ISSN Online: 2821-1693

Transactions on Machine Intelligence

Journal Homepage: https://tmachineintelligence.ir/index.php/TMI

Learning Path Prediction in Social Learning Network

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ARTICLE INFO

Article History:
Received 28 December 2022
Received in revised form
29 February 2023
Accepted 19 March 2023
Available online 20 March 2023

Keywords:
Social Learning Network, Collaboration Filtering, Learning Needs, Prediction

ABSTRACT

The rapid advancement and widespread adoption of Information Technology (IT) have significantly influenced the ways individuals engage with educational content, prompting a growing demand for more adaptive and intelligent learning environments. Social Learning Networks (SLNs), as dynamic platforms for collaborative learning, require continuous enhancement to meet the evolving needs of learners. A critical aspect of improving SLNs lies in the accurate prediction of learners' future educational requirements, which plays a fundamental role in facilitating the learning process and enhancing overall learner performance. This study introduces a novel interpreter framework specifically developed to predict the learning needs of users within SLNs. The interpreter analyzes users' historical learning patterns and intelligently recommends subsequent topics that align with their learning trajectories. To enhance the prediction accuracy, we propose a user-based Collaborative Filtering (CF) approach, which leverages similarities among users' learning behaviors to infer future needs. To validate the effectiveness of the proposed method, experiments were conducted using a dataset extracted from a widely recognized SLN. The experimental results reveal that users with similar learning histories tend to exhibit parallel learning needs, supporting the collaborative nature of the proposed approach. The system demonstrated a strong ability to forecast approximately 60% of learners' upcoming needs, as measured by recall performance metrics. The outcomes of this research underscore the potential of personalized, data-driven recommendation techniques in advancing SLNs, ultimately contributing to more effective and targeted learning experiences.

1. INTRODUCTION

Recent advancements in trajectory prediction and pedestrian motion learning have been marked by innovative approaches and methodologies. In their study, Sun et al. (2022) introduce Reciprocal Twin Networks, a novel framework comprising two networks, which notably outperforms state-of-the-art methods in effectively predicting human trajectory paths within complex scenes. This research, featured in the IEEE Transactions on Circuits and Systems for Video Technology, contributes significantly to the domain of pedestrian motion learning [1].

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http://dx.doi.org/10.47176/TMI.2023.37

Similarly, Fu et al. (2022) propose an enhanced walking strategy based on the User Behavior Proximity Network (UBPN). This strategy showcases improved trajectory prediction performance by skillfully extracting hidden information from social contacts. Published in the IEEE Transactions on Computational Social Systems, their work introduces a novel spatiotemporal behavior-enabled random walk strategy tailored for online social platforms. These studies collectively reflect the ongoing efforts to refine and innovate in the field of trajectory prediction and user behavior analysis [2].

In the era of Digital Learning, the landscape of individuals' learning experiences has undergone a profound transformation due to advancements in Information Technology [3-4]. Modern learners, especially novices, allocate substantial time to engaging with social media networks as a means to acquire knowledge. Learning resources encompass a wide range of topics and presentation formats, catering to diverse interests and capacities of students, teachers, and mentors. The added advantage of collaborative environments being accessible anytime and from anywhere further enhances the learning experience [4-5]. While social networks offer numerous features that augment learning opportunities, two key challenges impede learners' effective utilization of these platforms. The first challenge is information overload, arising from the sheer abundance of available information. Learners often grapple with the task of identifying suitable collaborators and relevant content, leading to prolonged periods of searching and reviewing diverse information [3,6].

Another impediment is metacognition issues, which involve a user's ability to critically assess the information they encounter. This suggests that learners may lack the expertise and skills needed to validate the learning materials within the vast array of available content and collaborators across numerous networks. Furthermore, learners may struggle to identify relevant topics aligning with their learning needs throughout their educational journey [3]. The notable dropout rate of approximately 10% in N:FMB MOOCs and the substantial number of unanswered questions on Q&A websites, exemplified by one million unanswered questions on Stack Overflow daily, may be attributed to barriers encountered in the development of Social Learning Networks (SLN). Addressing the metacognition barrier through the anticipation of learning requirements could significantly aid in directing learning resources, collaborative efforts, and content creation [3,5].

The objective of this study is to investigate the impact of learners' similarity on predicting their needs and designing an appropriate predictor in a SLN environment. We will explain all technical terms when first used, use clear and concise language, and maintain a formal register throughout the text. The study will aim for a logical flow of information, free from bias, and ensure that all words are precisely chosen and grammatically correct. The language will be objective, value-neutral, and avoid biased, figurative, or ornamental language. Consistent citation and footnote style will be used throughout, adhering to the appropriate style guide and formatting. The paper is structured as follows: <<Insert academic sections and titles following conventional structure>>. Section 2 examines the literature on predicting learners' needs in SLNs; Section 3 presents the proposed prediction method; Section 4 evaluates the method in one of the well-known SLNs and analyzes the results; and the concluding section summarizes the findings and outlines future work.

2. RELATED WORK

[7] Researchers utilized the factor analysis method to explore the correlation between learner behavior within the network and their performance, with the ultimate goal of forecasting future assessment scores. To predict performance, they applied the Collaborative Filtering (CF) method. [8] Introducing a machine learning approach focused on predicting learners' knowledge in specific domains, this study proposes a methodology to forecast learner performance in a learning environment by assessing the likelihood of accurate answers to questions. The determination of the prediction factor employed Maximum Likelihood Estimation and Bayesian solution methods. Notably, previous research [9] introduced tools for anticipating learners' drop-off rates in SLN, offering tailored support for motivated learners. However, it's important to highlight that the prediction of learning needs in SLN remained unexplored in the previously mentioned studies.

3. PROPOSED METHOD

The proposed method leverages the similarity among learners in specific topics to predict their needs. This implies that learners who share similarities with the target learner in the patterns of the mentioned topics exert a more significant influence on the prediction of their learning needs, and their trajectory exhibits higher accuracy in prediction. Given the expansive size of the Student Learning Network (SLN) and the diverse array of learning topics, predicting learners' needs necessitates a precise and time-efficient approach. Hence, we employ the Collaborative Filtering (CF) method to develop a prediction function. The language used throughout maintains objectivity, avoiding figurative or ornamental expressions in favor of clear and concise statements.

In this study, learners assess topics within the SLN, and the proposed technique utilizes the resemblance among learners' assessed topics to anticipate their requirements. If the learners set are defined$L = \{l_1.l_2.,,,.l_n\}$, the topic set $T = \{t_1.t_2.,,,.t_m\}$ and the target learner l_x the process of prediction is included[10]:

Step:1: Compute the similarities between l_x and other learners with cosine based similarity function that show in Eq 1:

$$sim(l_x.l_y) = \frac{\sum_{i=1}^{m} r_{x.i} r_{y.i}}{\sqrt{\sum_{i=1}^{m} r_{x.i}^2 \sum_{i=1}^{m} r_{y.i}^2}} \quad (1)$$

Where $r_{x,i}$ is a learner l_x rating for a topic t_i.

Step 2: Selects $K < n$ most similar learners with target learners: $l_{y_1},\ldots,l_{y_k}$

Step 3: The prediction of a learner's (l_x) ratings on a topic i is then computed with Nadaraya-Watson regression estimate method. It is shown in Eq2.

$$\hat{r}_{x.i} = \hat{E}(r_{x.i}|r_{x.-i}) = \sum_{k=1}^{K} w_{y_k}(r_{x.-i}) r_{y_k.i} = \frac{\sum_{k=1}^{K} sim(l_x.l_{y_k}) r_{y_k.i}}{\sum_{k=1}^{K} sim(l_x.l_{y_k}) r_{y_k.i}} \quad (2)$$

Where w_{y_k} is amount of learner's ratting (l_{y_k}) effect on predict topics i for target learner l_x. It can be calculated by learner's reputation in SLN.

4. EVALUATION AND RESULTS

To evaluate the proposed method, we used Stack Overflow data-set which were collected for the period of January 30, 2014 to March 3, 2014. These data include the ID of learners who asking or answering questions and the ID of questions and answers and topics related to them.

Table 1. Information of Data Set

Number of learners	14300
Number of questions	4800
Number of answers	21256
Average received answers per questior	4.43
Average received votes per learner	1.98
Number of topics	320

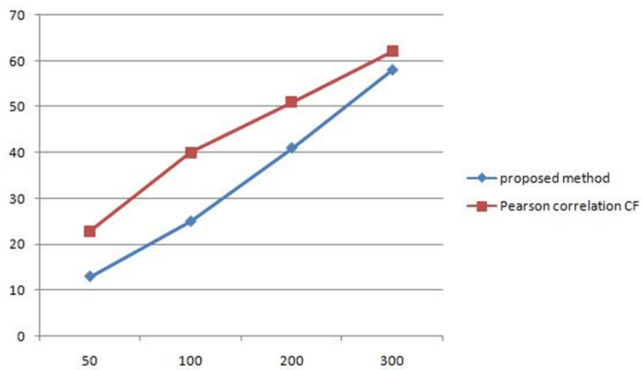

Fig. 1. Evaluation proposed in recall criteria based on number of topics

About 20 percents of questions and answers related to different topics are randomly deleted and the proposed method tries to recall the deleted information. The prediction threshold for accept the next topic is 0.51. We compared the performance of the proposed method and CF predictor with Pearson correlation-based similarity in fig1. The results show that there is a correlation between learners' behavior in ratting questions and answers and their learning needs. It is possible to predict the future learning needs based on their similarity. The proposed method could predict about 60 percent of the deleted topics.

5. CONCLUSION AND FUTURE WORK

The need for planning to enhance the learning environment in SLN highlights the significance of predicting learners' needs. This study presents a predictor for forecasting learners' requirements in the network, and also investigates the correlation between learners' behavior in rating topics and their learning needs. This predictor could guide learning services in learning network environments based on the experiences of similar learners and reduce cognitive barriers to achieve high performance. Future work could focus on evaluating the predictor's performance in familiar learning network settings, especially MOOCs, and implementing a hybrid approach to enhance its precision.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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