A Probabilistic Approach to Personalized Tag Recommendation

Meiqun Hu, Ee-Peng Lim and Jing Jiang

School of Information Systems
Singapore Management University
Social Tagging

- Social tagging allows *users* to annotate *resources* with *tags*.
  - organize
    - tags are keywords, serving as (personalized) index terms that group relevant resources
  - store
    - online storage gives mobility and convenience to access
  - share
    - published bookmarks can be viewed by other users
  - explore
    - to leverage collective wisdom to find interesting resources
Personalized Tag Recommendation

• Personalized tag recommendation aims to recommend tags to the query user for annotating the query resource.

• Recommendation eases the tagging process.
  – avoids misspelling, provides consistency
Why Personalize Recommendations?

• Tag recommendation should be personalized.
  – users exhibit individualized choice of tag terms
    • e.g., language preference
  – personalized index for personal consumption and consistency
Problem Formulation and A Basic Method

- Problem Formulation: \( p(t|r_q,u_q) \)

- A Basic Method: \textit{freq-r}, to recommend most frequent tags
  - assuming that \textit{the more people have used this tag, the more likely it will be used again}
  - Ref. [Golder & Huberman 2006]
  - current state-of-the-art in many social tagging sites, e.g.,
  - fails to personalize the recommendations for the query user
Three Scenarios

Scenario 1: ‘foto’ is an infrequent tag for the resource.

Scenario 2: ‘foto’ has not been used for the resource, but has been used by the user for annotating other resources in the past.

Scenario 3: ‘foto’ has not been used for the resource, neither has it been used by the query user, but has been used by other users for annotating other resources.
Collaborative Filtering Method

• A Method based on Collaborative Filtering: (knn)
  – select the \textit{k-nearest neighbors} of the query user, and
  – recommend tags used by these neighbors for annotating the resource
  – classic collaborative filtering, without ratings
    • Ref. [Marinho & Schmidt-Thienme 2008]
  – addresses scenario 1, but fails scenario 2,3
Personomy Translation Method

- To translate the resource tags to the user’s personal tags \(\text{trans-u}\)
  - to learn \(p(t=‘\text{foto}’|u=\text{Alice}, t_r=‘\text{photo}’)\)
    - Ref. [Wetzker et al. 2009]
  - addresses scenario 2, but fails scenario 3, since Alice has never used ‘foto’
To Address Scenario 3

Alice

Bob

borrow
translation

web

netz

foto

Alice

photo

image
1. Personomy Translation
2. A Framework
3. Measuring User Similarity

A PROBABILISTIC FRAMEWORK
Proposed Framework

\[ p(t|r_q, u_q) = \frac{\sum_u \text{sim}(u, u_q) \times p(t|r_q, u)}{\sum_u \text{sim}(u, u_q)} \]

- To learn \( p(t='\text{foto}'|u=\text{Bob}, t_r='\text{photo}') \) and \( \text{sim}(u=\text{Bob}, u_q=\text{Alice}) \)
Personomy Translation

• To learn $p(t=’\text{foto’}|u=\text{Alice},t_r=’\text{photo’})$

\[
p(t|r_q,u) = \sum_{t_r \in t_r} p(t|u,t_r) \times p(t_r|r_q) \\
p(t|u,t_r) = \sum_{r \in r_u} p(t|r,u) \times p(r|t_r)
\]

[Wetzker et al. 2009]
Measuring Similarity between Users

• \( \text{sim}(u,u_q) \)
  – assuming that *users are similar if they perform similar translations*

• User profile
Distributional Divergence between Users

\[ \text{sim}('\text{photo}') (u, u_q) \Sigma_{\text{tr}} \text{sim}(u, u_q) \]

\[ \text{sim}('\text{web}') (u, u_q) \]

\[ \sum \]

\[ \text{Ref. [Lee 1997]} \]

\[ \text{sim}_{JS} (X, Y) = 10^{-\beta D_{JS}(X,Y)} \]

Ref. [Lee 1997]
Remark on the 3 Scenarios

- This framework is able to address all three scenarios

\[
p(t|r_q, u_q) = \frac{\sum_u \text{sim}(u, u_q) \times p(t|r_q, u)}{\sum_u \text{sim}(u, u_q)}
\]

- addresses scenario 1 by allowing self-translation, e.g., \(p(\text{‘photo’}|u, \text{‘photo’})\)
- addresses scenario 2 by allowing the query to be most similar to himself, e.g., \(\text{sim}(u_q, u_q)\)
- addresses scenario 3 by enabling borrowed translations
EXPERIMENTS

1. Data Collection
2. Experimental Setup
3. Recommendation Performance
# Dataset from BibSonomy

<table>
<thead>
<tr>
<th></th>
<th>train</th>
<th>validation</th>
<th>test</th>
</tr>
</thead>
<tbody>
<tr>
<td>time frame</td>
<td>start ~ DEC 08</td>
<td>JAN 09 ~ JUL 09</td>
<td>JUL 09 ~ DEC 09</td>
</tr>
<tr>
<td>number of resources</td>
<td>22,389</td>
<td>667</td>
<td>258</td>
</tr>
<tr>
<td>number of users</td>
<td>1,185</td>
<td>136</td>
<td>57</td>
</tr>
<tr>
<td>number of tags</td>
<td>13,276</td>
<td>862</td>
<td>525</td>
</tr>
<tr>
<td>number of assignments</td>
<td>253,615</td>
<td>2,604</td>
<td>1,262</td>
</tr>
<tr>
<td>average posts per user</td>
<td>53.695</td>
<td>5.699</td>
<td>4.895</td>
</tr>
<tr>
<td>average tag tokens per user</td>
<td>3.955</td>
<td>3.360</td>
<td>4.523</td>
</tr>
<tr>
<td>average distinct tags per user</td>
<td>61.833</td>
<td>13.191</td>
<td>14.667</td>
</tr>
</tbody>
</table>

Note:
users in test set must have been appeared in validation set.
Experimental Setup

• Methods to compare
  – trans-n1, trans-n2
  – trans-u1, trans-u2
    • [Wetzker et al. 2009], [Wetzker et al. 2010]
  – knn-ur, knn-ut
  – interpolating with freq-r

• Evaluation metric
  – pr-curve at top 5
  – macro-average for users

• Parameter tuning
  – macro-average f1@5
  – global vs. individual settings
Recommendation Performance
Global Setting

(a) Global Setting, without freq-r  
(b) Global Setting, with freq-r
Recommendation Performance
Individual Setting

(c) Individual Setting, without freq-r

(d) Individual Setting, with freq-r
## Recommendation Case Study

### Scenario 3 Tags

<table>
<thead>
<tr>
<th>u</th>
<th>r</th>
<th>tags assigned</th>
<th>top 5 recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td>920</td>
<td>a45...</td>
<td>2008, bookmarking, folksonomy, social, spam, folksonomies, tagorapub, web20, 20, integpub, systems, tagger, web</td>
<td>diplomathesis, captcha, folksonomybackground, closelyrelatedfolksonomy</td>
</tr>
<tr>
<td></td>
<td>57f</td>
<td></td>
<td>folksonomy, tagging, social, web20, web</td>
</tr>
<tr>
<td>1119</td>
<td>d16...</td>
<td>it, news, technology, blog, feed, technologie</td>
<td>kultur, online, radio, kunst, cd</td>
</tr>
<tr>
<td></td>
<td>b50</td>
<td></td>
<td>news, web20, blog, software, technology</td>
</tr>
<tr>
<td>3217</td>
<td>467...</td>
<td>annotation, ontology, knowledge, semantic</td>
<td>sql, erd, eclipse, tagging, folksonomy, ontology, web20</td>
</tr>
<tr>
<td></td>
<td>655</td>
<td></td>
<td>tools, survey, smilegroup, semantics, ontology</td>
</tr>
</tbody>
</table>

**freq-r**
- spam
- social
- myown
- mining
- folksonomy
Conclusion

• We propose a probabilistic framework for solving the personalized tag recommendation task, which incorporate personomy translation and borrowing translation from neighbors.

• We devise to use distributional divergence to measure similarity between users. Users are similar if they exhibit similar translation behavior.

• We find the proposed methods give superior performance than translation by the query user only and classic collaborative filtering.
Future Work

• Performance gain in successfully recommending scenario 3 tags.
  – e.g., compared with freq-r
  – e.g., resources that are inadequately tagged

• Recommendations strategies from the resources’ perspective.

Thank you
## References

<table>
<thead>
<tr>
<th>Reference</th>
<th>Abstract</th>
</tr>
</thead>
</table>