Acknowledging Dynamic Aspects of Trust in Recommender Systems

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ABSTRACT

Trust-based recommender systems emerged as a solution to different limitations of traditional recommender systems. These social systems rely on the assumption that users will adopt the preferences of users they deem trustworthy in an online social setting. However, most trust-based recommender systems consider trust to be a static notion, thereby disregarding crucial dynamic factors that influence the value of trust between users and the performance of the recommender system. In this work, we intend to address several challenges regarding the dynamics of trust within a social recommender system. These issues include the temporal evolution of trust between users and change detection and prediction in users' interactions. By exploring the factors that influence the evolution of human trust, a complex and abstract concept, this work will contribute to a better understanding of how trust operates in recommender systems.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

trust, recommender systems, temporal evolution, change detection

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1 INTRODUCTION

Trust-based recommender systems offer great potential to effectively address many issues that hinder recommender systems, such as data sparsity, cold start problems, and lack of personalization. However, most trust-based recommender systems ignore the timestamps associated with trust values or ratings. They are based on one dataset snapshot where the data is not sorted chronologically. Thus, the data is considered to be completely static, which is not a faithful representation of reality. As highlighted by the authors in [8], incorporating temporal information when modeling the evolution of trust in an online setting can improve trust prediction and rating prediction.

Although the temporal dynamics of trust have been explored in peer-to-peer systems [3] [7] and commercial transactions [9], limited attention has been given to its evolution in the context of a social recommender system. In these systems, trust between users evolves in interesting ways through time and according to interactions.

Understanding and predicting how trust operates in recommender systems over time can yield insights into how a user's behavior evolves in a social setting. It can enable the identification of recurrent patterns of interest, the detection of sudden shifts in trusting behavior, and the modeling of users' evolving preferences. Furthermore, the main advantage of such systems is the fact they are centered around the human experience, thereby making them more responsive.

In the same context, the system's responsiveness is contingent upon its ability to promptly update itself according to the changes in the user's trusted circle. Such properties can be achieved if the interactions between the users are considered a continuous stream of data instead of working with a fixed dataset and updating periodically from it since changes may occur between two updates, and the system will not take them into consideration until the next update [1]. Therefore, investigating efficient methods for detecting changes in trust between users presents an exciting opportunity to enhance the system's performance.

Generally, in this research project, we are interested in studying different dynamic aspects of trust in recommender systems. We are particularly interested in exploring how incorporating these dynamic elements can render the system more realistic and improve its performance and safety.

2 RESEARCH QUESTIONS

After exploring the literature around trust in recommender systems, the following research questions can be formulated:

RQ 1: To what extent are trust-based recommender systems relevant and beneficial in enhancing user experience?

To answer this question, we conducted a comprehensive survey that focused on reviewing papers about trust-based recommender systems. The survey analyzed the building blocks of a trust-based recommender system and proposed a taxonomy of existing works based on different trust incorporation techniques. Additionally, it reviewed various trust-based metrics and approaches and discussed the main challenges and future research directions for trust-based recommender systems. The survey also listed the advantages that

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distinguish trust-based recommender systems from traditional recommender systems.

Trust-based recommender systems offer a wide range of merits, including detecting fake profiles used for shilling attacks, scoring better prediction accuracy, alleviating data sparsity, and solving the problem of cold-start users in certain settings.

RQ 2: How can we model and incorporate the temporal evolution of trust relationships in a trust-based recommender system, and what impact does this have on the performance of the system?

We are currently in the process of developing a time-aware trust-based recommender system utilizing a hidden Markov model (HMM). The HMM is being employed to model the dynamic nature and temporal evolution of trust between users. Its primary function is to decode the trust level between users based on observations and predict future trends in the evolution of trust. After decoding the hidden state of trust, we identify recently trusted users in the network and the timestamp where the target user started considering them trustworthy. The output of this module is a timestamped list of rated items for each trustworthy user. In the recommendation module, the scores of items based on similarity and recency are computed for all trustworthy users. The resulting score is then used to provide top-n recommendations for the target user. It is crucial to update the recommender system periodically as trust relationships surrounding the target user change. The implementation of the system is nearing completion.

RQ 3: How can we spot trust changes on time to keep the system up-to-date and relevant? How to deal with abrupt changes as efficiently as possible?

To push the presented framework toward a more realistic approach, instead of updating the recommender system periodically, it would be more compelling to analyze user interactions in a social setting as a stream of information and adapt the system to abrupt changes. Trust exhibits interesting characteristics, as it takes a significant amount of time to establish but can quickly deteriorate following a negative event [4]. Additionally, trust relationships can naturally decay over time without any major incidents. Another important consideration is that malicious neighbors will not consistently provide dishonest feedback or ratings but rather alternate between ratings or feedback that may appear honest and dishonest [3]. Therefore, a change detection module should be able to identify such abnormalities in interaction. It would be interesting to work on the change detection module to analyze how it can detect recurrent, abrupt, and casual changes in the trust relationships between users. Leveraging these changes can potentially enhance the safety and performance of recommender systems.

RQ 4: What are other dynamic aspects of trust in social recommender systems that can be considered?

Other dynamic aspects of trust have been generally disregarded due to their complexity. Specifically, the influence of personal biases and social interactions with other users in the system on the value of trust, whether explicitly expressed or inferred, in a recommender system has not been explored enough in the existing literature. Some works discussed the subject in other contexts. The authors in [6] state that trust bias is an important concept in social science and an integral part of the final trust decision. The work in [2] presents a survey about bias and debias in recommender systems, including a discussion about bias in social networks but in relation to user ratings and models. Another study [5] focuses on social influence bias on ratings in recommender systems and aims to mitigate its effects using machine learning.

Biases that distort users' judgment can significantly impact their perception of other users in the system. For example, conformity bias pushes a user to assimilate with a group of users rather than express their own judgment. As a result, the user may deem someone as trustworthy to conform with another group of people. It is, therefore, necessary to mitigate the harmful effects of these biases to account for the fact that users' statements may not accurately reflect their genuine personal judgment.

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