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Adaptive model for recommendation of news

Matúš Medo[1(a)], Yi-Cheng Zhang[1(b)] and Tao Zhou[1,2]

[1] *Physics Department, University of Fribourg - CH-1700 Fribourg, Switzerland*
[2] *Department of Modern Physics, University of Science and Technology of China - Hefei 230026, PRC*

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Abstract – Most news recommender systems try to identify users' interests and news' attributes and use them to obtain recommendations. Here we propose an adaptive model which combines similarities in users' rating patterns with epidemic-like spreading of news on an evolving network. We study the model by computer agent-based simulations, measure its performance and discuss its robustness against bias and malicious behavior. Subject to the approval fraction of news recommended, the proposed model outperforms the widely adopted recommendation of news according to their absolute or relative popularity. This model provides a general social mechanism for recommender systems and may find its applications also in other types of recommendation.

Introduction. – People were always hungry for information. To satisfy their needs, many information sources have been created and now they are competing for our attention [1,2]. News distribution on the Internet is also still fashioned the old, centralized way. Even the new services like `digg.com`, `reddit.com`, `wikio.com` and others, where the traditional news distribution paradigm is challenged by assuming that it is the readers who contribute and judge the news, have a serious drawback: every reader sees the same front page. As a result, only news items of very general interest can become popular. Niche items, *i.e.* those that target a particular interest or locality, do not have much chance to reach their audience.

An alternative approach is to deliver "the right news to the right readers" as provided by systems for adaptive news access [3]. These systems accommodate the interests of their users and provide a personalized set of interesting news for each individual. They reflect their readers' actions by either *news aggregation* (where each user can choose preferred sources and topics), *adaptive news navigation* (this is achieved mainly by creating lists of most popular news —a technique which is adapted by most newspaper websites but can be implemented also in a more sophisticated way as recently suggested in [4]), *contextual news access* (providing news according to the currently viewed information), or by *content personalization* on the basis of past user's preferences. The last option mentioned is a specific application of recommender systems —a widely applied tool for information filtering [5,6].

Various systems for personalized news recommendation were proposed in past. Possibly the simplest approach, known also as "collaborative filtering", is based on using the correlations between users' ratings [7]. Often used is learning the keywords of interest for each individual user and recommending the news that contain them [8]. Similarly, when both news and readers' interests can be described by a couple of categories, recommendations can be obtained by matching news's attributes with user's preferences [9,10]. Most news recommender systems are constructed in this way, only that the handful of categories is replaced by a more general user's reading profile which is inferred from the user's feedback on previously read news [11–13]. In some cases, separate models addressing user's short-term and long-term interests are used and the final recommendation is obtained as a mix of the two results [14]. Explicit user ratings of news can be replaced by implicit ratings (for example, the mere access of a news may be interpreted as the user's satisfaction) or by ratings inferred from reading times (when "short" and "long" reading times are interpreted as user's dissatisfaction or satisfaction respectively) [11]. For an overview of this rapidly developing field see [3,10].

The news recommender model which we propose and study in this paper is different from the systems described above. While preserving the user-posting-news feature

(a) E-mail: `Matus.Medo@unifr.ch`
(b) E-mail: `Yi-Cheng.Zhang@unifr.ch`

which is often used by popular websites, we aim at personalized news recommendation by observing readers' past reading patterns, identifying their taste mates and constructing a directed local neighborhood network. In our model, users read news and either "approve" or "disapprove" them. When a news is approved, it spreads in the neighborhood network to the next prospective readers. This process is similar to an epidemic spreading in a social network [15,16] or to rumor spreading in a society [17,18]. Simultaneously with the spreading of news, the network of contacts gradually evolves to best capture users' similarities.

To summarize, with the reading community acting as a collective social filter, we aim to navigate news items to their intended readership. The model's reliance on connecting the users with similar reading interests is motivated by the basic paradigm of recommender systems: you get recommended what your taste-mates already liked [6]. However, recommendation of news has an important flavor which is missing in most other applications of recommender systems: novelty is of crucial importance there. In our case, the challenge of fast news delivery is addressed by the exponentially fast spreading of good news (which is a direct consequence of the spreading mechanism) while the importance of novelty is reflected by a later introduced continual time decay of the recommendation scores.

Description of the model. – Here we describe the adaptive news recommendation model, assuming no other information than ratings of news by users.

Notation. In this paper, U is the total number of users, S is the number of trusted sources (authorities) assigned to each user, and s_{ij} is the estimated similarity of reading tastes of users i and j. We use Latin letters to label the users and Greek letters to label the news. Evaluation of news α by user i, $e_{i\alpha}$, is either $+1$ (liked/approved), -1 (disliked/disapproved) or 0 (not evaluated yet). The recommendation score of news α for user i is $R_{i\alpha}$.

Estimation of user similarity. User similarity is estimated from users' assessments of the news. When users i and j match in evaluations of m news and mismatch in evaluations of M news, the overall probability of agreement can be estimated as $m/(m+M)$ and this number can be used as a measure of similarity of these users. However, such an estimate is prone to statistical fluctuations: it is the user pairs with a small number of commonly evaluated news $m+M$ that are likely to achieve "perfect" similarity 1. Since in sampling of n trials, the typical relative fluctuation is of the order of $1/\sqrt{n}$, we estimate the user similarity as

$$s_{ij} = \frac{m}{m+M}\left(1 - \frac{\theta}{\sqrt{m+M}}\right), \tag{1}$$

where θ is a factor determining how strongly we penalize user pairs with few commonly evaluated news. The value $\theta = 1$ yielded optimal results in our tests and we use it in all simulations presented in this paper. When $m+M=0$ (no overlap), we set $s_{ij}=\varepsilon$ where ε is a small positive number: this reflects that even when we know no users' evaluations, there is some base similarity of their interests.

Propagation of news. One can use all currently available user evaluations to estimate similarities s_{ij} for all user pairs. Since the memory needed to store the result grows quadratically with the number of users, this is not a scalable approach to the problem. To decrease the memory demands, we keep only S strongest links for each user. Those S users who are most similar to a given user i we refer to as authorities of i and, conversely, those who have user i as an authority we refer to as followers of i. Notice that while the number of authorities for each user is fixed, a highly valued user may have a large number of followers. Lacking any prior information, we assume random initial assignment of authorities. As the system gathers more evaluations, at regular time intervals it evaluates the data and selects the best authorities for each user.

The directed network of authorities and followers described above serves as a basis for news propagation in our model. After news α is introduced to the system by user i, its initial recommendation score is zero for all users: $R_{i\alpha}=0$. In addition, the news is "passed" to all followers of i. For each such user j, the recommendation score increases by s_{ij} (*i.e.*, the higher the similarity with the news's originator, the stronger the recommendation). When news α is approved by user j, it is passed further to all followers of j and for each of those users, the recommendation score is increased by their similarity with j. That means, when user j approves news α, recommendation scores of this news are updated as

$$R'_{k\alpha} = R_{k\alpha} + s_{kj}, \tag{2}$$

where k is a follower of j. For user i, the available unread news are sorted according to $R_{i\alpha}$ (high scores at the top). As is illustrated in fig. 1, when a user receives the same news from multiple authorities, the news's recommendation score increases multiple times and hence the news is more likely to get to the top of the user's recommendation list and be eventually read.

In effect, the above algorithm implies that news spread in a directed network of users. Since similarities s_{kj} are positive, recommendation scores updated according to eq. (2) can only grow with time which gives unjustified advantage to old news. We shall introduce a time decay of the scores in the following section.

Updating the assignment of authorities. Authorities of user i should be always those S users who have the highest rating similarity with i. While this requires continual updating of authorities, as the optimal assignment is approached, the updating can be done less frequently. For simplicity, we update the assignment of authorities every ten time steps in all numerical simulations.

Numerical validation of the model. – We devise a simple agent-based approach to test and optimize

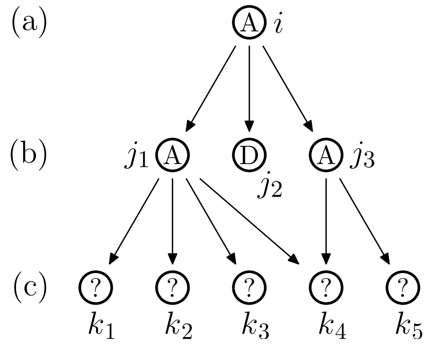

Fig. 1: Illustration of the news propagation. (a) User i added a new news, which is automatically considered as approved (A) and sent to users j_1, j_2, j_3 who are i's followers. (b) While user j_2 dislikes (D) the news, users j_1 and j_3 approve it and pass it further to their followers $k_1, \ldots, k_5$ who have not evaluated the news yet (which is denoted with question marks). (c) User k_4 receives the news from the authorities j_1 and j_3, yielding the news's recommendation score $s_{j_1 k_4} + s_{j_3 k_4}$. At the same time, user k_5 receives the news only from the authority j_3 and hence for this user, the recommendation score is only $s_{j_3 k_5}$.

the proposed model (for an introduction to agent-based modeling see [19]). It's not our goal to provide a perfect model of readers' behavior. Instead, we aim to make plausible assumptions allowing us to study the model under various circumstances.

Agent-based model. To model user's judgment of read news we use a vector model where tastes of user i are represented by the D-dimensional taste vector $\boldsymbol{t}_i = (t_{i,1}, \ldots, t_{i,D})$ and attributes of news α are represented by the D-dimensional attribute vector $\boldsymbol{a}_\alpha = (a_{\alpha,1}, \ldots, a_{\alpha,D})$. We use $D = 16$ and set the taste vectors such that each user has preference for $D_1 = 6$ of 16 available tastes (hence, each taste vector has six elements equal to one and the remaining ten elements equal to zero). There are $\binom{D}{D_1} = 8008$ such vectors and hence there are 8008 users in our system who all have mutually different taste vectors. Satisfaction of user i with news α is assumed in the form

$$\Omega(i, \alpha) = Q_\alpha(\boldsymbol{t}_i, \boldsymbol{a}_\alpha), \tag{3}$$

where the scalar product $(\boldsymbol{t}_i, \boldsymbol{a}_\alpha)$ represents the overlap of i's tastes and α's attributes and the multiplier Q_α represents the overall quality of news α (similar vector models are often used in semantic approaches to recommendation [10]). When a news is introduced to the system, its attributes are set identical with the tastes of its originator and Q_α is drawn from the uniform distribution $\mathcal{U}(0.5, 1.5)$. We assume that user i approves news α only when $\Omega(i, \alpha) \geqslant \Delta$; the news is disapproved otherwise.

Simulation time advances in steps. We assume that in each time step, a given user is active with the probability p_A. Each active user reads top R news from the recommendation list (this is motivated by the study showing that users mostly visit pages that appear at the top of search-engine results [20]) and with the probability p_S submits a new news.

Performance measures. The ratio of news' approvals to all assessments is an obvious measure of the system's performance. This number, which we refer to as *approval fraction*, tells us how often are users satisfied with the news they get recommended.

In the computer simulation, we have the luxury of knowing users' taste vectors and hence we can compute the number of differences between the taste vector of a user and the taste vectors of the user's authorities. By averaging over all users, we obtain the average number of differences. Obviously, the less are the differences, the better is the assignment of authorities. Since we assume that all taste vectors are mutually different, the smallest number of differences is two and hence we introduce *excess differences* which is the average number of differences minus two and the optimal value of this quantity is zero[1].

Results. First we study if the system is able to evolve from the initial random assignment of authorities into a more appropriate state. Instead to the described updating of authorities, one can think of a simple "replace the worst" scheme: in each step, every user confronts the least-similar authority with a randomly selected user k. When the authority's similarity with the user is lower than k's similarity (and k is not the user's authority yet), the replacement is made. Such random sampling is obviously less computationally demanding than the original optimal approach which, on the other hand, makes use of all the information available at the moment. A compromise of the two approaches is to replace i's least-similar authority with one of the users who are authorities for i's most-similar authority (hence the name "best authority's random authority", BARA).

We compare the three updating rules for $S = 10$ (ten authorities per user), $p_A = 0.02$ (*i.e.*, on average, a user is active every 50 steps), $R = 3$ (active user reads three top news from the recommendation list), $p_S = 0.01$ (on average, one of hundred active users submits a news), $\Delta = 3$, and $\varepsilon = 0.001$. As can be seen in fig. 2, the optimal choice of authorities yields higher approval fractions and lower excess differences than the other two methods. The worst performing is the BARA updating —while it initially converges slightly faster than the random sampling, it reaches only a strongly sub-optimal assignment of authorities. The initial plateau of the excess differences is due to the little information available to the system at the beginning of the simulation. The initial value of excess differences in fig. 2(b), 5.5, corresponds to the random initial assignment of authorities[2].

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[1] When the number of authorities S is large (in our case, when $S > (D - D_1)D_1$), it's impossible to reach zero excess differences.

[2] This number depends on the parameters chosen —denoting the number of ones in each of the D-dimensional taste vectors as D_1, the average number of differences can be computed as $\bar{d} = 2\sum_{d=1}^{D_1} d\binom{D_1}{d}/\binom{D-D_1}{d}/[\binom{D}{D_1} - 1]$.

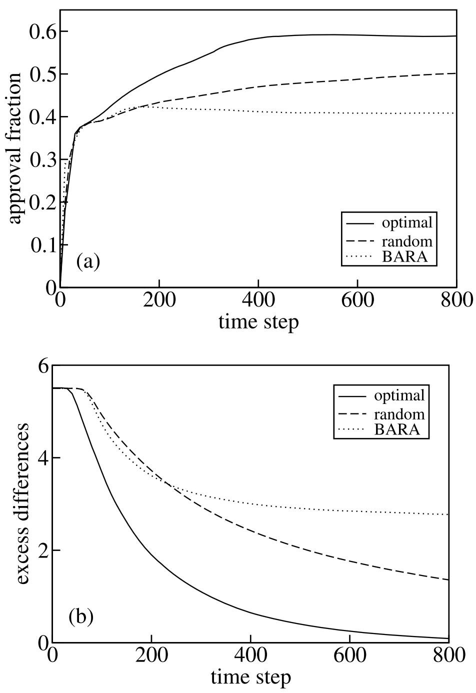

Fig. 2: Comparison of various rewiring procedures: approval fraction (a) and excess differences (b) as a function of time for optimal, random, and BARA updating of authorities (results were averaged over ten independent realizations).

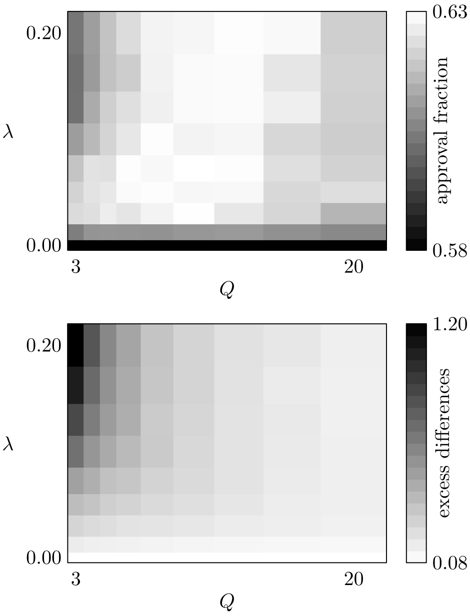

Fig. 3: Effects of the time decay on the system's performance at time step 800, when the system is almost equilibrated (results were averaged over ten independent realizations).

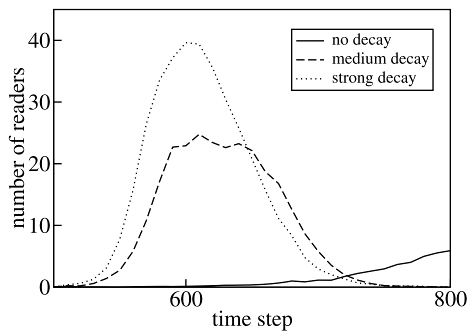

Fig. 4: Evolution of the number of readers per time step for ten high quality news introduced shortly after $T = 500$: no decay ($\lambda = 0$), medium decay ($Q = 10$, $\lambda = 0.1$), strong decay ($Q = 10$, $\lambda = 4.0$).

An important flavor is still missing in the proposed model: a time decay of news' recommendation scores. With no decay present, recommendation scores never decrease and a news is removed from a user's reading list only as it eventually gets read. In addition, with many old news queued, it is hard for good fresh news to get to the top of a recommendation list and catch the user's attention. A simple solution for all these problems is achieved by incremental decreasing of recommendation scores with time. We implement the time decay in the following way: in each time step, when a user has more than Q queued news, we decrease their recommendation scores by a small value λ and news with $R_{i,\alpha} \leqslant 0$ are removed from the list. As shown in fig. 3, an appropriately set time decay significantly increases the number of excess differences and enhances the approval fraction.

Apart from the moderate improvement of both performance measures, the decay of recommendation scores is crucial in promotion of fresh news. To illustrate this effect we did simulations where first ten news introduced after time step 500 (when the system is almost equilibrated) had particularly high qualities. We used this setting to examine how the average attention paid to those superior news evolves with time. As can be seen in fig. 4, without decay, good news stay queued for exceedingly long time before they reach their audience (solid line). On the other hand, when the decay is too strong, even good news may be eliminated prematurely (dotted line). As a compromise between promotion of fresh news and two performance measures (approval fraction and excess differences), we use $Q = 10$ and $\lambda = 0.1$ in all following simulations.

Having seen that the proposed system is able to improve the assignment of authorities and thus filter the news, a natural question is: how would a different system do? To find out, we use three different systems for comparison. When "recommending" at *random*, news are simply chosen at random from the pool of available news. When recommending by *absolute popularity*, a news is recommended according to the number of users who approved it. When recommending by *relative popularity*, a news is recommended according to the ratio of its number of approvals to the number of its evaluations. In fig. 5(a), we compare the three simple systems with our adaptive model for various values of the acceptance threshold Δ (the lower the threshold, the less demanding the users). As can be

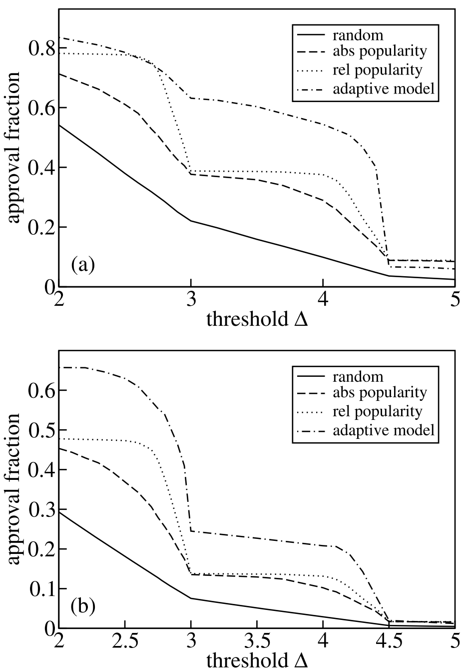

Fig. 5: Comparison of three simple filtering mechanisms with the proposed adaptive model. On the horizontal axis we have the evaluation threshold Δ which characterizes how demanding the users are. (a) The original setting with 6 active tastes out of 16. (b) The total number of tastes is 24, only 6 of them are "active".

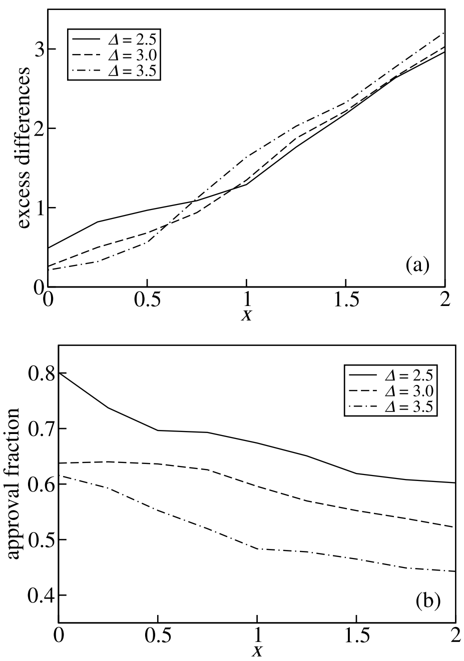

Fig. 6: Dependency of the system's performance on the amplitude of users' evaluation errors x.

seen, our system outperforms the others over a wide range of Δ. Only when users demand little ($\Delta \lesssim 3$), recommendation by relative popularity is able to work similarly well. However, notice that performance of popularity-based systems is strongly influenced by how much users differ in their tastes —this effect is shown in fig. 5(b) where 6 active tastes out of 24 are assumed. Within the described artificial framework, one can test also the correlation-based recommendation method by Resnick *et al.* [7]. Our results show that the learning phase of this method is longer and the resulting performance is worse than those achieved with the adaptive model.

Real people are not judging machines and hence unintentional errors are always present in their evaluations (intentional bias is often a problem too, we discuss it later). To include these errors in our simulations, we generalize eq. (3) to the form

$$\Omega(i,\alpha) = Q_\alpha(\boldsymbol{t}_i, \boldsymbol{a}_\alpha) + xE, \tag{4}$$

where E is a random variable drawn from the uniform distribution $\mathcal{U}(-1,1)$ and $x > 0$ is the error amplitude. As shown in fig. 6, evaluation errors have negative influence on the system's performance. However, while the number of excess differences grows greatly (in fig. 6, the increase is more than ten-fold), the approval fraction, which is a more practical measure, is much less sensitive (in fig. 6, the decrease is less than 20%). We can conclude that the presented system is rather robust with respect to unintentional evaluation errors.

Real users are heterogeneous not only in their tastes (as we have studied above) but also in the frequency and pattern of system's usage, in the threshold levels of news judgment, in the amplitude of judgment errors, and other aspects. These effects are easy to be studied within the presented framework. For example, our simulations show that noisy users have less followers than more careful users. The frequency of usage, while very important in the initial learning phase (when heavy users have more followers than casual users), is of little importance when the system has approached the optimal assignment of authorities.

Discussion. – We introduced a novel news recommender model and studied its behavior and performance in an artificial environment. We tried to keep the model as simple as possible, yet not sacrificing its performance to simplicity. For example, one can think of replacing the maximization of the similarity s_{ij} with a more sophisticated technique for the selection of authorities. We tested a technique based on the factorization of the matrix of users' ratings [21] but despite substantially higher computational complexity, the improvement obtained with this method is none or little. Yet, the possibility of merging the presented recommendation model with a different method by *hybridization* [22] remains open.

Apart from the agent-based simulations presented here, we would like to discuss some aspects of the model's application in real life. For any information filtering technique, its vulnerability to malicious behavior is of crucial importance. Hence it is important to notice that the presented system is resistant to actions of spammers. To illustrate this, let us imagine that a spammer introduces a new junk news to the system. Two things happen then. First, the news is sent to a small number of the spammer's followers (if there are some) and after it is disapproved by them, the news is effectively removed from the system after "harming" only a handful of users. Second, spammers tend to disagree with their followers (who dislike their spam news) and hence they loose these followers fast and soon are left without any influence on the system at all. Surprisingly, a similar thing would happen to a renowned news agency which would decide to act as a user and feed the system with the agency's news. Since agencies usually produce news covering many different areas, most users would find a large fraction of those news not interesting and the system would attach them to another users with more refined preferences and hence a higher similarity value. In other words, our model favors "selective sources" of information over high-quality non-selective sources.

In any real application of the model, there are many technical issues which need to be addressed. For example, the initial random assignment of authorities can be easily improved when users are asked to provide some information about their preferences. This information can be transformed to a semi-optimal initial assignment which is further improved on the basis of users' evaluations. There is also the cold start problem: at the beginning, most users have no news recommended (the same holds also later for fresh users). To overcome this, one can think of merging the proposed spreading-based recommendation model with simple popularity based recommendation. Further, users may be given the possibility to choose some or all of their authorities by themselves. While hard to model in a computer agent-based simulation, this freedom of choice may significantly improve users' satisfaction and their trust in the system. The recent popularity of online social applications tells us that regardless how sophisticated a mathematical algorithm is, users often prefer recommendations from sources who they know and trust [23]. Finally, one can object that in our model, reputation of the user who introduces a news to the system is of zero importance. In practice it is easy to reflect this reputation by, for example, increasing the recommendation score of news introduced by users with a good submission record.

The ultimate test of the system's performance and viability can be provided only by tests with real users. We are looking forward to this stage of our research.

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