Postprint: Research on Collaborative Filtering Recommendation Algorithms Integrating Domain Expert Trust and Similarity

Authors: Tan Xueqing, Zhang Lei, Huang Cuicui, Rowling

Date: 2017-11-08T00:00:00+00:00

Abstract

Objective: To leverage the combined advantages of domain expert trust and similarity to address the limitations of traditional collaborative filtering recommendation algorithms in recommendation accuracy and long-tail item mining.

Method: A dataset from MovieLens with a sparsity of 0.9605, comprising rating records from 1,102 users with extensive rating histories for 2,920 movies, was selected. The optimal number of expert users and the recommendation weight coefficient α value were determined through a phased experimental method, and algorithm performance was evaluated using comparative analysis.

Results: Experimental results demonstrate that both the accuracy and coverage of recommendation results are influenced by the number of expert users. When the recommendation weight coefficient is 0.6, recommendation accuracy significantly outperforms traditional algorithms. Moreover, as the proportion of expert users increases from 2% to 20%, coverage increases by 0.21, indicating that the algorithm substantially enhances the recommendation system' s capability to mine long-tail items.

Limitations: Potential correlations between different domain categories are not considered.

Conclusion: The algorithm can effectively overcome data sparsity and the cold-start problem, significantly improving recommendation quality and accuracy in recommendation systems.

Full Text

3. Combining Domain Expert Trust and Similarity for Collaborative Filtering

Empirical studies have demonstrated that incorporating user trust relationships can significantly alleviate collaborative filtering systems' inability to make accurate recommendations for new users. However, this body of research has not adequately addressed the challenges of data sparsity and cold-start problems, nor has it enhanced the algorithm' s capacity to mine long-tail items. Previous work on trust-based collaborative filtering has primarily focused on direct and indirect, implicit and explicit trust relationships between users, without considering the influence of domain expert trust or improving the algorithm' s ability to uncover long-tail items. We argue that introducing authoritative domain experts who have contributed numerous reliable ratings in each item domain, and incorporating expert trust weights into the rating prediction process, can improve prediction accuracy and facilitate the discovery of long-tail items while mitigating cold-start issues.

Research on trust-based collaborative filtering includes theoretical discussions, such as Jøsang et al. [?], who surveyed trust and reputation systems and argued these should serve as security mechanisms in collaborative filtering. Experimental studies have also validated trust' s benefits: Zhang et al. [?] and Wu et al. [?] introduced indirect trust relationships and community features, demonstrating significant improvements in recommendation accuracy. Massa et al. [?], Hwang et al. [?], Moradi et al. [?], and Yu et al. [?] replaced traditional similarity weights with trust weights, confirming that trust-based collaborative filtering enhances prediction accuracy and coverage. While these studies affirm trust' s value in addressing data sparsity, cold-start, and accuracy issues, they have not leveraged domain expert trust or improved long-tail item mining.

In addressing data sparsity and cold-start through trust, Du et al. [?] introduced trust relationships into traditional user-based collaborative filtering, designing a hybrid trust network combining user prestige and local trust to optimize sparsity. Jamali et al. [?] proposed the TrustWalker model, which outperformed both trust-based and standard collaborative filtering methods on the Epinions dataset. Chen et al. [?] used trust and distrust networks to identify reliable users, optimizing cold-start problems. Bedi et al. [?] integrated dynamic trust and optimal neighbor selection via ant colony optimization. Lai et al. [?] established a hybrid personal trust model using rating trust models and explicit trust criteria. Jing et al. [?] proposed an expert trust-prioritized collaborative filtering algorithm, demonstrating superior accuracy over traditional nearest-neighbor methods. These studies verified trust' s effectiveness against sparsity and cold-start but did not address long-tail mining. Victor et al. [?] identified three key social network figures—knowledgeable experts, socially central connectors, and prolific raters—and experimentally confirmed their ability to improve recommendation effectiveness.

We therefore propose applying expert user influence from social networks to the recommendation process. By calculating user similarity within domains and combining domain experts with similar users for recommendations, we present the Expert Trust and Similarity Collaborative Filtering (ETS-CF) algorithm. Figure 1 [Figure 1: see original paper] compares this approach with user-based collaborative filtering.

3.1 Identifying Domain Expert Users

In real life, expert opinions strongly influence decision-making. If we classify social network populations as leaders (expert users) and followers, followers tend to accept leaders' viewpoints due to their high trustworthiness and significant impact on follower preferences. In collaborative filtering systems, we can identify experts based on both the quantity and quality of their ratings—higher values increase expert likelihood. Within a domain, we first identify users with numerous rating records, then calculate each user' s rating accuracy.

To evaluate rating accuracy for each score user u gives to item i in domain x, we propose the following formula based on Billsus et al. [?]:

Pr (u) 1

where $r_{u,i}$ is user u' s rating for item i, $avgR$ is item i' s average rating, and r is the maximum rating for item i. For $avgR$ calculation, we first eliminate ratings that deviate significantly from the mean. Based on Jing et al. [?], we propose:

Expert influence can be measured through cumulative rating accuracy. Building on Billsus et al. [?] and Jing et al. [?], we propose the cumulative rating accuracy formula:

Pr (u)

where M_{max} is the maximum number of ratings by any user in domain x, and M is the total number of items rated by user u in domain x.

3.2 Domain-Based User Similarity Calculation

We classify items co-rated by users into domains and calculate similarity between two users based on different domains. Drawing on Pearson correlation coefficients [?] and Breese et al. [?], we propose the domain-based similarity formula:

sim (u, v) R)(r

where I is the set of items co-rated by users u and v in domain x, $r_{u,i}$ is user u' s rating for item i, u_R is user u' s average rating in domain x, and v_R is defined similarly.

3.3 Recommendation Algorithm Based on Domain Expert Trust and Similarity

During rating prediction, we first distinguish between expert user and similar user sets, then combine their recommendations. When selecting nearest neighbors for target users, we include both domain experts and domain-similar users. Using Best-k neighbor techniques, we select the top k users with highest trust as experts and the top n users with highest similarity values as similar users. Figure 2 [Figure 2: see original paper] illustrates this recommendation process.

Different algorithms apply to cold-start versus non-cold-start users:

(1) **Cold-start users**: With no or minimal rating history, user interest domains are unknown. We recommend suggestions from domain experts. Based on Ahn [**?**], we propose:

P (i) Pr (u) Pr (u) vP (i)

where $vP(i)$ is user v' s predicted rating for item i in domain x, $xPr(u)$ is expert user u' s trustworthiness in domain x, k is the number of experts in domain x, and $r_{u,i}$ is expert u' s rating for item i.

(2) **Non-cold-start users**: We recommend items by combining expert opinions and similar users within domains. Based on Ahn [**?**], we propose:

P (i) R Pr (u) Pr (u) sim (u, v) sim (u, v)

where u_R is user u' s average rating in domain x, $sim(u, v)$ is similarity between users u and v in domain x, and α balances expert and similar user rating weights.

4. Experiments

4.1 Dataset Collection and Preparation

We evaluated our algorithm using the MovieLens dataset from GroupLens. We used the medium-sized dataset, extracted a subset, and densified it. The final dataset comprised 126,784 movie ratings from 1,102 active users on 2,920 movies, using a 5-point scale with sparsity 0.9605. Observing download patterns and sales data reveals that while popular items attract most users, even unpopular items have some admirers—this long-tail distribution also exists in MovieLens. Effectively mining these long-tail items is crucial for recommendation systems.

4.2 Evaluation Metrics

We employed rating accuracy and recommendation coverage to evaluate performance. For accuracy, we used Mean Absolute Error (MAE). Let I_u be the test set user collection, $R_{u,i}$ be the actual rating, and $\hat{R}_{u,i}$ be the predicted rating from the training set. The MAE formula is [**?**, **?**]:

u i I

We also evaluated coverage to assess long-tail mining effectiveness. Higher coverage indicates better recommendation of lesser-known but valuable items. The coverage formula [?] is:

Coverage R(u) | | I |

Coverage represents the proportion of items appearing in final recommendation lists relative to the total item collection. When nearly all items are recommended to at least one user, coverage approaches 100%.

4.3 Experimental Steps

Due to constraints, we conducted offline experiments using movie categories as domains. The steps were:

(1) Randomly split the densified MovieLens dataset into M folds ($M = 10$), using one fold for testing and $M - 1$ for training. We performed 10-fold cross-validation, repeated five times with different random splits, averaging results to prevent overfitting.

(2) Identify experts per movie category. Using MovieLens training data, we categorized rating records from `movies.dat` into 18 domains (Action, Drama, Children, Adventure, etc.). For each domain, we sorted users by rating count, calculated rating accuracy (expert trust), and selected the top k most professional experts, using their trust values as prediction weights.

(3) Calculate user similarity. We built behavior record tables between items and users per category, counting users who rated each movie. This produced comprehensive tables of co-rated items for all user pairs within each domain.

(4) Record expert users and their trust values per domain, along with pairwise user similarities. Recommend N items liked by domain experts and most similar users (sorted by rating). When no similar users exist in a domain, recommend expert-suggested items.

(5) Evaluate each recommendation by calculating system accuracy and coverage.

The validation comprised three phases: Phase 1 determined the optimal k for user-based CF; Phase 2 fixed k and identified optimal expert count and α via MAE curves; Phase 3 measured expert count’ s impact on coverage.

We compared three algorithms: traditional user-based CF (USER-CF), expert trust-prioritized CF (EPT-CF), and our ETS-CF.

5. Experimental Results

5.1 Results

(1) Traditional USER-CF and Determining k

We evaluated USER-CF on MovieLens. The algorithm requires selecting k nearest neighbors for each user, then recommending N items (fixed at 10). Testing k values of 10, 20, 30, 40, and 50 yielded the results in Table 1 and Figure 3 [Figure 3: see original paper].

Table 1 shows that MAE decreases (accuracy increases) with larger k, while coverage decreases because users only trust most-similar neighbors, reducing recommended items and long-tail mining capability. $k = 30$ offered optimal performance balancing accuracy and coverage.

(2) Expert Count and α Impact on Accuracy

We selected varying numbers of experts per domain by thresholding expert trust values. In the Action domain, trust values ranged from 0.01 to 0.803, with approximately 58% below 0.1, 18% in [0.1, 0.2), and 20% above 0.2—following Pareto distribution.

Fixing similar neighbors at 30 and recommendation length at 10, we varied expert ratios from 2% to 20% and tested α values of 0.2, 0.4, 0.6, and 0.8 (Table 2 , Figure 5 [Figure 5: see original paper]). MAE decreased significantly as experts increased, but rose slightly beyond 14% due to lower-trust experts degrading predictions. $\alpha = 0.6$ proved optimal—over-reliance on experts ignores personal preferences, while underweighting them reduces their influence, particularly for cold-start users.

(3) Expert Count Impact on Coverage

With $\alpha = 0.6$, $k = 30$, and $N = 10$, we varied expert ratios from 2% to 20%. Table 3 and Figure 6 [Figure 6: see original paper] show coverage increasing with expert count. Unlike USER-CF, which only recommends highly-rated items from similar users, expert users can recommend unpopular yet classic, high-value films, enhancing diversity and long-tail discovery.

5.2 Algorithm Comparison

We compared USER-CF, EPT-CF, and ETS-CF using $\alpha = 0.6$ and varying k (Table 4 , Figure 7 [Figure 7: see original paper]). ETS-CF consistently achieved the lowest MAE, particularly with few neighbors, because expert opinions provide reliable recommendations even when similar users are scarce.

Our ETS-CF algorithm effectively addresses data sparsity and cold-start problems while significantly improving recommendation quality and accuracy. However, limitations remain: the algorithm is domain-category based and doesn' t consider cross-domain correlations, limiting cross-domain recommendations.

Additionally, without expert participation during initial deployment, the algorithm cannot solve cold-start problems fundamentally.

Future research will explore incorporating contextual factors (time, location) to meet growing demand for affective computing, and optimizing scalability and complexity for real-world datasets far larger than MovieLens.

References

[1] Jøsang A, Ismail R, Boyd C. A Survey of Trust and Reputation Systems for Online Service Provision[J]. Decision Support Systems, 2006, 43(2): 618-644.

[2] Zhang B, Huang Z, Yu J, et al. Trust Computation for Multiple Routes Recommendation in Social Network Sites[J]. Security & Communication Networks, 2005, 12(12): 159-174.

[3] Wu Yingliang, Yao Huaidong, Li Cheng' an. An Improved Collaborative Filtering Recommendation Algorithm with Indirect Trust Relationship[J]. New Technology of Library and Information Service, 2015(9): 38-45.

[4] Massa P, Avesani P. Trust-Aware Recommender Systems[C]. In: Proceedings of the 1st ACM Conference on Recommender Systems. 2007.

[5] Hwang C S, Chen Y P. Using Trust in Collaborative Filtering Recommendation[A]. // New Trends in Applied Artificial Intelligence[M]. Springer Berlin Heidelberg, 2007: 1052-1060.

[6] Moradi P, Ahmadian S. A Reliability-Based Recommendation Method to Improve Trust-Aware Recommender Systems[J]. Expert Systems with Applications, 2015, 42(21): 7386-7398.

[7] Yu Yan, Qiu Guanghua. Research on Collaborative Filtering Recommendation Algorithm by Fusing Social Network[J]. New Technology of Library and Information Service, 2012(6): 54-59.

[8] Du Yongping, Huang Liang, He Ming. Collaborative Filteration Recommendation Algorithm Based on Trust Computation[J]. Pattern Recognition and Artificial Intelligence, 2014, 27(5): 417-425.

[9] Jamali M, Ester M. TrustWalker: A Random Walk Model for Combining Trust-Based and Item-Based Recommendation[C]. In: Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, 2009: 397-406.

[10] Chen C C, Wan Y H, Chung M C, et al. An Effective Recommendation Method for Cold Start New Users Using Trust and Distrust Networks[J]. Information Sciences, 2013, 224(2): 19-36.

[11] Bedi P, Sharma R. Trust Based Recommender System Using Ant Colony for Trust Computation[J]. Expert Systems with Applications, 2012, 39(1): 1183-1190.

[12] Lai C H, Liu D R, Lin C S. Novel Personal and Group-Based Trust Models in Collaborative Filtering for Document Recommendation[J]. Information Sciences, 2013, 239(4): 31-49.

[13] Jing Minchang, Tang Diguan, Yu Yinghui. A Recommending Method Based on Expert Prior Trust in Collaborative Filtering[J]. Library and Information Service, 2012, 56(11): 105-108.

[14] Victor P, Cornelis C, De Cock M, et al. Key Figure Impact in Trust-enhanced Recommender Systems[J]. AI Communications, 2008, 21(2-3): 127-143.

[15] Billsus D, Pazzani M J. Learning Collaborative Information Filters[C] In: Proceedings of the 15th International Conference on Machine Learning. 1998.

[16] Rodgers J L, Nicewander W A. Thirteen Ways to Look at the Correlation Coefficient[J]. American Statistician, 1988, 42(1): 59-66.

[17] Breese J S, Heckerman D, Kadie C. Empirical Analysis of Predictive Algorithms for Collaborative Filtering[C]. In: Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence. 2013: 43-52.

[18] Ahn H J. A New Similarity Measure for Collaborative Filtering to Alleviate the New User Cold-Starting Problem[J]. Information Sciences, 2008, 178(1): 37-51.

[19] Shardanand U, Maes P. Social Information Filtering: Algorithms for Automating "Word of Mouth" [C]. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 1995.

[20] Herlocker J L. Evaluating Collaborative Filtering Recommender Systems[J]. ACM Transactions on Information Systems, 2004, 22(1): 5-53.

Author Contributions

Tan Xueqing: Conceived research idea, designed study, revised manuscript. Zhang Lei, Huang Cuicui: Conducted experiments, collected and analyzed data, drafted manuscript. Luo Lin: Revised research plan, finalized manuscript.

Conflict of Interest Statement

All authors declare no conflict of interest.

Supporting Data

Supporting data is available in the journal's online version at http://www.infotech.ac.cn: [1] Zhang Lei, Huang Cuicui. Movielens.xlsx. Raw sample data for the collaborative filtering recommendation algorithm study based on domain expert trust and similarity. [2] Zhang Lei, Huang Cuicui. observedata.xlsx. Observational data for the collaborative filtering recommendation algorithm study

based on domain expert trust and similarity. [3] Zhang Lei, Huang Cuicui. cfusingdata.xlsx. Sample data for the collaborative filtering recommendation algorithm study based on domain expert trust and similarity.

Received: 2016-04-04; Revised: 2016-05-23

Note: Figure translations are in progress. See original paper for figures.