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Online Product Recommendation by Users Digital Features and Trust Score

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Abstract – **The rapid expansion of web-based services has driven a significant shift toward online platforms, where users actively share opinions and experiences through social rating systems. This growing reliance on online feedback has created new research opportunities to understand and predict user behavior by analyzing digital interactions within social networks. In this study, we present a model that combines two key sources of information: social web service ratings and social community interactions. Users are first identified from the dataset, and their reputations are estimated based on historical rating patterns. Subsequently, a learning framework is designed to continuously update social features related to both users and web services, allowing the model to capture how these factors influence a user's rating behavior over time. Experimental results, when compared with an existing baseline approach, demonstrate that the proposed method achieves improved prediction performance.**

Keywords – **Data Mining, Product Recommendation, User Trust.**

I. INTRODUCTION

Recommender systems support users in selecting appropriate web services by suggesting options that align with their preferences and interests. These systems rely on various data collection techniques, where user information is obtained either explicitly, such as through ratings and reviews, or implicitly, by analyzing user behavior and interaction patterns. By utilizing such data, recommender systems deliver personalized experiences, which are considered highly valuable for e-commerce platforms seeking to improve user engagement and decision-making efficiency [1,2].

Over the years, numerous recommendation approaches have been proposed and successfully deployed on large-scale commercial platforms such as Amazon and Netflix, which serve users with highly diverse tastes and requirements [3,4]. Despite extensive research in this domain, there is still significant potential for enhancing recommender systems by effectively incorporating social relationships among users.

Conventional recommender systems typically assume that users act independently and are uniformly distributed. This assumption often leads to the neglect of social interactions and trust relationships between users [5]. In practice, however, social connections play a crucial role in shaping user behavior and influencing future ratings and choices. Since many similarities observed within a network arise from user interactions and mutual influence, it is reasonable to design social recommender systems that explicitly model these relationships [6].

Social recommender systems aim to reduce information overload by presenting users with the most relevant recommendations through the integration of social interaction data. Nevertheless, most online retail platforms still overlook important social factors such as friendship links and trust, thereby underutilizing the power of social influence. Conversely, social networking platforms often ignore e-commerce–related information such as purchase history and service ratings [7].

In addition to social connections, trust relationships significantly impact user decisions and should be incorporated into recommendation models. In social networks, trust and social connections are distinct concepts; users who are socially connected may not necessarily trust each other. Moreover, different connections do not exert equal influence on a user's opinions and choices. Alongside trust, users with similar purchasing preferences tend to exhibit comparable behavior when rating web services, further highlighting the importance of combining trust, social relationships, and preference similarity in recommender systems [8,9].

II. RELATED WORK

Nguyen et al. [5] conducted a re-rating experiment using the MovieLens dataset, which involved 386 users and 38,586 ratings. To identify and address potential sources of error in the rating process, they designed four different user interfaces: a baseline interface with minimal support, an interface that displayed labels, one that provided rating examples, and a fourth interface that combined both labels and examples. Their study was based on two key assumptions: first, that users may not always remember their experiences with web services accurately, and second, that users may find it difficult to consistently map their internal preferences onto a numerical rating scale. The results showed that although rating support improved consistency in user ratings, participants generally preferred simpler, baseline-style interfaces due to their ease of use. However, among the interfaces offering rating support, the example-based interface achieved the lowest RMSE, the smallest minimum RMSE, and the least amount of inherent noise, indicating superior rating accuracy.
In another study [7], the authors examined a relatively underexplored source of rating error in mobile recommender systems, namely the impact of input methods on user ratings. Their work focused on recommender

systems deployed on smartphones, where users interact through different input techniques such as touchscreen gestures and freestyle motions. Touchscreen interactions involve direct contact with the screen using buttons, sliders, or other interface elements, whereas freestyle gestures rely on device movements without direct screen contact. Building on their earlier research, the authors analyzed user preferences for different interaction techniques in recommender system tasks and highlighted how input modality can influence both usability and rating outcomes.

Similarly, the study in [6] aimed to map common recommender system tasks—such as rating web services—to intuitive gesture- and motion-based interaction patterns. For each task, the authors implemented at least two different input techniques, allowing for a comparative analysis of user interface designs. A user study was conducted to evaluate these alternatives, and the findings revealed that users consistently favored simpler and easier-to-control gestures over more complex interaction methods.

The work presented in [8] introduced the concept of a rating schedule to model users' daily rating behavior. By measuring similarities between users' rating schedules, the authors captured interpersonal similarities in rating behavior. Their model integrates four key factors—individual interest, interpersonal interest similarity, interpersonal rating behavior similarity, and interpersonal rating behavior distribution—within a matrix factorization framework to predict service ratings more accurately. By directly incorporating interpersonal factors as constraints on users' latent features, the proposed approach reduces model complexity while more effectively exploiting user rating behavior.

Finally, the study in [9] addressed the problem of false reputation, which arises when reputations are distorted by unfair or malicious ratings. To tackle this issue, the authors proposed a method called TRUE-REPUTATION, an iterative algorithm that adjusts reputation scores based on the confidence level of each user rating. Unlike methods that discard suspicious ratings, the proposed framework evaluates the reliability of all ratings and updates reputations accordingly. By weighting reputations using confidence scores, the algorithm minimizes the influence of unfair evaluations while preserving the contributions of genuine users, thereby computing a more accurate and trustworthy reputation score.

III. PROPOSED METHODOLOGY

The proposed work is divided into two main modules. The first module focuses on identifying and filtering fake users from the dataset. In this stage, users who rate web services with unusually high frequency and whose ratings deviate significantly—either much higher or much lower—from the normal rating distribution of a web service are considered suspicious. The second module analyzes the rating behavior of genuine users, and this part of the methodology is inspired by the approach presented in [8].

Dataset Processing

The dataset contains information related to web service evaluations. Each record represents a scenario in which a user (e.g., U1) has used, experienced, or reviewed a particular web service (e.g., P1) and assigned a rating based on their perception, such as best, very good, good, average, or ok.

Since the dataset includes a large number of ratings between users and web services, it is first transformed into a structured format suitable for analysis. The data is organized into a matrix where the first column represents the user ID, the second column represents the web service ID, and the third column contains the rating value. Textual ratings are converted into numerical values for computational convenience. A zero value in the matrix indicates that the corresponding user has not used or rated the given web service.

Users Reputation Users who rate a large number of web services are considered more active. The activeness of a user u, denoted as a_u, is measured by the total number of ratings provided by that user ($|R_u|$). Constants α and μ are used to normalize this value within the range [0, 1].

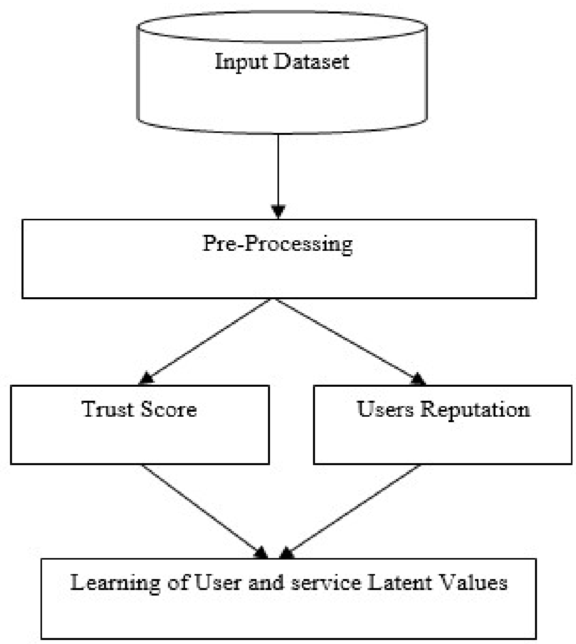

Figure 1: Block diagram of proposed work.

The deviation of a user's rating from the overall reputation of a web service plays a key role in identifying fake users. If a user's ratings closely match the general reputation of a service, the user is considered more reliable. Conversely, larger deviations indicate lower loyalty. The loyalty score of a rating, denoted as o_r, is calculated using the service reputation (r_m) and its standard deviation (s_m).

$$O_r = \left| \frac{r - r_m}{s_m} \right|$$

Users whose calculated false reputation score exceeds a predefined threshold are labeled as fake users, while the remaining users are treated as genuine. The false reputation score is computed as:

False_reputation = au*or

Thus, users who are highly active and whose ratings show abnormal objectivity are more likely to be identified as fake users.

Digital Relation of Customers: This dataset captures social interactions among users. It records various types of connections between users—such as likes, comments, shares, messages, friend requests, group participation, mutual friends, video calls, and chats. For each pair of users, the frequency of these interactions is stored, representing the strength of their social relationship.

Trust Score: To generate interaction intervals, a network matrix is constructed in which each user is treated as a node, rows represent possible friend combinations, and columns correspond to different interaction features between users. For each pair of users, the frequency of every feature is counted in both directions, forming an interval that captures mutual interaction behavior; for example, if user U1 sends four messages to user U2 and U2 sends two messages to U1, the interval is represented as [4, 2]. This process is repeated for all user pairs to obtain an interval-based interaction matrix. These interval values are then transformed into a single numerical measure called the membership degree by computing the upper membership value. Finally, the membership degrees of all interaction features between two users are aggregated to produce a score relation, which represents the overall strength or trust of their relationship. If this score exceeds a predefined threshold, the corresponding user pair is considered a highly trusted connection and is treated as a potential future edge in the network.

Learning of User and Service Latent Value

In this study, the latent representations of users, web services are learned and refined using the matrices obtained from the preceding stages. The learning process follows the objective function described in [8], where all derived matrices jointly contribute to updating the initial latent factors. By incorporating information from multiple sources, the model is able to more accurately capture user preferences and service characteristics.

IV. EXPERIMENT AND RESULTS

The performance of the proposed approach is evaluated by comparing it with the RNMF method (Exploring Users' Rating Behaviors) presented in [8], which is considered the baseline technique in this work.

Figure 2 illustrates the average precision values for different user sets. It can be observed that the proposed method consistently outperforms RNMF, achieving higher precision in web service rating prediction. As the dataset size increases, the prediction task becomes more challenging due to increased user diversity and randomness, which leads to a general decline in prediction accuracy for both methods.

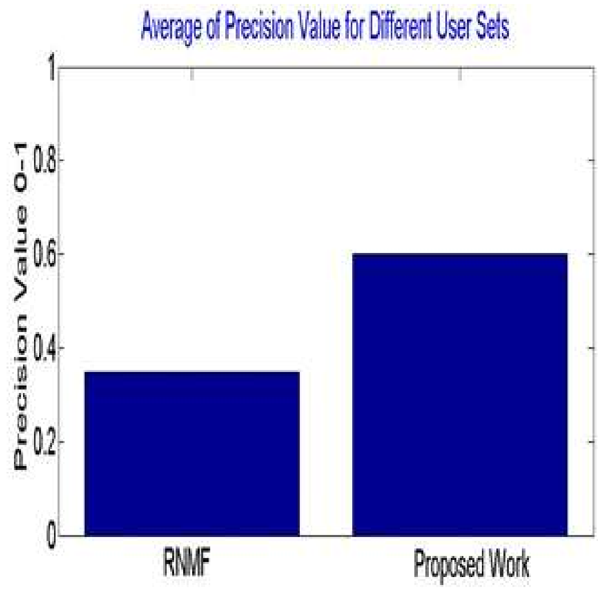

Figure 2: Average precision value of different set of users.

Table. 1. Comparison of True positive and false positive values between proposed work as well as RNMF method.

Users	RNMF		Proposed Work	
	TP	FP	TP	FP
20	9	11	13	7
30	10	20	17	13
50	13	37	29	21

Table 1 presents a comparison of true positive (TP) and false positive (FP) values between the proposed approach and RNMF. The results clearly show that the proposed method yields a higher number of true positives and fewer false positives across all dataset sizes, indicating improved prediction reliability. Similar to the precision results, performance decreases with larger datasets due to increased uncertainty in user behavior.

Table. 2. Comparison of Precision values between proposed work and RNMF method at different dataset size.

Precision Value Comparison		
Users	RNMF	Proposed Work
20	0.4500	0.65
30	0.3333	0.5667
50	0.26	0.58

Table 2 compares the precision values of both methods for different numbers of users. The proposed approach demonstrates significantly higher precision than RNMF at all dataset scales, confirming its superior ability to predict accurate web service ratings even as the dataset grows.

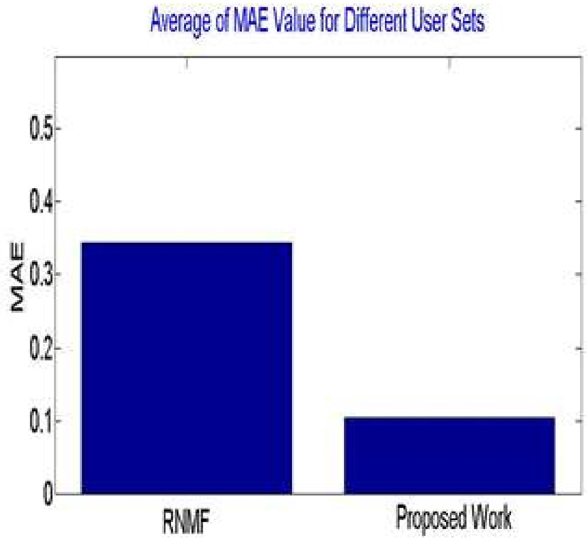

Figure 3: Average MAE value of different number of users.

Figure 3, along with the corresponding MAE results, shows that the proposed model achieves lower Mean Absolute Error compared to RNMF. This indicates that the predicted ratings are closer to the actual user ratings. Although MAE increases with the number of users due to growing behavioral complexity, the proposed approach maintains better performance than the baseline method across all scenarios.

Figure 4, it is evident that the proposed approach achieves better web service rating prediction performance than the RNMF method, as indicated by its lower RMSE values. Although the overall prediction accuracy decreases as the dataset size and number of users increase, this trend is expected due to the growing diversity and randomness in user behavior, which introduces additional uncertainty into the prediction process.

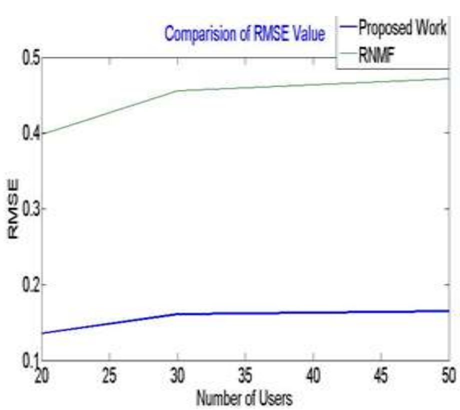

Figure 4: Comparison of RMSE value of proposed and previous work.

V. CONCLUSION

With the continuous expansion of online markets, the number of users interacting with web services is rapidly increasing. As a result, accurately identifying and targeting the right customers has become a fundamental requirement for organizations. Motivated by this need, this study presents a web service rating prediction model that integrates both social network information and web service rating data. The experimental results demonstrate that combining these two sources of information leads to more accurate and reliable predictions. However, as the dataset grows larger, prediction performance gradually declines due to increased behavioral variation among users. Since research in this domain is ongoing, future work may incorporate additional factors, such as company or service profiles, to further enhance prediction accuracy.

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