)

- People tend to reuse hashtags that were **used very recently** by their own or by their followees
- Activation processes in human memory should be helpful to **model the reuse of hashtags**

RQ4 Hashtag Recommendation Approach



RQ4 Methodology

- Same evaluation protocol and metrics as for RQ 2+3
  - **Most recent tweet into test set** → rest for training
  - Precision, Recall, **F1-score**, MRR, nDCG, **MAP**
- Recommendation algorithm
  - *Scenario 1*: MostPopular (MP), MostRecent (MR), FolkRank (FR), Collaborative Filtering (CF) → **$BLL_{I,S}$**
  - *Scenario 2*: SimRank (SR), TemporalCombInt (TCI) [Harvey & Crestani, 2015] → **$BLL_{I,S,C}$**
- **TagRec:** Open-source tag recommender benchmarking framework: https://github.com/learning-layers/TagRec

Kowald, D., Kopeinik, S., & Lex, E. (2017). The TagRec Framework as a Toolkit for the Development of Tag-Based Recommender Systems. In *Proc. of the 25th Conference on User Modeling, Adapation and Personalization (UMAP'2017)*. ACM.

RQ4 Results (*Scenario 1*)

- *Can we predict the hashtags of **a given user** using activation processes?*

Dataset	Metric	MP_I	MR_I	BLL_I	MP_S	MR_S	BLL_S	MP	FR	CF	$BLL_{I,S}$
CompSci	F1@5	.086	.098	**.101**	.022	.076	**.118**	.006	.083	.099	**.153**
	MAP@10	.143	.195	**.202**	.033	.128	**.205**	.007	.136	.169	**.285**
Random	F1@5	.160	.169	**.175**	.072	.103	**.138**	.012	.159	.165	**.208**
	MAP@10	.279	.315	**.335**	.116	.171	**.240**	.024	.279	.296	**.389**

- **BLL_I > MP_I, MR_I**
- **BLL_S > MP_S, MR_S**
- **$BLL_{I,S}$ > MP, FR, CF**

RQ4 Results (*Scenario 2*)

- *Can we predict the hashtags of a **given user and a given tweet** using activation processes?*

Dataset	Metric	SR	TCI	$BLL_{I,S,C}$
CompSci	F1@5	.139	.182	**.200**
	MAP@10	.283	.354	**.417**
Random	F1@5	.181	.243	**.261**
	MAP@10	.374	.472	**.530**

- **TCI, $BLL_{I,S,C}$ > SR**
- **$BLL_{I,S,C}$ > TCI**

→ **Activation processes in human memory** can be utilized for **hashtag recommendations in Twitter**

Contributions

RQ1 Activation processes in human memory (i.e., **frequency, recency and semantic context**) have an influence on tag usage practices

RQ2 The **activation equation of ACT-R** can be used to design a tag reuse prediction algorithm termed **BLL_{AC}**

RQ3 **BLL_{AC}** can be extended with **tag imitation processes** to realize a tag recommendation algorithm (**BLL_{AC}+MP_r**) that outperforms state-of-the-art approaches

RQ4 This approach can also be utilized for related **hashtag recommendations in Twitter**

→ All evaluations have been conducted using the open-source **TagRec** framework developed in Learning Layers

- https://github.com/learning-layers/TagRec

Future Work

- Validate the use of other **cognitive processes** for tag and hashtag recommendations
  - e.g., using models of human **categorization**
- Use **content information** of resources (e.g., title or description) to model the current semantic context
- **Hybrid models** based on dataset characteristics (set β)
- Verify the offline evaluation results in an **online setting**
- Improve the hashtag recommendation algorithm by incorporating **social information** (e.g., edge weights)
- ***Long-term goal***
  - Use these insights to realize other types of **cognitive-inspired / hybrid recommender systems** (e.g., resource recommendations)

Thank you for listening!

Do you have questions / suggestions?

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References (i)

- **[Anderson et al., 2004]** J. R. Anderson, D. Bothell, M. D. Byrne, S. Douglass, C. Lebiere, and Y. Qin. An integrated theory of the mind. *Psychological review*, 111(4):1036, 2004.
- **[Anderson & Schooler, 1991]** Anderson, J. R. and Schooler, L. J. Reflections of the environment in memory. *Psychological science*, 2(6), 1991
- **[Dellschaft & Staab, 2012]** Dellschaft, K. and Staab, S. (2012). Measuring the influence of tag recommenders on the indexing quality in tagging systems. In *Proceedings of Hypertext'12*, pages 73-82. ACM.
- **[Floeck et al., 2010]** Floeck, F., Putzke, J., Steinfels, S., Fischbach, K., and Schoder, D. (2010). Imitation and quality of tags in social bookmarking systems - collective intelligence leading to folksonomies. In *On collective intelligence*, pages 75-91. Springer.
- **[Font et al., 2015]** Font, F., Serrà, J., & Serra, X. (2015). Analysis of the impact of a tag recommendation system in a real-world folksonomy. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *7*(1), 6.
- **[Fu, 2008]** Fu, Wai-Tat. The microstructures of social tagging: a rational model. In *Proceedings of CSCW' 08*, pages 229-238. ACM, 2008
- **[Hadgu & Jäschke, 2014]** A. T. Hadgu and R. Jäschke. Identifying and analyzing researchers on twitter. In *Proceedings of WebSci '14*, pages 23-30, New York, NY, USA, 2014.

References (ii)

- **[Harvey & Crestani, 2015]** M. Harvey and F. Crestani. Long time, no tweets! Time-aware personalised hashtag suggestion. In *Proceedings of ECIR'15*. Springer, 2015.
- **[Hotho et al., 2006]** Hotho, A., Jäschke, R., Schmitz, C., and Stumme, G. (2006). Information retrieval in folksonomies: search and ranking. In Proceedings of ESCW'06, pages 411-426. Springer.
- **[Rendle & Schmidt-Thieme, 2010]** Rendle, S. and Schmidt-Thieme, L. (2010). Pairwise interaction tensor factorization for personalized tag recommendation. In *Proceedings of WSDM'10*, pages 81-90. ACM.
- **[Seitlinger & Ley, 2012]** Seitlinger, P. and Ley, T. (2012). Implicit imitation in social tagging: familiarity and semantic reconstruction. In *Proceedings of CHI'12*, pages 1631-1640. ACM.
- **[Wagner et al., 2014]** Wagner, C., Singer, P., Strohmaier, M., and Huberman, B. A. (2014). Semantic stability in social tagging streams. In *Proceedings of WWW'14*, pages 735-746. ACM.
- **[Wang et al., 2012]** Wang, M., Ni, B., Hua, X. S., & Chua, T. S. (2012). Assistive tagging: A survey of multimedia tagging with human-computer joint exploration. *ACM Computing Surveys (CSUR)*, *44*(4), 25.
- **[Zhang et al., 2012]** Zhang, L., Tang, J., and Zhang, M. (2012). Integrating temporal usage pattern into personalized tag prediction. In *Web Technologies and Applications*, pages 354-365. Springer.