Modeling Activation Processes in Human Memory to Improve Tag Recommendations

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Social Tagging

- Social tagging is the process of collaboratively annotating content
- Essential instrument of Web 2.0 to structure and search Web content

- Issues
  - No rules for tags → can be freely chosen
  - Hard for people to come up with a set of descriptive/relevant tags by their own
  - People are lazy in applying tags
  - Synonyms, homonyms, spelling errors, singular/plurals, etc.
Solution: Tag Recommenders

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Benefits of Tag Recommendations

• Help the individual to find relevant tags → better find the bookmarked resources

• Help the collective to consolidate a shared tag vocabulary [Lipczak, 2012] → create a shared understanding in a group

• Personalized tag recommender can increase the indexing quality of resources [Dellschaft & Staab, 2002]
  – It is easier to understand the content of an indexed resource based on the tags
Lot of research available about how people access words in their memory
  - i.e., activation processes in human memory
• Current tag recommender approaches ignore these insights from cognitive science
  - or apply them in a very rudimentary or incomplete way

• Some of the approaches are highly computational expensive → hard to integrate in a live recommender system
• Often evaluated only in simulated folksonomies (i.e., p-cores) → hard to determine their usefulness in real-world settings
There is a lack of knowledge about (1) how activation processes in human memory can be modelled for the task of tag recommendations and (2) if this could lead to improvements in terms of recommender accuracy and computational costs in real-world folksonomies.
Research Questions

• **RQ1**: Which activation processes in human memory are appropriate to account for a tag’s probability of being reused in a social tagging system?

• **RQ2**: Can the activation equation of the cognitive model ACT-R, that accounts for the activation processes in human memory, be exploited to effectively predict a user’s tag reuse?

• **RQ3**: To what extent can a tag recommender algorithm, that extends the activation equation of the cognitive model ACT-R with tag imitation processes, compete with current state-of-the-art approaches in terms of recommender accuracy and computational costs?
Which activation processes in human memory are appropriate to account for a tag’s probability of being reused in a social tagging system?

- Parts of this RQ have been submitted to the Journal of Web Science
Activation Processes in Human Memory

• Account for the probability that a memory unit (e.g., word/tag) will be used (activated)

• Empirical research on human memory (Anderson & Schooler, 1991) showed that the activation of a human memory unit depends on its general usefulness in the past:
  – usage-frequency (1) (how often it was used) and
  – recency (2) (time since last usage → power-law of forgetting)

• And its usefulness in the current context (3) [Anderson et al., 2004]

• **Question:** How do these insights relate to social tagging systems (e.g., Flickr)?
(1) Tag-Frequency: Flickr
(2) Tag-Recency: Flickr

Power distribution
$R^2 = 84\%$

Exponential distribution
$R^2 = 61\%$ (e.g., Zhang et al., 2014)

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(3) Current Context

- **Open issue**
- Could be tackled in a similar way
- **Current context** is the target resource to be tagged (defined by the already given tags by other users $\rightarrow$ context cues)
- **Assumption**
  - Higher co-occurrence with current context cues $\rightarrow$ higher reuse probability

- **Conclusion**
  - Tag-frequency, recency and the current context seem to be important factors to predict the reuse of tags $\rightarrow$ cognitive model could formalize this
The Cognitive Model ACT-R

- Developed mainly by John Robert Anderson
- Defines the basic cognitive operations that enable human memory

- Declarative Memory Module
  - Is about access to memory units
  - Activation processes that control this access via activation equation

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Can the activation equation of the cognitive model ACT-R, that accounts for the activation processes in human memory, be exploited to effectively predict a user’s tag reuse?


Implementation

- **Activation equation**
  
  \[ A_i = B_i + \sum_j (W_j \cdot S_{j,i}) \]

- Activation of memory unit \(i\) (tag) = base-level activation of \(i\) (general usefulness) + associative activation of \(i\) (relevance to current context cues)

- **Base-level learning (BLL) equation** (Anderson & Schooler, 1991)
  
  \[ B_i = ln(\sum_{j=1}^{n} t_j^{-d}) \]

- Integrates **frequency** and **recency** of the usage of \(i\) with a power function
Evaluation Results: BibSonomy

Conclusion

• GIRP > MP_u
• BLL > GIRP
• BLL_{AC} > BLL

(same for other datasets)

⇒ Also other processes are important to realize a „full“ tag recommender
Micro- and Macro-Level Processes

• Social tagging is an interplay between micro-(individual) and macro-level (collective) processes [Fu, 2008]
• A tag-recommender needs to implement both types of processes

• Micro-level: \( \text{BLL}_{\text{AC}} \) (activation equation)
• Macro-level: Tag-imitation (e.g., Wagner et al., 2014)
RQ3

To what extent can a tag recommender algorithm, that extends the activation equation of the cognitive model ACT-R with tag imitation processes, compete with current state-of-the-art approaches in terms of recommender accuracy and computational costs?

- Work in progress
Implementation: Tag Imitation

- Usually a social tagging system shows a tag-cloud for a resource
- Contains the tags that have already been assigned to the target resource
- People tend to reuse these tags (e.g., Wagner et al., 2014)

→ Most popular tags by resource ($\text{MP}_r$)

- Hybrid approach:

$$\tilde{T}_k(u, r) = \arg \max_{t \in T} (\beta \|A(t, u, r)\| + (1 - \beta)\|\text{Y}_{t,r}\|)$$

$$\underbrace{\text{BLL}_{AC}}_{\text{BLL}_{AC} + \text{MP}_r}$$
RQ3: Evaluation Plan

• Datasets
  – BibSonomy, CiteULike, Delicious, Flickr, MovieLens, LastFM

• Computational costs
  – Runtime and memory

• Other RS metrics
  – Not only accuracy and ranking
  – Diversity and novelty

• Rich set of state-of-the-art algorithms
  – CF, FolkRank, PITF ...

• Work in progress
Further Contribution: TagRec

- **TagRec framework ([https://github.com/learning-layers/TagRec/](https://github.com/learning-layers/TagRec/))**

- Contains everything that is needed to develop and evaluate new tag recommender algorithms
  - Object-oriented data structures
  - Implementation of state-of-the-art algorithms
  - Evaluation protocols (i.e., train-/test-set splitting)
  - Evaluation metrics

- Extended for other types of recommendations (resource and user)
- Used as recommender engine in the Learning Layers EU project
Next Steps

- Open points from RQ1
  - Show empirically the importance of the current context
  - „Better“ way to prove the power-law of tag recency [Clauset et al., 2007]
- Evaluation for RQ3
- Use content data of the resources as context cues
- Better modeling of tag imitation
  - $M_{P_r}$ is not enough (unpersonalized) $\rightarrow$ each user imitates other tags
- Evaluate „real“ user acceptance
  - Online evaluation in a live recommender system
  - Learning Layers field studies

- **Vision for future work**
  - Use these insights from cognitive science for other types of recommendations/personalization services (e.g., resource recommender)
Thank you for your attention!

Questions?

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