Self-adjusting Hybrid Recommenders based on Social Network Analysis

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1. Background

- **Notion of recommendation**
  - **Information filtering** process aimed at suggesting information items (movies, music, books, news, images, web pages, scientific papers, etc.) or social elements (e.g. people, events or groups) that are likely to be of interest to **the user**

$$\forall u \in U,\ i^{max,u} = \arg\max_{i \in I} g(u, i)$$

- **Main types of recommendation strategies**
  - **Content-based filtering (CBF)**: recommends the user *items similar* to the ones she preferred in the past
  - **Collaborative filtering (CF)**: recommends the user items that *people* (called *neighbours* in the literature) *with similar tastes* and interests liked in the past
  - **Social recommenders (SF)**: recommends the user items that *explicit friends* liked in the past
- **Hybrid recommender systems** (Burke, 2002)
  - Combination of several recommendation approaches
  - **Ensemble recommender systems** consist of a linear combination of recommenders

$$g(u, i) = \lambda \cdot g_1(u, i) + (1 - \lambda) \cdot g_2(u, i)$$

with λ ranging between 0 and 1

2. Introduction

- **Motivation**
  - Hybridization in ensemble recommender systems is conducted in a static way,. i.e. once **the value of λ is fixed**, item suggestions from each recommender receive the same weight, independently of the target user
  - The optimal weight…
    - has to be found empirically by relying on current recommender performance, dataset characteristics, etc., which are subject to change
    - may not be found the same for all the users since the system gathers different amount of information from each user, and thus, one recommender may be more useful than other in certain situations
- **Goals**
  - Alleviate the **social cold start situation**
  - Decide dynamically which recommender should receive a higher weight in the ensemble by using the concept of **adjusting factors**

3. Approach

- Explore **a self-adjusting ensemble recommender** approach that makes use of **adjusting factors** to boost one of the combined recommenders for certain users

$$\lambda = \lambda(u)$$

- **Use graph-based metrics for measuring the user's strength in the social network**
  - **User degree**: the user's number of friends
  - **Average neighbour degree**: mean degree of all the user's friends (De Choudhury et al., 2010)
  - **Two-hop neighbourhood size**: sum of all the user's friends plus all the user's friend's friends (De Choudhury et al., 2010)
  - **HITS score**: a good authority is pointed by many good hubs and a good hub points to many good authorities (Kleinberg, 1999)
  - **PageRank score**: considered as a user connectivity measure (Brin & Page, 1998)
  - **Betweeness centrality**: an indicator of whether the user can reach others in relatively short paths (Freeman, 1977)
  - **Clustering coefficient**: the probability that the user's friends are friends themselves (Watts & Strogatz, 1998)
  - **Ego components size**: number of connected components remaining when the user and her friends are removed from the social network (De Choudhury et al., 2010)

4. Experiments

- **Combined recommenders**
  - **UB10**: user-based CF (Adomavicius & Tuzhilin, 2005), with neighbourhood size of 10
  - **PureSocial**: user-based CF in which the user's nearest neighbours are replaced by the user's (explicit) friends (inspired by (Liu & Lee, 2010))
  - **Personal**: user distances within the social networks are incorporated into the user-based CF formula
- **Ensemble recommenders**
  - **H1** = UB10 + Personal (friendship distance threshold = 2)
  - **H2** = UB10 + PureSocial (friendship distance threshold = 1)
  - **H3** = UB10 + PureSocial (friendship distance threshold = 2)
- **Dataset**
  - CAMRa'10 dataset: provided at the ACM RecSys'10 challenge on context-aware movie recommendation
    - Test set: 878 users, have of them (439) with no friends, and the other half with at least 2 friends

5. Results

Performance results for the three ensembles tested. The best absolute value is underlined. Improvements over the best static are shown in bold font, and over the static 0.5 with italics. Statistical significant ($p<0.05$) differences between self-adjusted hybrid recommenders and static 0.5, best static, and both are marked with *, †, and ‡, respectively.

	P@5			nDCG@5		
	H1	H2	H3	H1	H2	H3
Average Neigh Deg	**0.219***	**0.092***	0.199	**0.240***	**0.097***	0.215
Centrality	**0.222***	**0.106‡**	0.188†	**0.242***	**0.111‡**	0.204†
Clustering coef	0.211*	**0.094***	0.188†	0.231*	**0.100***	0.202†
Degree	<u>**0.233‡**</u>	**0.095***	0.197	<u>**0.256‡**</u>	**0.099***	0.213
Ego Comp Size	**0.227‡**	**0.096***	<u>**0.201***</u>	**0.249‡**	**0.101***	0.215
HITS	**0.225***	<u>**0.110‡**</u>	0.197	**0.248***	<u>**0.114‡**</u>	0.212
PageRank	**0.227‡**	**0.097***	0.200	**0.247***	**0.101***	<u>**0.216**</u>
Two Hop Neigh	**0.229‡**	**0.093***	0.195	**0.250‡**	**0.100***	0.212
Static 0.5	0.186	0.077	0.189	0.205	0.081	0.206
Best static	0.218	0.091	0.199	0.239	0.096	0.215

6. Discussion

- **Conclusions**
  - Self-adjusted recommenders got a general advantage over the static configurations
    - The **PageRank hybrid recommender** was better that static configurations in all cases
    - All methods, except centrality and clustering in H3, improved over the 0.5 static configuration – and the best posterior static configuration in most cases
  - The best static configuration was different for each ensemble: λ=0.9 for H1, λ=0.1 for H2, and λ=0.8 for H3
    - This configuration is the *posterior best static* (and thus, not real), which a manually tuned λ would not guarantee
- **Future work**
  - Explore **alternative adjusting factors**, not only those based on the social network structure: e.g. distributional properties of user ratings

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