Knowledge Sharing via **Social Login**: Exploiting Microblogging Service for Warming up Social Question Answering Websites

Yang Xiao, Wayne Xin Zhao, Kun Wang, Zhen Xiao
NC&IS LAB, Peking University, China
Outline

• Motivation
  • Social Login
  • Cold start in CQA

• Our Method
  • System Design
  • Features

• Experiment
  • Experiment Setup
  • Results Analysis

• Conclusion
The Social World

- Twitter: 555 million Users, 58 million Tweets Per Day
- Facebook: 1,310,000,000 Active Users, 18 minutes Spent Per Visit
- Weibo: 560 million Users
- Renren: 220 million Users
- Mobile QQ cover all smartphones.
Social Login

- Users can surf the Internet using **Consistent Identities**
- Collect crowds of users in **Short** time
- Gain **Reliable** user profiles
- Weibo Open API:
  - **600,000** third party websites, **60,000,000** external websites visits daily
However,

- Despite that social media data is **Abundant**, only **Simple** profiles are leveraged via social login...
- Mine **more value** from social login?
Community Question Answering
Zhihu Q&A site

• First social network based Q&A
  • User graph
  • User topic graph
  • User question graph

• High-quality questions and answers
  • True domain experts participation
  • Primary experience
Long Tail Phenomenon

• Most contributions in CQA services are made by a small number of users.
  • 85% of users answer fewer than 10 questions
  • 60% of users answer fewer than 4 questions
  • Hard to estimate users’ expertise

• New comers are prone to leave CQA services very soon

Make users on the long tail stay longer
Discover experts at an early stage
Outline

• Motivation
  • Social Login
  • Cold start in CQA

• **Our Method**
  • System Design
  • Features

• Experiment
  • Experiment Setup
  • Results Analysis

• Conclusion
Bridge the gap
Bridge the gap

Candidates Rank = \(<\text{Weibo Footprints}\>) + \(<\text{Zhihu Performance}\>)
Weibo and Zhihu Features
Weibo: Relationship Perspective

- Users who have **higher prestige** tends to provide **better** answer

- PageRank
  - \( s^{n+1} = \mu M^T s^n + (1 - \mu) y \)

- **Performance Biased** Random Walk
  - \( y \) represents the user performance on Zhihu
Weibo: Content Perspective

• Users who are more interested in the question related topic tend to provide better answer.

• Model the relevance between a question and a user.

• Relevance: KL divergence

\[ \text{Rel}(q, u) = - KL(\theta^q, \theta^u) = \sum_{\omega \in V} p(\omega | \theta^q) \log \frac{p(\omega | \theta^q)}{p(\omega | \theta^u)} \]
Weibo: Content Perspective

- $\theta^q$ estimation
  - Question sparsity problem
  - Translation model
  - $\theta^q_\omega \propto \sum_{t \in q} p(\omega, t) = \sum_{t \in q} p(\omega | t)p(t | q)$

- $\theta^u$ estimation
  - Tweets accumulation
  - $\theta^q_\omega = \frac{\#(\omega, u) + 1}{\sum_{\omega' \in \mathcal{V}} \#(\omega', u) + |\mathcal{V}|}$

Use tags to index questions
Zhihu Features

• In order to test Weibo effect, we take Zhihu features as baseline.

<table>
<thead>
<tr>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Best Answers</td>
</tr>
<tr>
<td>Number of Answers</td>
</tr>
<tr>
<td>Number of Received Votes</td>
</tr>
<tr>
<td>Average Number of Votes</td>
</tr>
<tr>
<td>Smoothed Average number of Votes</td>
</tr>
<tr>
<td>Best Answer Ratio</td>
</tr>
<tr>
<td>Smoothed Best Answer Ratio</td>
</tr>
<tr>
<td>Average Answer Length</td>
</tr>
</tbody>
</table>
Outline

• Motivation
  • Social Login
  • Cold start in CQA

• Our Method
  • System Design
  • Features

• Experiment
  • Experiment Setup
  • Results Analysis

• Conclusion
Experiment Setup
Dataset

• Crawling Zhihu
  • Snowball-crawled Webpages
  • 266K users, 819K questions, 2.7 million answers
  • 50% of users log in using Sina Weibo account

• Crawling Weibo
  • Crawl the linked users’ weibo pages and relationships

• Dataset

<table>
<thead>
<tr>
<th>Users</th>
<th>Questions</th>
<th>Answers</th>
<th>Topics</th>
<th>Tweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>20,742</td>
<td>335,145</td>
<td>883,373</td>
<td>44,333</td>
<td>21,121,955</td>
</tr>
</tbody>
</table>
Hypothesis testing

• Spearman Correlation Test
• Prestige
  • Grouping users into buckets
  • Rho = 0.561
• Relevance
  • 14.48% question threads conveys that relevance is correlated with user performance.
Experiment Setup

• Tasks:
  • Best Answer prediction
  • User ranking prediction

• Ground Truth

• SVMRank is adopted as the learning framework

• Evaluation Metrics:
  • P@n
  • MRR
  • NDCG@n
Experiment Results
**Experiment Results**

### Best answer prediction MRR

<table>
<thead>
<tr>
<th>Threads</th>
<th>Baseline</th>
<th>Prestige+HisG</th>
<th>Baseline+Weibo</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;=3</td>
<td>0.4</td>
<td>0.45</td>
<td>0.5</td>
</tr>
<tr>
<td>&lt;=5</td>
<td>0.45</td>
<td>0.5</td>
<td>0.55</td>
</tr>
<tr>
<td>&lt;=10</td>
<td>0.5</td>
<td>0.55</td>
<td>0.6</td>
</tr>
</tbody>
</table>

### Best answer prediction P@1

<table>
<thead>
<tr>
<th>Threads</th>
<th>Baseline</th>
<th>Prestige+HisG</th>
<th>Baseline+Weibo</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;=3</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>&lt;=5</td>
<td>0.2</td>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td>&lt;=10</td>
<td>0.3</td>
<td>0.4</td>
<td>0.5</td>
</tr>
</tbody>
</table>

### Best answer Prediction P@3

<table>
<thead>
<tr>
<th>Threads</th>
<th>Baseline</th>
<th>Prestige+HisG</th>
<th>Baseline+Weibo</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;=3</td>
<td>0.56</td>
<td>0.6</td>
<td>0.62</td>
</tr>
<tr>
<td>&lt;=5</td>
<td>0.58</td>
<td>0.62</td>
<td>0.64</td>
</tr>
<tr>
<td>&lt;=10</td>
<td>0.6</td>
<td>0.64</td>
<td>0.66</td>
</tr>
</tbody>
</table>

The charts illustrate the performance of different models in predicting the best answer, measured by MRR and P@1/P@3, across different numbers of question threads.
Experiment Results

User Ranking Prediction NDCG@1

- <=3 question threads
- <=5 question threads
- <=10 question threads

Baseline | Prestige + HisG | Baseline + Weibo

User Ranking Prediction NDCG@5

- <=3 question threads
- <=5 question threads
- <=10 question threads

Baseline | Prestige + HisG | Baseline + Weibo

User Ranking Prediction NDCG@3

- <=3 question threads
- <=5 question threads
- <=10 question threads

Baseline | Prestige + HisG | Baseline + Weibo
Outline

• Motivation
  • Social Login
  • Cold start in CQA

• Our Method
  • System Design
  • Features

• Experiment
  • Experiment Setup
  • Results Analysis

• Conclusion
Conclusion

• Weibo knowledge is effective to improve prediction results on Zhihu

• Scalability
  • Recommendation system also experience serious cold start problem
  • The method can extend to many other third party startup websites to boost the system
Q&A