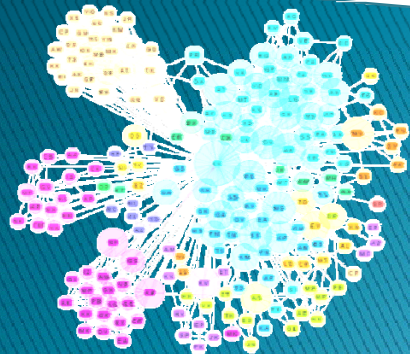


A study on social network metrics and their application in trust networks

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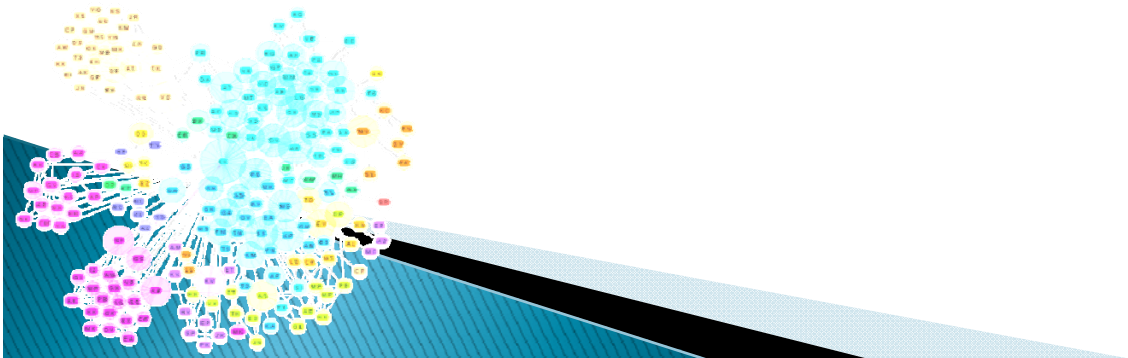
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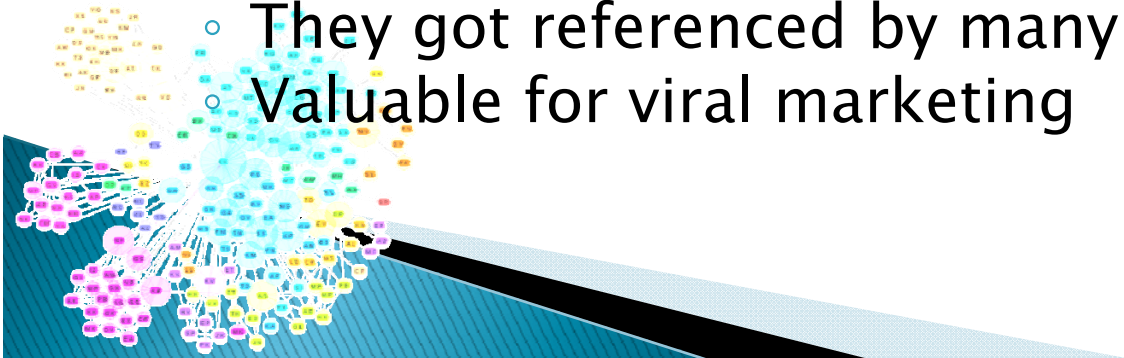
Social Networks

- ▶ **High popularity:** many participants in blogs, collaborative tagging and customer review sites etc.
- ▶ **Increased research interest:** sociologists, computer scientists, marketers etc.
- ▶ **Unique characteristics:** authorship, shared authorship, multitude of user-provided tags, inherent connectivity between users and posted items, frequent updates



Dynamics of the social network

- ▶ The members of a network
 - link to members they trust
 - publish new information
 - read information published by other members
 - reference and comment on information provided by other members
- ▶ **Influential members**
 - Many people link to them
 - They publish first
 - They receive a lot of comments
 - They got referenced by many users
 - Valuable for viral marketing



At a glance

- ▶ Globally important members can be *influentials*
- ▶ Finding **locally influential members**, i.e. the members that influence the most a specific member or a group of members, is ideal for targeting this member or group
- ▶ Our model
 - creates a graph for the social network
 - employs social network analysis metrics for finding globally important members
 - combines global with local influence scores
 - provides **personalized rankings** of members for each community member



Social Network Analysis metrics

- ▶ Measures of importance or prominence
- ▶ **Centrality**: important actors typically occupy strategic locations in a network (undirected)

- Degree centrality

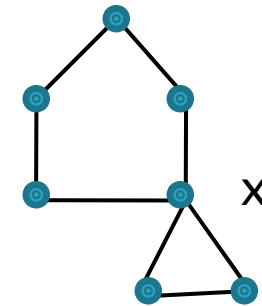
$$Gd(i) = \frac{d(i)}{n - 1}$$

- Closeness centrality

$$Gc(i) = \frac{n - 1}{\sum_{j=1}^n d(i, j)}$$

- Betweenness centrality

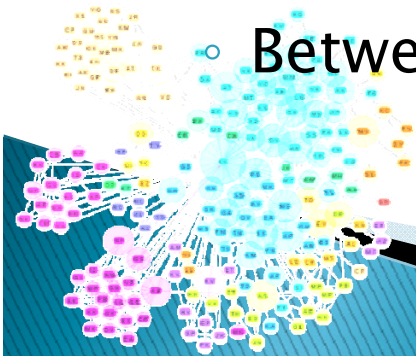
$$Gb(i) = \sum_{j < k} \frac{sp_{jk}(i)}{sp_{jk}}$$



$$Gd(x) = 4/6$$

$$Gc(x) = 6/8$$

$$Gb(x) = 15/21$$



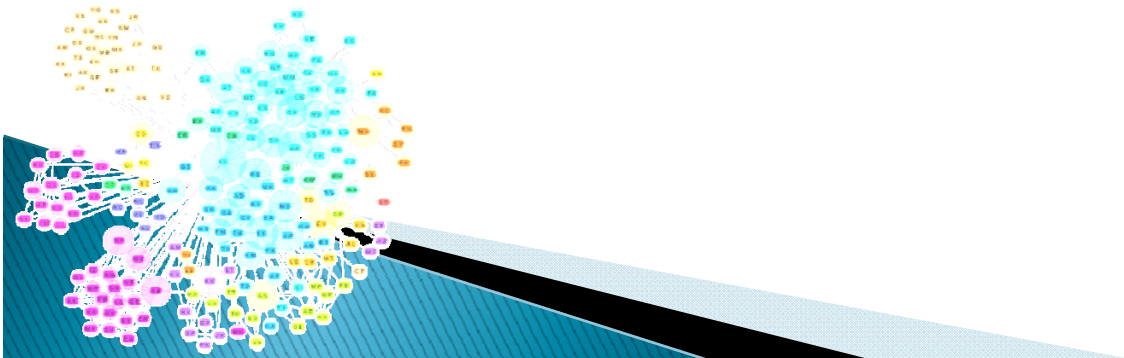
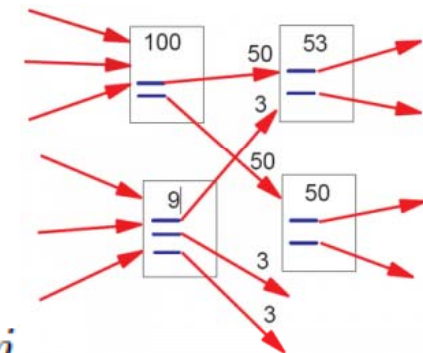
Social Network Analysis metrics

- ▶ **Prestige**: important actors point or are pointed by important users

- Hub
$$Ga(i) = \sum_{(j,i) \in E} Gh(j)$$

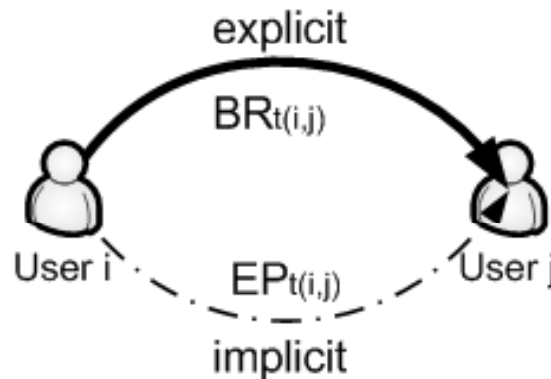
- Authority
$$Gh(i) = \sum_{(i,j) \in E} Ga(j)$$

- PageRank
$$Gp(i) = (1 - d) + d \sum_{(j,i) \in E} \frac{Gp(j)}{O_j}$$

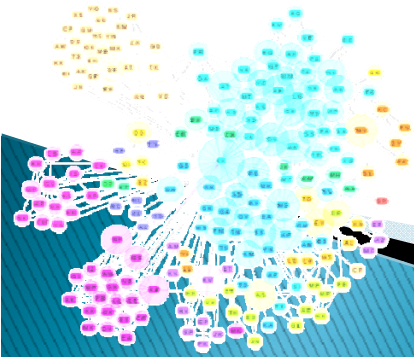


Local (direct) user score

- ▶ A user i *directly* trusts or is interested on another user j
- ▶ Direct trust or interest is based on explicit and implicit statements



$$LS_t(i, j) = w_{BR} \cdot BR_t(i, j) + w_{EP} \cdot EP_t(i, j)$$

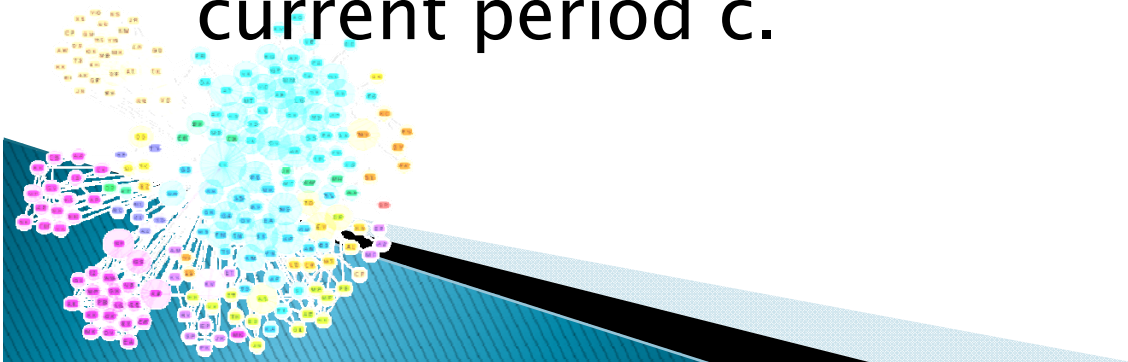


Local accumulative user score

- ▶ Direct statements to user j are added by user i constantly, thus refreshing her/his interest to user j .

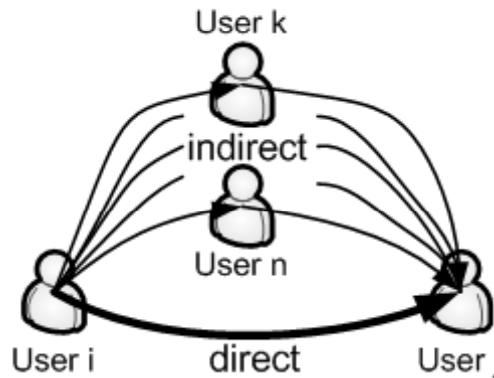
$$LAS_c(i, j) = \sum_{\substack{t=c-m+1 \\ t > 0}}^c w_t \cdot LS_t(i, j)$$

- ▶ A rating system takes into account the m most frequent ratings starting from the current period c .

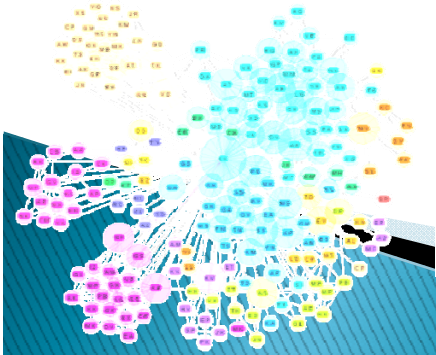


Collaborative local accumulative score

- ▶ Aggregates the direct accumulative scores $LAS_c(i, j)$, assigned by i to any user j , with the indirect accumulative scores $LAS_c(k, j)$ assigned to j by all users k that i trusts



$$CLS_c(i, j) = w_i \cdot LAS_c(i, j) + \sum_{\substack{(i, j) \in E \\ (k, j) \in E \\ (i, k) \in E}} w_k \cdot LAS_c(k, j)$$

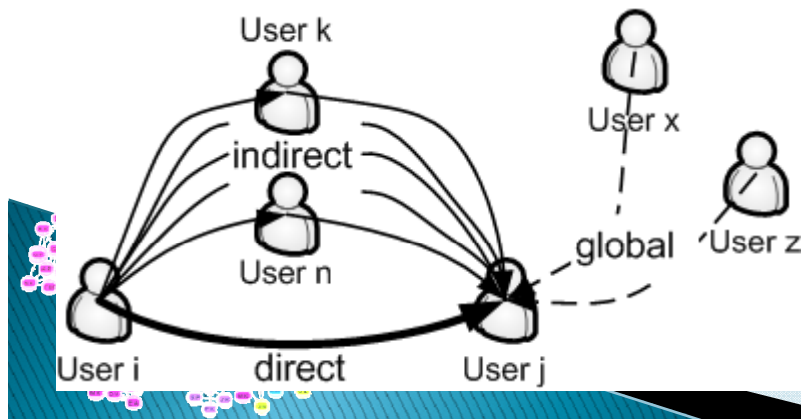


Influence

- ▶ We define global influence of a node to be the weighted sum of all the network analysis metrics

$$GI(i) = w_d \cdot Gd(i) + w_c \cdot Gc(i) + w_b \cdot Gb(i) + w_h \cdot Gh(i) + w_a \cdot Ga(i) + w_p \cdot Gp(i)$$

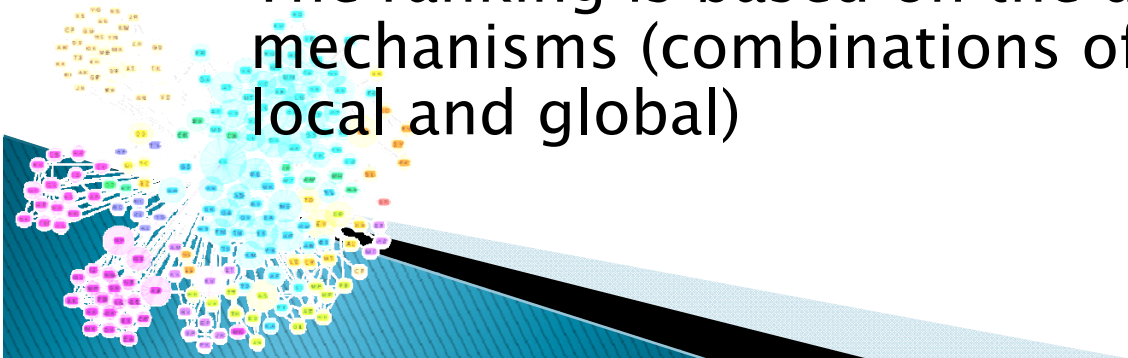
- ▶ We extend the collaborative local accumulative score to include the opinion of globally influential nodes



$$INF_c(i, j) = w_{local} \cdot LAS_c(i, j) + w_{collab} \cdot \sum_{\substack{(i, j) \in E \\ (k, j) \in E \\ (i, k) \in E}} w_k \cdot LAS_c(k, j) + w_{global} \cdot \sum_{(m, j) \in E} GI(m) \cdot LAS_c(m, j)$$

Experiments

- ▶ Compare the performance of local and global models of influence in providing recommendations to the users of social networks and combine them in a single model
- ▶ Methodology
 - Provide for each user i a ranking for all users that i links to (directly or indirectly)
 - The ranking is based on the different rating mechanisms (combinations of local, collaborative local and global)



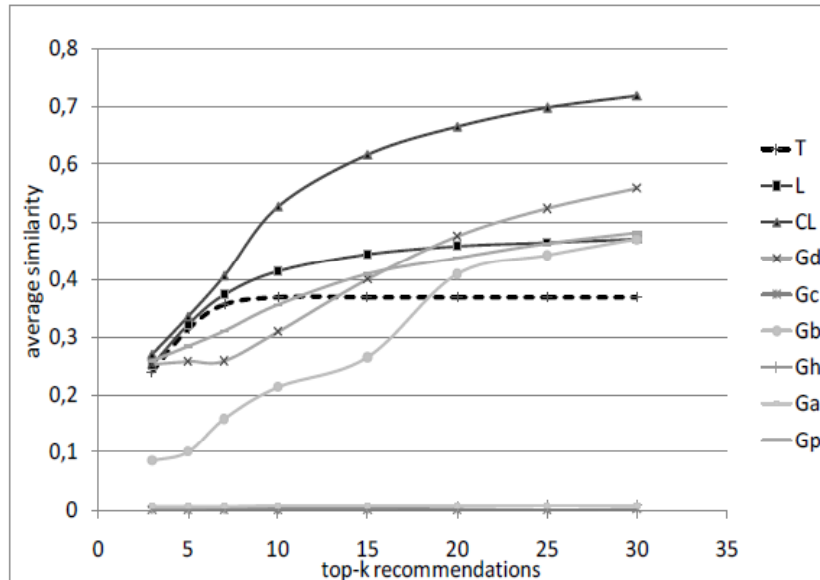
Dataset – Metrics

- ▶ We employed the *extended Epinions dataset*
 - 132,000 users who issued 841,372 statements
 - 717,667 positive implicit user-to-user trust ratings
 - 2 subsets of equal size (~5500 users)
 - Set A: users with few friends (5 to 10)
 - Set B: users with many friends (more than 30)
- ▶ Ratings
 - baseline: direct explicit links only (T)
 - local accumulative (L), collaborative local (CL)
 - degree centrality (Gd), closeness centrality (Gc), betweenness centrality (Gb), hub (Gh), authority (Ga), PageRank (Gp)
 - combinations: CL+individual Global , CL+combo Global



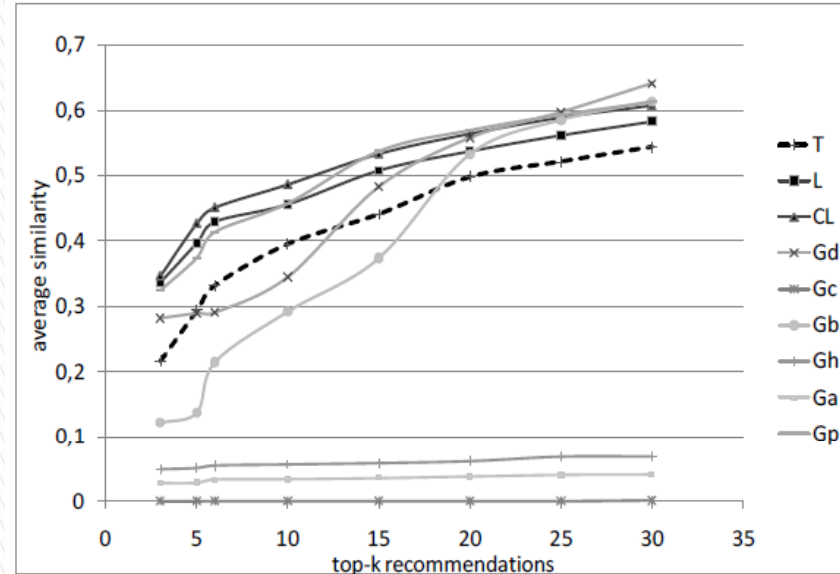
Results (local vs global)

set A



- CL significantly improves the performance of the baseline (T), especially for users with a small circle of trust (set A)
- It is useful to check for suggestions beyond the direct neighbors of a node, in the extended neighborhood of users

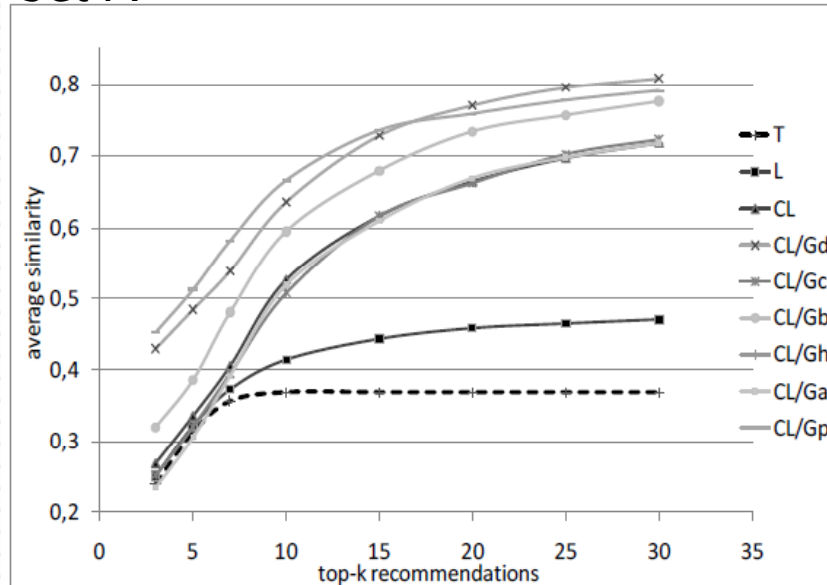
set B



- For users with many neighbors (set B), certain global models (i.e. degree, betweenness and PageRank) perform better than local models examined

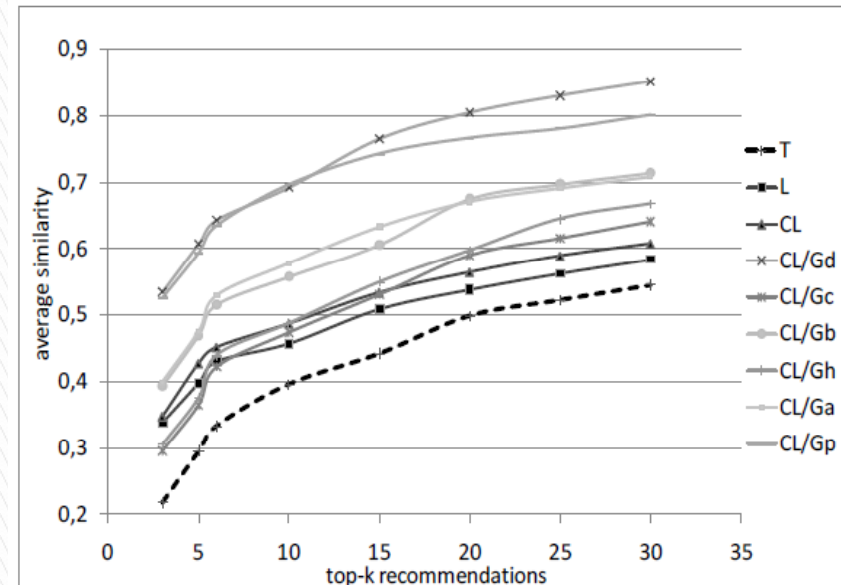
Results (CL plus global)

set A



- highly ranked users (i.e. influential users) may provide additional recommendations which are useful to all authors
- The average improvement for all the values of k is 0.12, 0.13 and 0.06 for (CL/Gd), (CL/Gp) and (CL/Gb) respectively

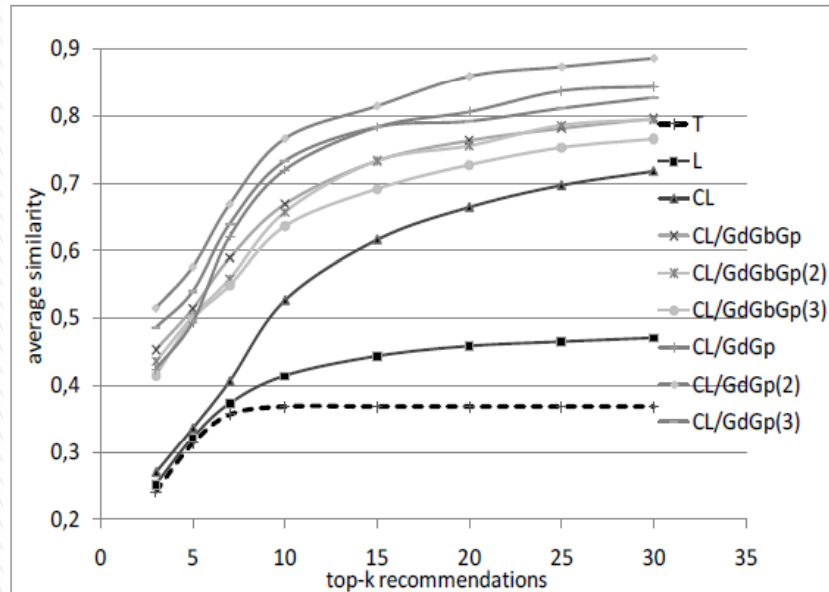
set B



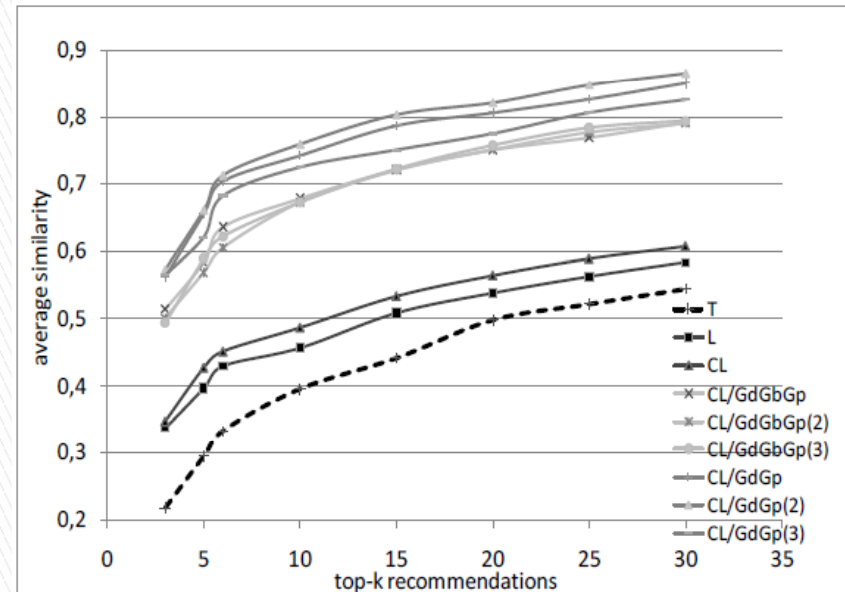
- the local methods demonstrate slightly improved results for set B in comparison to set A (average improvement is 0.037)
- the combined methods further increase this improvement (average improvement for PageRank and degree is 0.05)

Results (CL plus combo global)

set A



set B



Combinations of global metrics:

- CL/GdGbGp: $w_d = 0.2$, $w_b = 0.2$, $w_p = 0.6$
- CL=GdGbGp(2): $w_d = 1/3$, $w_b = 1/3$, $w_p = 1/3$
- CL=GdGbGp(3): $w_d = 0.2$, $w_b = 0.4$, $w_p = 0.4$
- CL=GdGp: $w_d = 0.5$, $w_p = 0.5$
- CL=GdGp(2): $w_d = 1/3$, $w_p = 2/3$
- CL=GdGp(3): $w_d = 2/3$, $w_p = 1/3$

- most of the combinations improve the results of the baseline and the collaborative local model with the combinations of PageRank and degree to outperform all other combinations

Conclusions

- ▶ We studied the contribution of various measures in identifying similar or influential actors in a social network in order to recommend them to a specific user
- ▶ Global measures are not very useful by themselves in providing recommendations to users
- ▶ When combined with the collaborative local measures have a positive impact in the final recommendation set
- ▶ Especially for users with few “friends”

