Long Time No See

The Probability of Reusing Tags as a Function of Frequency and Recency

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Many Thanks To

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What will this talk be about?

- Social tags
- Prediction/recommendation of social tags
- Using an equation derived from human memory theory to implement a novel tag recommender
Social tagging is the process of collaboratively annotating content.

Essential instrument of Web 2.0.

Helps users to:
- classify and structure Web content [Zubiaga et al., 2012]
- navigate large knowledge repositories [Helic et al., 2012]
- search and find information [Trattner et al., 2012]
Problem:
People are typically lazy in applying social tags (!)
**Solution: Tag Recommenders**

- Tag recommendation algorithms support the users in applying appropriate tags for resources and can be based on:
  - Tag Frequencies (MP)
  - Collaborative Filtering (CF)
  - Graph Structures (APR, FR)
  - Factorization Models (FM, PITF)
  - Hybrid approaches

- **Issues**
  - Usually users change their tagging behavior **over time**
  - **BUT** all of these approaches **ignore the time component**

[Huang et al., 2014]
What’s about the time component?

- Only a few time-based approaches available

- The Temporal Tag Usage Pattern approach (GIRPTM) of Zhang et al. (2012) shows that the time component is important for tag recommenders
  - Models the time component using an exponential function

- Empirical research on human memory (Anderson & Schooler, 1991) showed that the reuse-probability of a word depends on its usage-frequency and recency in the past
  - Models the time component using a power function
Which function fits better to model the drift of interests in social tagging systems?
Empirical Analysis: BibSonomy (1)

- Linear distribution with log-scale on Y-axis $\rightarrow$ exponential function

- Linear distribution with log-scale on X- and Y-axes $\rightarrow$ power function
Empirical Analysis: BibSonomy (2)

Exponential distribution
$R^2 = 35\%$

Power distribution
$R^2 = 65\%$

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Our Approach

• **Base-Level learning (BLL) equation** - part of ACT-R model [Anderson et al., 2004]:

\[ BLA(t, u) = \ln\left( \sum_{i=1}^{n} (\text{timestamp}_{\text{ref}} - \text{timestamp}_i)^{-d} \right) \]

• Also the context (resource) is important
  – Modeled with the most frequent tags of the resource \((\text{MP}_r)\)

\[ \widetilde{T}(u, r) = \arg \max_{t \in T} (\beta \|BLA(t, u)\| + (1 - \beta)\|Y_{t,r}\|) \]

• **Linear runtime**: \(O(|Y_{t,u}| + |Y_{t,r}|)\)

• **Code**: [https://github.com/learning-layers/TagRec/](https://github.com/learning-layers/TagRec/)
How does it perform?

• 3 freely-available folksonomy datasets
  – BibSonomy (1.5 Million tag assignments)
  – CiteULike (16.7 million tag assignments)
  – Flickr (3.5 million tag assignments)

• Original datasets and $p$-core pruned datasets (core 3)

• Leave-one-out evaluation (for each user latest bookmark/post in test-set, rest in training-set)

• IR metrics: Precision, Recall, F1-score, MRR, MAP
Results: Precision-Recall plots

(a) BibSonomy (no core)  
(b) CiteULike (no core)  
(c) Flickr (no core)

- The **time-dependent** approaches outperform the state-of-the-art
- **BLL+C** reaches the highest level of accuracy

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• **BLL+C** needs only around 1 second to provide accurate tag-recommendations for 5,500 user-resource pairs in the test set.

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What we have shown

1) The **time component** is an important factor for tag-recommendations

2) The BLL-equation can be used to implement an effective tag recommender
   • Models the time component with a **power function** rather than an exponential function
   • Outperforms current state-of-the-art algorithms despite its **simplicity**
   • Computationally efficient: **linear runtime**

3) Effective principles of recommenders in social tagging can be implemented if human memory processes are taken into account
What are we currently doing?

• In previous work we presented a tag recommender based on human categorization (3Layers) [Seitlinger et al., 2013]
  – Combine this recommender with BLL to model the time component on a lexical and semantic layer

• Better modelling of the (resource) context (MP_r)
  – Spreading activation
  – Content-based approaches

• Adapt BLL+C also for the recommendation of resources

• Conduct online evaluation (BibSonomy)
Thank you for your attention!

Code and framework:
https://github.com/learning-layers/TagRec/

Questions?

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Backup
Results: Core 3

(d) BibSonomy (core 3)  
(e) CiteULike (core 3)  
(f) Flickr (core 3)
## Results: F1@5, MRR, MAP

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## Runtime Complexities

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## Runtimes for BibSonomy

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