Modeling Activation Processes in Human Memory to Improve Tag Recommendations

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Advisor: Ass-Prof. Elisabeth Lex

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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
The blue social bookmark and publication sharing system.

edit your bookmark post

general information

URL
https://github.com/learning-layers/TagRec
This field is required.

title
TagRec framework
This field is required.

Description
Open-source tag recommendation evaluation framework

[tags - describe the post]

tags
learning-layers recommender tagrec
space separated

recommendation
recommender tagrec eval google learning-layers

post visibility

visibility settings
public
private
other

save save and rate

[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 $\rightarrow$ ACT-R [Anderson et al., 2004]

  - **Activation equation** $\rightarrow$ 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.

Modeling Activation Processes in Human Memory to Improve Tag Recommendations

**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**: 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: \( \text{BLL}_{\text{AC}} \)*

**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: \( \text{BLL}_{\text{AC}} + \text{MP}_r \)*

**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: \( \text{BLL}_{15} \) & \( \text{BLL}_{15,c} \)*

**Future Work**: Cognitive-inspired recommender systems (e.g., resource recommendations)

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

RQ1 Results

- 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.

[CiteULike, 2016]
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?


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]

\[ B_i = \ln(\sum_{j=1}^{\infty} t_j^{-d}) \]
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 (MPu), MostRecent (MRu), GIRP [Zhang et al., 2012], FolkRank (FR) [Hotho et al., 2006], PITF [Rendle & Schmidt-Thieme, 2010] → BLLAC
RQ2 Results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Metric</th>
<th>$MP_u$</th>
<th>$MP_r$</th>
<th>GIRP</th>
<th>$BLL_{AC}$</th>
<th>FR</th>
<th>PITF</th>
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<td>Flickr</td>
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<td>.371</td>
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<td>.327</td>
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<td>.275</td>
</tr>
</tbody>
</table>

- $BLL_{AC}$ 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)
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?

RQ3: Tag Imitation and Hybrid Approach

- Tag imitation is realized via the most popular tags assigned to the resource ($\text{MP}_r$) [Floeck et al., 2010]
  \[
  \tilde{T}_k(u, r) = \arg \max_{t \in T_r} \left| Y_{t,r} \right|
  \]

- $\text{BLL}_{\text{AC}}$ and $\text{MP}_r$ are mixed using a linear combination
  \[
  \tilde{T}_k(u, r) = \arg \max_{t \in T_u \cup T_r} \left\{ \beta \sigma_{T_u}(A(t, u, r)) + (1 - \beta)\sigma_{T_r}(\left| Y_{t,r} \right|) \right\}
  \]

- $\beta$ can be used to assign weights to the components (currently set to 0.5)
- $\sigma$ maps the components on a common range ($0 - 1$)
### RQ3 Results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Metric</th>
<th>MP_u</th>
<th>MP_r</th>
<th>GIRP</th>
<th>BLL\textsubscript{AC}</th>
<th>FR</th>
<th>PITF</th>
<th>BLL\textsubscript{AC}+MP\textsubscript{r}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flickr</td>
<td>(F_1@5)</td>
<td>.371</td>
<td>.000</td>
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<td>Delicious</td>
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<tr>
<td>MovieLens</td>
<td>(F_1@5)</td>
<td>.077</td>
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<td>.160</td>
<td>.188</td>
<td>.253</td>
<td>.275</td>
<td>.276</td>
</tr>
</tbody>
</table>

- This **hybrid approach** (BLL\textsubscript{AC}+MP\textsubscript{r}) outperforms all related algorithms in all datasets (narrow and broad)

\(\Rightarrow\) **BLL\textsubscript{AC}** can be combined with **MP\textsubscript{r}** to model tag imitation processes
Given that activation processes in human memory can be modeled to improve tag recommendations, can they also be utilized for hashtag recommendations in Twitter?

RQ4: Hashtags in Twitter

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[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?

- 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

**Scenario 1: Hashtag rec. w/o current tweet**
- User $u$
  - Followees $F_u$
- Hashtags of $u$ $HT_u$
- Hashtags of $F_u$ $HT_{F_u}$
- Individual reuse $BLL_t$
- Social reuse $BLL_s$

**Scenario 2: Hashtag rec. w/ current tweet**
- Current tweet $t$
  - Terms in $t$ $C_t$
  - $TF-IDF$
- All tweets $T$
  - Similar tweets $St$
- Content analysis $C$
- Hashtags of $St$ $HT_{St}$
- Individual reuse + social reuse + content analysis $BLL_{t,s,c}$

Hybrid combination
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](https://github.com/learning-layers/TagRec)

### RQ4 Results (Scenario 1)

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

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Metric</th>
<th>MP_I</th>
<th>MR_I</th>
<th>BLL_I</th>
<th>MP_S</th>
<th>MR_S</th>
<th>BLL_S</th>
<th>MP</th>
<th>FR</th>
<th>CF</th>
<th>BLL_I,S</th>
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</thead>
<tbody>
<tr>
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<td>.086</td>
<td>.098</td>
<td>.101</td>
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</tbody>
</table>

- \( \text{BLL}_I > \text{MP}_I, \text{MR}_I \)
- \( \text{BLL}_S > \text{MP}_S, \text{MR}_S \)
- \( \text{BLL}_{I,S} > \text{MP, FR, CF} \)
RQ4 Results (Scenario 2)

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

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Metric</th>
<th>SR</th>
<th>TCI</th>
<th>BLL\textsubscript{I,S,C}</th>
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<tbody>
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<td>.374</td>
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</table>

- TCI, BLL\textsubscript{I,S,C} > SR
- BLL\textsubscript{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\textsubscript{AC}.

RQ3 BLL\textsubscript{AC} can be extended with tag imitation processes to realize a tag recommendation algorithm (BLL\textsubscript{AC}+MP\textsubscript{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 $\beta$)
- 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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- Thesis available at:
  https://online.tugraz.at/tug_online/wbAbs.showThesis?pThesisNr=62671
References (i)


References (ii)


