Recommending Users: Whom to Follow on Federated Social Networks

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Many federated networks exist...
The "unofficial" Information Retrieval Mastodon Instance.

Goal: Make idf.social a viable and valuable social space for anyone working in Information Retrieval and related scientific research.

Everyone welcome but expect some level of geekiness on the instance and federated timelines.
... but most are void of any recommender systems.

Whom to follow?

Who should I mention?

What to write about?

What hashtags to use?

What to share?
Whom to Follow?

- We propose a **method** for federated social networks
- **Evaluate** in offline and online setting
- Experiments on **Mastodon**
- Discover **practical considerations**
Online Evaluation

Balanced interleaving

Recommendation Algorithms

Random (baseline)
Collaborative filtering
Topology-based

Offline Evaluation

Data collection: Metropolis Hastings Random Walk
Find participants

precision@k
success@k
MAP

Online Evaluation

Balanced interleaving
Recommendation Algorithms
Collaborative-filtering with BM25

**Input:** users with their followers and followings

**Indexing** (each ID is a term):

{ user: "@followdon",
  following: [u1, u2, u3],
  followers: [u2, u4, u5]
}

{ user: "@followdon",
  following: [u1, u2, u3],
  followers: [u2, u4, u5],
  combined: [u1, u2, u3, u4, u5]
}

**Query:**
- Create document for target user
- Compute retrieval score
- Take \( k \) documents with highest score

Hannon, J., et al. (2010). Recommending twitter users to follow using content and collaborative filtering approaches
Topology-based Recommendations with PageRank

**Input:** User graph and target user

**Query:**
- Run personalized PageRank
- Take $k$ nodes with highest rank

Gupta P., et al. (2013). Wtf: the who to follow service at twitter
Evaluation Setup
Offline Evaluation Setup

Complete **data unavailable**
Idea: sample initial graph and **update later**

<table>
<thead>
<tr>
<th>Time 1 (training)</th>
<th>Time 2 (testing)</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Graph" /></td>
<td><img src="image2.png" alt="Graph" /></td>
</tr>
</tbody>
</table>

New!
Mastodon Graph Sampling

- Metropolis-Hastings Random Walk
- 253k nodes (3400 visited)
- 754k edges
- Second snapshot 5 days later: tradeoff (activity vs. availability)

Online Evaluation

Results and Discussion
Collaborative filtering superior, PageRank better than Random (Offline Evaluation)

success@10
Online Evaluation: It’s a draw

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants</td>
<td>19</td>
</tr>
<tr>
<td>Collaborative filtering wins</td>
<td>5</td>
</tr>
<tr>
<td>Pers. PageRank wins</td>
<td>5</td>
</tr>
<tr>
<td>Draw</td>
<td>2</td>
</tr>
<tr>
<td>No user interaction</td>
<td>7</td>
</tr>
<tr>
<td>New followings (avg.)</td>
<td>1.8</td>
</tr>
</tbody>
</table>
Limitations and Practical Considerations

- **Costly data collection** (both offline and online)
- No single API: *data may become unavailable*
- Profile-based recommendation: **IDF penalizes popular users**
- 5 day **crawling window** unexplored
Future Work

- Impact of incomplete data?
- Incorporate user context (e.g., location, interests)
- Popularity scorer
- Decentralized recommenders: integrate with ActivityPub?
Conclusion

- First experiences for recommender systems in decentralized networks
- Standard algorithms are applicable
- Practical considerations: how to implement?
Table 2: Experimental results of offline evaluation. Significance for model in line $i > 1$ is tested against line $i - 1$.

<table>
<thead>
<tr>
<th>ID</th>
<th>System</th>
<th>MAP</th>
<th>s@1</th>
<th>s@5</th>
<th>s@10</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>Random</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>0.055</td>
</tr>
<tr>
<td>R2</td>
<td>Profile (following)</td>
<td><strong>0.019</strong></td>
<td><strong>0.033</strong></td>
<td><strong>0.085</strong></td>
<td><strong>0.152</strong></td>
</tr>
<tr>
<td>R3</td>
<td>Profile (followers)</td>
<td><strong>0.019</strong></td>
<td><strong>0.030</strong></td>
<td><strong>0.100</strong></td>
<td><strong>0.167</strong></td>
</tr>
<tr>
<td>R4</td>
<td>Profile (combined)</td>
<td><strong>0.018</strong></td>
<td><strong>0.033</strong></td>
<td><strong>0.106</strong></td>
<td><strong>0.173</strong></td>
</tr>
<tr>
<td>R5</td>
<td>Pers. PageRank</td>
<td><strong>0.014</strong></td>
<td><strong>0.018</strong></td>
<td>0.061 ▼</td>
<td>0.082 ▼</td>
</tr>
</tbody>
</table>
precision@k for different recommenders

- R1 (following)
- R2 (followers)
- R3 (combined)
- R4 (Pers. PageRank)