

Generating ordered list of Recommended Items: A Hybrid Recommender System of Microblog

Yingzhen Li and Ye Zhang

School of Mathematics & Computational Science, Sun Yat-sen University, Guangzhou, China



中山大学
SUN YAT-SEN UNIVERSITY

Introduction

- ▶ A solution of KDD Cup 2012, track 1 task, which requires predicting users a user might follow in Tencent Microblog.
- ▶ Tencent Microblog has some special properties which we'll introduce.
- ▶ The system consists of:
 - ▷ keyword analysis
 - ▷ user taxonomy
 - ▷ item ranking
 - ▷ (potential)interests extraction
 - ▷ item recommendation(grading process)

Speciality of Tencent Microblog

- ▶ It attracted a lot of registered users and became one of the dominant microblog platforms in China based on the large user group of its instant messaging service QQ.
- ▶ It is embedded in Tencent's other leading platforms.
- ▶ It considers those who frequently write(including retweet and comment) or read microblog messages - no matter on the website or other associated platforms - as active users.

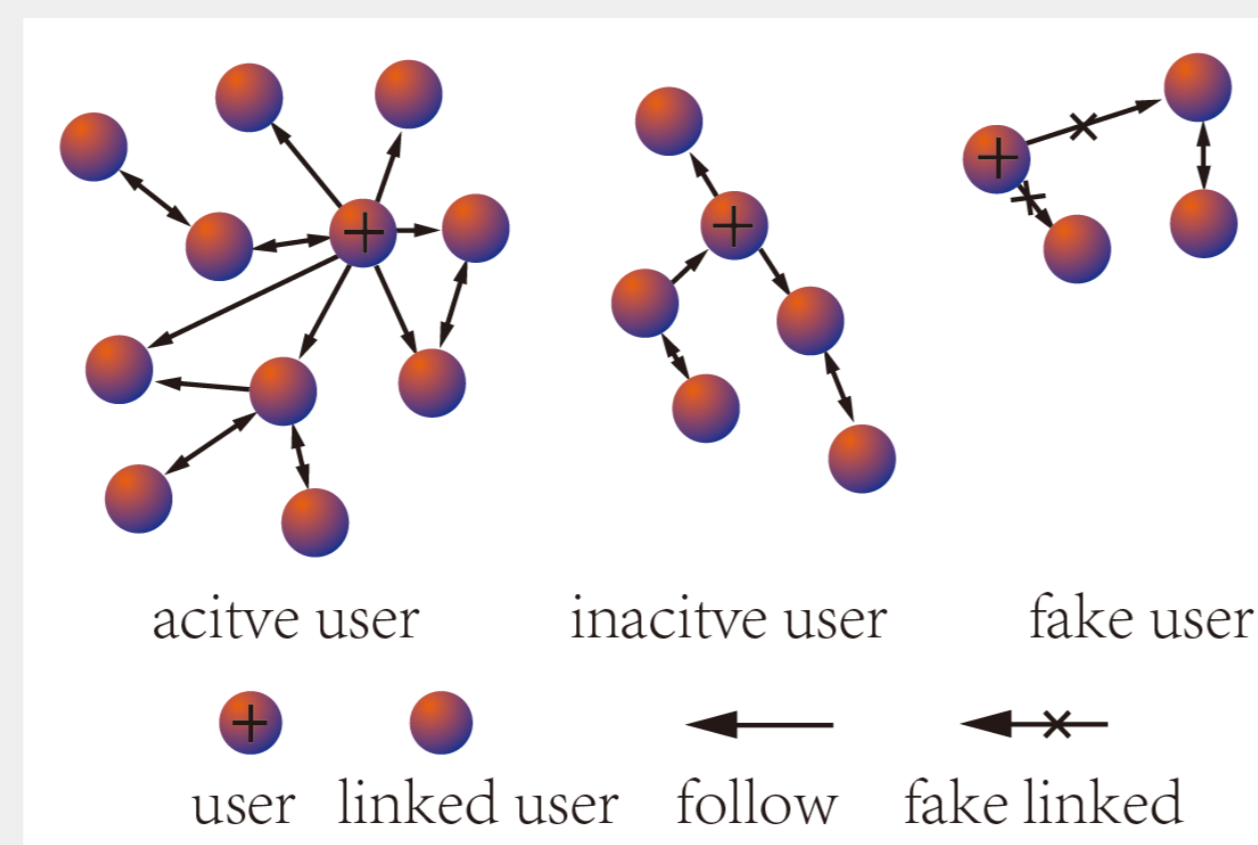


Keyword Analysis

- ▶ Applying association rule algorithm to find them directly in the huge keyword set is unrealistic.
- ▶ We parallel this process by adopting revised FDM and insert the ambiguous keywords into different classes simultaneously.
- ▶ The necessity and sufficient condition for a frequent itemset is the frequency of all its subsets.
- ▶ User set: $U = \{u_1, u_2, \dots, u_m\}$
- ▶ u_j 's keyword set: $K_j = \{k_{j1}, k_{j2}, \dots, k_{jn_j}\}$ with weights $\mathcal{W}_j = \{w_{j1}, w_{j2}, \dots, w_{jn_j}\}$
- ▶ keyword class = $\{class_1, class_2, \dots, class_N\}$, $class_i = \{k_{i1}, k_{i2}, \dots, k_{im}\}$.

User Taxonomy

- ▶ We divide the users into 3 groups by **user_class(u_j)**:
 - ▷ Active - lots of tweets/interactions;
 - ▷ Inactive - few messages/interactions;
 - ▷ Fake - they don't login the platform directly, and their messages are synchronized from related platforms.

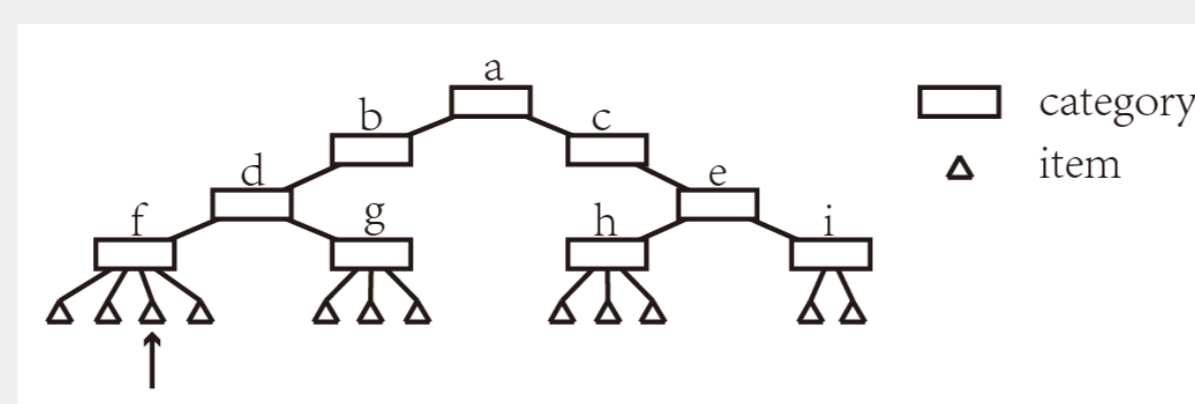


$$\text{user_class}(u_j) = \begin{cases} \text{active,} & \text{act}(u_j) \geq \text{min_activeness} \\ \text{inactive,} & 0 \leq \text{act}(u_j) < \text{min_activeness} \\ \text{fake,} & \text{act}(u_j) = 0 \end{cases}$$

- ▶ $\text{act}(u_j) = \text{tweet} \times \text{is_fake}(u_j)$
- ▶ $\text{is_fake}(u_j) = \frac{1 + \text{sgn}(\text{at} + \text{retweet} + \text{comment} - \text{min_action})}{2}$

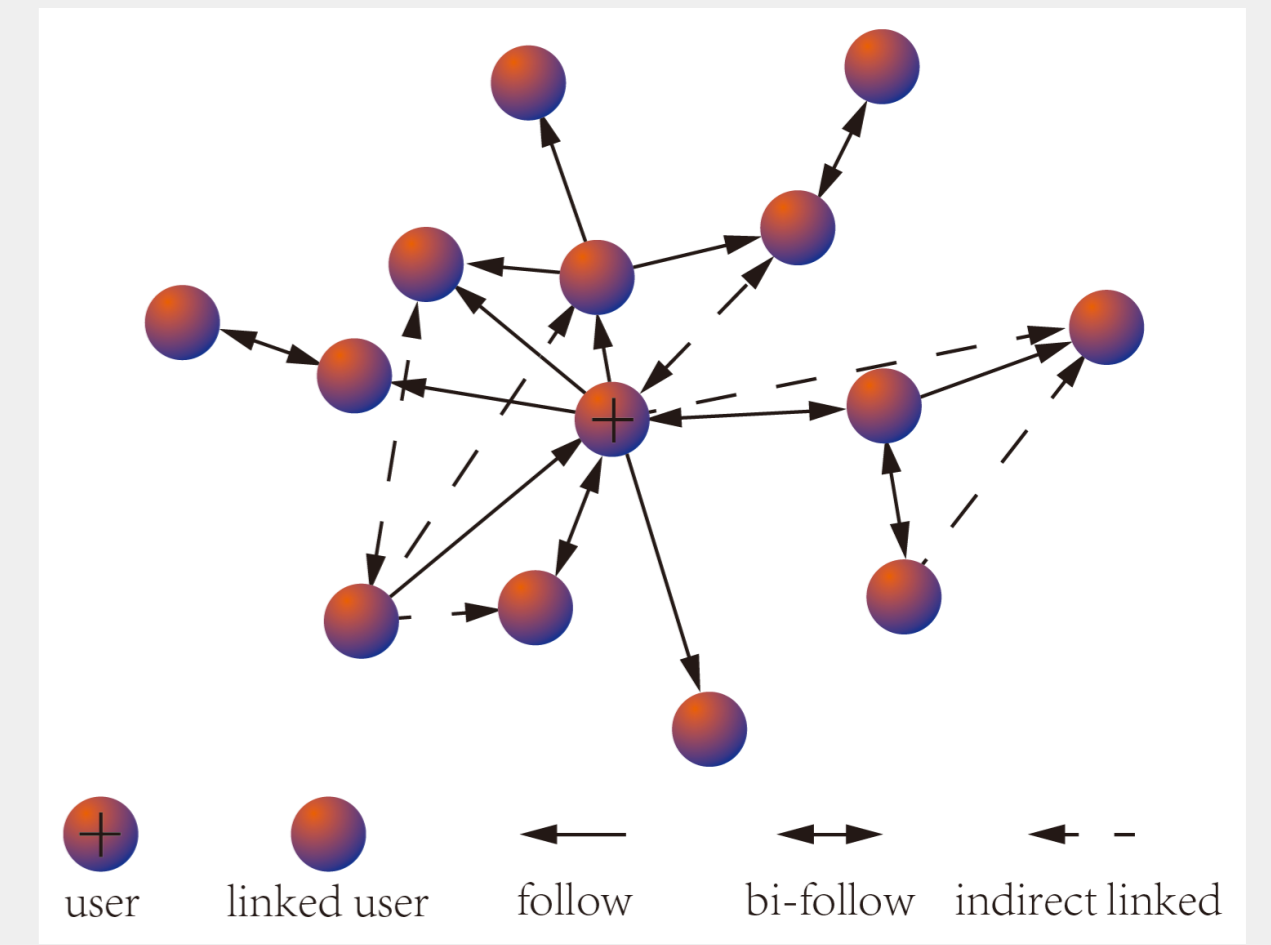
Item Ranking

- ▶ Items are organized in different categories of professional domains by Tencent to form a hierarchy.
- ▶ The pointed item belongs to the category a.b.d.f.
- ▶ Item set: $I = \{i_1, i_2, \dots, i_n\}$ ($i_k \in h_k$)
- ▶ Category set: $H = \{h_1, h_2, \dots, h_n\}$
- ▶ Counts the number of i_k 's followers and return its ranking in $h_k(I)$:
 - ▷ The rank of i_k in h_k : $\text{hot}_k = \text{get_hot_rank}(i_k, h_k)$
 - ▷ The rank of i_k in I : $\text{HOT}_k = \text{GET_HOT_RANK}(i_k)$



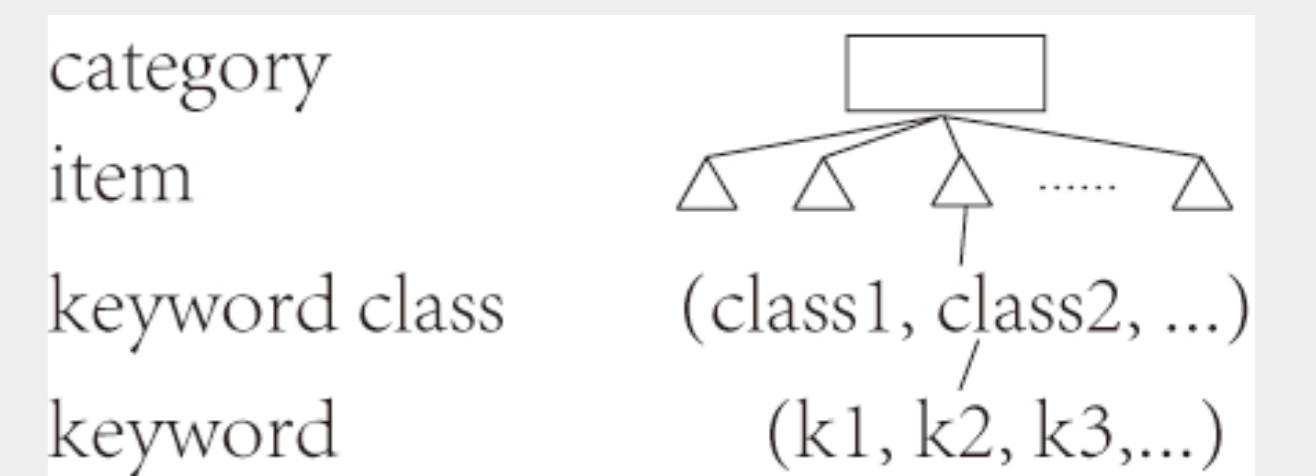
(Potential)Interest Extraction

- ▶ $\text{key_class}(u_j) = \{class_{ji}\}$
- ▶ $\bar{W}_{ji} = \sum_{k_i \in K_j \cap class_{ji}} w_i$
- ▶ $\text{potential_key}(u_j) = \{class_{ji}\} = \bigcup_{u_k \in \text{related_users}(u_j)} \text{key_class}(u_k)$
- ▶ $\tilde{W}_{ji} = \sum_{u_k \in \text{related_users}(u_j), class_{k_i} \in class_{ji}} \bar{W}_{k_i} \text{fami}(u_j, u_k)$
- ▶ $\text{fami}(u_j, u_k) = \omega_1 f(\text{at}) + \omega_2 f(\text{retweet}) + \omega_3 f(\text{comment})$
- ▶ $\text{interests}(u_j) = \text{key_class}(u_j) \cap \text{potential_key}(u_j) = \{class_{ji}\}$
- ▶
$$W_{ji} = \begin{cases} \bar{W}_{ji}, & class_{ji} \in \text{key_class}(u_j) \\ \tilde{W}_{ji}, & class_{ji} \in \text{potential_key}(u_j) \\ \frac{1}{2}(\bar{W}_{ji} + \tilde{W}_{ji}), & class_{ji} \text{ in both sets} \end{cases}$$



Item Recommendation(Grading Process)

- ▶ $\text{KH}(h_k) = \{class_{kj}\}$
- ▶ $\hat{W}_{kp} = \text{average}(\bar{W}_{j_i})$
- ▶ $class_{j_i} = class_{k_p} \in \text{key_class}(i_j)$
- ▶ $\text{fond}(u_j, h_k) = g(\text{class_weight}(u_j) \cdot \text{class_weight}(h_k), 100)$
- ▶ $\text{grade}(u_j, i_k) = 2\text{fond}(u_j, h_k)(\alpha_1 \text{hot}_k + \alpha_2 \text{sim}(u_j, i_k)) - 1$
- ▶ $\text{sim}(u_j, i_k) = n(|\text{class_weight}(u_j) - \text{class_weight}(i_k)|)$
- ▶ $\alpha_1 + \alpha_2 = 1, \alpha_i \geq 0$ (obtained in the training process)
- ▶ $n(x)$ and $g(x, y)$ are the normalization functions.
- ▶ The top-3 items are picked out for recommendation.



Results: Training Results of the Parameters

- ▶ $\omega_i = \frac{1}{3}$
 - ▶ α_1 reflects the inclination of accepting popular items.
- | | class | user | followee | interaction | keyword | α_1 |
|--|----------|------|----------|-------------|---------|------------|
| | active | 3919 | 46 | 87 | 10 | 0.33 |
| | inactive | 1194 | 27 | 42 | 8 | 0.18 |
| | fake | 825 | 18 | 2 | 5 | / |

Result: Evaluation of the Performance

- ▶ Evaluation metric: average precision (which KDD Cup's organizers adopted):
 - ▶ $\text{AP@3}(u_j) = \sum_{i=1}^3 p(i) \Delta r(i)$
 - ▶ $p(i)$ is the precision of the i^{th} recommended item,
 - ▶ $\Delta r(i)$ is the change in the recall from $i - 1$ to i .
- | | | active | inactive | fake | total |
|--|--------------|------------|----------|----------|---------|
| | MAP@3 | 0.41066 | 0.46879 | 0.33606 | 0.41198 |
| | AP@3 | | | | |
| | u_j | user class | item | accepted | |
| | 2071402 | active | 1606902 | 1606902 | 0.83 |
| | | | 1760350 | 1774452 | |
| | | | 1774452 | | |
| | 942226 | inactive | 1606902 | 1606902 | 1.00 |
| | | | 1606609 | | |
| | | | 1774452 | | |
| | 193889 | fake | 1760642 | 1774862 | 0.33 |
| | | | 1774684 | | |
| | | | 1774862 | | |

About

- ▶ Yingzhen Li
Senior Year Undergraduate
Department of Mathematics
liyzen2@mail2.sysu.edu.cn
<http://www.yingzhenli.net/>
- ▶ Ye Zhang
Senior Year Undergraduate
Department of Mathematics
zhangye5@mail.sysu.edu.cn
<http://dantepy.ylsig.org/>