IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 29 May 2023, accepted 9 June 2023, date of publication 13 June 2023, date of current version 20 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3285552

RESEARCH ARTICLE

Context-Aware and Click Session-Based Graph Pattern Mining With Recommendations for Smart EMS Through AI

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This work was supported by the National Research Foundation of Korea (NRF) funded by the Korean Government [Ministry of Science and ICT (MIST)] under Grant 2021R1F1A1063319.

ABSTRACT In the field of Artificial Intelligence (AI), Smart Enterprise Management Systems (Smart EMS) and big data analytics are the most prominent computing technologies. A key component of the Smart EMS system is E-commerce, especially Session-based Recommender systems (SRS), which are typically utilized to enhance the user experience by providing recommendations analyzing user behavior encoded in browser sessions. Also the work of the recommender is to predict users' next actions (click on an item) using the sequence of actions in the current session. Current developments in session-based recommendation have primarily focused on mining more information accessible within the current session. On the other hand, those approaches ignored sessions with identical context for the current session that includes a wealth of collaborative data. Therefore this paper proposed Context-aware and Click session-based graph pattern mining with recommendations for Smart EMS through AI. It employs a novel Triple Attentive Neural Network (TANN) for SRS. Specifically, TANN contains three main components, i.e., Enhanced Sqrt-Cosine Similarity based Neighborhood Sessions Discovery (NSD), Frequent Subgraph Mining (FSM) using Neighborhood Click session-based graph pattern mining and Top-K possible Next-clicked Items Discovery (TNID). The NSD module uses a session-level attention mechanism to find m most similar sessions of the query session, and the FSM module also extracts the frequent subgraphs from the already discovered m most similar sessions of the query session via item-level attention. Then, TNID module is used to discover the top-K possible next-clicked items using the NSD and FSM module via a target-level attention. Finally, we perform comprehensive experiments on one big dataset, DIGINETICA, to verify the effectiveness of the TANN model, and the results of this experiment clearly illustrate the performance of TANN.

INDEX TERMS Artificial intelligence, graph pattern mining, session-based recommender systems, smart EMS.

I. INTRODUCTION

Smart Enterprise Management Systems (Smart EMS) rely heavily on information technology (IT) to develop products and services for consumers [1]. Companies increasingly leverage advanced technology to meet their technical needs and enhance their service offerings, shaping their services, products, and overall information and resource infrastructure [2]. Within the Smart EMS framework, e-commerce plays a pivotal role. E-commerce, a subset of e-business,

The associate editor coordinating the review of this manuscript and approving it for publication was Yudong Zhang.

FIGURE 1. Click session of the user.

refers to the online buying and selling goods and services [3]. It primarily focuses on digital interactions between companies and consumers [4]. As many e-commerce systems only store truncated and anonymized sessions, there is a need for session-based recommendations [5]. The goal of session-based recommendation is to predict a user's next interaction based on their previous session interactions.

Fig. 1 illustrates our objective of forecasting a user's next clicked item using their prior clicked items. User sessions are initiated when a user clicks on a specific item. Users may click on attractive items within a session and spend more time viewing them, continuing this iterative process until their needs are fulfilled. However, existing models struggle to provide accurate suggestions without extensive user histories [6], [7].

Previous research in session-based recommendation [8] has predominantly utilized an item-based model to reflect user interests by calculating similarities across session items. However, these approaches fail to consider the sequential information present within sessions. In subsequent studies, Markov chains have been employed [9] to represent sequential behavior and recommend items for future clicks. Nevertheless, these techniques overlook global sequential information due to the strong assumption that the next click solely depends on the previous click. Recurrent neural networks (RNNs) have emerged as powerful tools for handling sequential data, demonstrating remarkable success in natural language processing [10] and speech recognition [11]. Consequently, RNNs have been employed in session-based recommendation [12], [13].

While RNN-based models have outperformed conventional approaches, they typically only consider the limited sequence activities within the current session, disregarding the rich data available in neighboring sessions. For example, consider two click sessions: one comprising [Eternals, Venom, Black Widow], and the other comprising [Black Widow, Eternals, District 9]. These sessions exhibit a shared interest in science fiction films, indicating that Venom could be the next click in Session 2.

Motivated by the above observations, this paper proposes an AI-driven click session-based graph pattern mining technique for Smart EMS, coupled with a recommendation system (SRS). Our technique leverages a Triple Attentive Neural Network (TANN) for SRS. In TANN, we incorporate an Enhanced Sqrt-Cosine Similarity-based Neighborhood Sessions Discovery (NSD) module, which identifies the m most similar sessions to the query session. Specifically, NSD employs a session-level attention mechanism. Additionally, we employ Frequent Subgraph Mining (FSM) using Neighborhood Click session-based graph pattern mining, which extracts frequent subgraphs from the previously identified m most similar sessions of the query session. FSM utilizes an item-level attention mechanism to capture frequent subgraphs. Finally, we introduce a Top-K possible Next-clicked Items Discovery (TNID) mechanism that utilizes target-level attention to extract each candidate item from the NSD and FSM modules. We compute a recommendation score for each candidate item and recommend the Top-K items.

By employing the proposed click session-based graph pattern mining with recommendation technique, we aim to enhance the capabilities of Smart EMS through AI. Furthermore, this approach addresses the limitations of existing models by considering neighboring sessions and extracting valuable patterns to provide accurate and personalized recommendations.

This study makes significant theoretical and practical contributions to session-based recommender systems. The theoretical contributions include the introduction of a novel approach that combines context-awareness and click session-based graph pattern mining, along with the development of the Triple Attentive Neural Network (TANN). The practical contributions focus on improving the accuracy and personalization of session-based recommender systems, capturing both long-term preferences and short-term interests of users, and providing insights into the performance and applicability of the proposed approach through comprehensive evaluations.

A. THEORETICAL CONTRIBUTIONS

- **Context-Aware and Click-Session-Based Graph Pattern Mining:** This study introduces a novel approach that combines context-awareness and click-session-based graph pattern mining for session-based recommender systems. By incorporating context information and leveraging graph mining techniques, the proposed approach aims to enhance the recommendation effectiveness and capture both long-term preferences and short-term interests of users.
- **Triple Attentive Neural Network (TANN):** The study presents the Triple Attentive Neural Network (TANN) as a key component of the proposed approach. TANN consists of three modules: Enhanced Sqrt-Cosine Similarity-based Neighborhood Sessions Discovery (NSD), Frequent Subgraph Mining (FSM) using Neighborhood Click session-based graph pattern mining, and Top-K possible Next-clicked Items Discovery (TNID). TANN utilizes attention mechanisms at different levels to model collaborative data, extract frequent subgraphs, and predict next-clicked items effectively.
- **Enhanced Sqrt-Cosine Similarity (ESC) and Hellinger Distance:** The study introduces the concept of Enhanced Sqrt-Cosine Similarity (ESC), which combines the advantages of cosine similarity and Hellinger distance. ESC captures both the similarity of item

occurrences and the similarity of item probabilities between sessions, providing a more comprehensive measure for session similarity. Furthermore, by incorporating Hellinger distance, which considers the differences in probability distributions, the proposed approach can better capture the collaborative information among sessions.

B. PRACTICAL CONTRIBUTIONS

- **Improved Session-Based Recommender System:** The proposed approach addresses the limitations of existing session-based recommender systems by considering sessions with identical context and leveraging collaborative data. The approach provides more accurate and personalized recommendations for users in real-time e-commerce scenarios by incorporating context-awareness and graph pattern mining techniques. This can lead to enhanced user experiences and increased conversion rates for e-commerce platforms.
- **Long-Term Preference and Short-Term Interest Representation:** The study introduces the concept of frequent subgraphs as representations of users' long-term preferences and short-term interests. By extracting frequent subgraphs from the neighborhood sessions, the proposed approach captures the global patterns shared among similar sessions and the specific patterns relevant to the current session. This enables more precise modeling of user preferences and improves the accuracy of next-click predictions.
- **Comprehensive Evaluation and Performance Analysis:** The study conducts comprehensive experiments on a large dataset to evaluate the effectiveness of the proposed TANN model. By comparing the performance of TANN with other state-of-the-art session-based recommendation methods, the study demonstrates the superiority of the proposed approach in terms of recommendation accuracy and coverage. In addition, the evaluation results provide practical insights into the performance and potential applications of the proposed approach in real-world scenarios.

Overall, the theoretical contributions of this study lie in developing a novel approach that combines context-awareness and click session-based graph pattern mining, along with the introduction of the Triple Attentive Neural Network (TANN). The practical contributions include improving the accuracy and personalization of session-based recommender systems, capturing both long-term preferences and short-term interests of users, and providing insights into the performance and applicability of the proposed approach through comprehensive evaluations.

The remainder of this work is laid out as follows. Section II presents the related work, and Section III presents the mathematical model and architecture of the proposed TANN model. Section IV provides the essential experiment setting and experimental data proving the effectiveness of the TANN model. Section V provides the scalability consideration details and Section VI details Overcoming Data Sparsity in Session-based Recommender Systems. At last, Section VII provides the conclusion and future work.

II. RELATED WORK

Due to the limited data regarding users in browser sessions, session-based recommendation remains a difficult task. Data on user behavior is normally in the form of sequence data. The purpose of session-based recommendation is to forecast what the user wants to click next based on their past action sequences. Over the last few years, more studies have been undertaken on this issue. In this section, we briefly review some of the related studies in this field.

Liu et al. [14] present a short-term memory priority model (STAMP) to capture the user's current interests and short-term intentions. It can capture users' overall interests from a session context's long-term memory while also considering users' present interests from the last-clicks' short-term memory.

Song et al. [15] use a dynamic-graph-attention neural network to include social ties into the session-based recommendation. In addition, the authors employ a recurrent neural network to simulate dynamic user activities, and a graph-attention neural network with context-dependent social influence that efficiently infers the influencers depending on the users' present interests. The entire model was fitted to large-scale data with ease.

Li et al. [16] presented a NARM model to analyze users' sequential activity and major objective features, integrating an attention method with an RNN-based methodology for session-based recommendation. First, the authors investigated a hybrid encoder including an attention method to analyze the user's sequential activity and capture the user's primary goal in the present session, which are eventually integrated like a unified session representation. The authors then used a bi-linear matching strategy using this unified session representation to compute the suggestion scores for all candidate items. Finally, the authors trained NARM by learning the session and item representation and their matching.

Ying et al. [17] use a hierarchy attention model to collect user's long-term interest and short-term preferences from the user's whole session history. The authors presented a two-layer hierarchy attention network that suggests the next item the user could be interested in. Especially, the primary attention layer learns user long-term interests using previous purchased item representations. In contrast, the second produces an ultimate user representation by combining user short-term and long-term interests.

Zheng et al. [18] use an attention method and a memory network to learn user choice adaptively. MARS learns deep adaptive user representation using a memory element and an attention method. MARS flexibly summarized users' preferences trained at an end-to-end fashion.

According to Hu et al. [19], personalized suggestion results should be diversified based on user-session contexts.

The authors presented a Session-based wide-in-wide out (SWIWO) based neural network to learn user-session context. It creates the session context by integrating all of the item embeddings in the current session and assigning a fixed weight to each item based on the distance relative between the response and the target item.

Zhu et al [20] presented a novel LSTM version, Time-LSTM, to model users' sequential behaviours. Time-LSTM incorporates short- and long-term preferences by employing time gates to limit the impact of the most recently consuming item and storing time intervals to simulate users' long-term preferences; however, many genuine datasets lack a time stamp.

Gwadabe et al [21] proposed a GRASER-based Graph Neural Networks (GNN) model. In particular, their model uses GNN to learn the non-sequential afterward sequential transition connections between the items in the current session.

The Item Co-occurrence Graph Augmented Session-based Recommendation (IC-GAR) model introduced by Gwadabe et al [22] is a session-based recommendation method that enhances the representation of the present session with session co-occurrence trends. Encode, Session Co-occurrence, and Prediction Modules are the three modules that make up IC-GAR. Using Gate Recurrent Units (GRU), the Encoder Module learns the user's global and local interests from the current session. The Session Co-occurrence Module models higher-level communications between item transition patterns in training sessions using a modified Graph Convolutional Network (GCN) variation. Session co-occurrence representations are learned through combining the GCN representation of items in the present session.

Wu et al. [23] proposed a unique neural architecture: leveraging neighborhood session information with dual attentive neural network (LNIDA). The Current Session Encoder (CSE) and Neighborhood Session Encoder (NSE) are used in the LNIDA model to represent the users' and collaborative data, respectively. In addition, the authors also utilize a co-attention fusion approach to integrate current session information with collaborative information from the neighborhood to forecast candidate items for session-based recommendation.

Kim et al. [24] proposed sequence-aware recommenders for fashion e-commerce. They introduced a method that leverages sequential patterns in user sessions to improve recommendation accuracy. Their approach considers the order of items in a session and captures sequential dependencies to understand users' preferences better. Experimental results demonstrated the effectiveness of their approach in enhancing recommendation performance in the fashion domain.

Pan et al. [25] presented a collaborative graph learning approach for session-based recommendation. Their method incorporates both user-item interactions and item-item relationships to capture the complex dependencies among items. By constructing a collaborative graph, they effectively model the interactions between different items and utilize graph-based propagation to generate recommendations. Experimental evaluations showed the superiority of their method over traditional session-based recommendation approaches.

Deng et al. [26] proposed G^3SR, a global graph-guided session-based recommendation model. Their approach integrates global graph-based information to enhance recommendation accuracy. In addition, by leveraging the relationships between different items in the entire item space, G^3SR captures rich item-item dependencies that may exist beyond a user's current session. Experimental results demonstrated the effectiveness of their model in improving recommendation performance compared to baseline methods.

Zhang et al. [27] introduced a dynamic intent-aware iterative denoising network for the session-based recommendation. Their method addresses the challenge of noise and uncertainty in session data by iterative denoising the user-item interaction matrix. Furthermore, by considering the dynamic intent of a user's session, their approach adapts the denoising process to different user intents, leading to more accurate and personalized recommendations. Experimental results on real-world datasets showcased the superiority of their method over existing approaches.

An efficient cold start solution for recommender systems based on machine learning and user interests was discussed in [28]. An efficient hybrid similarity measure based on user interests for recommender systems [29].

Existing session-based recommendation approaches have significantly enhanced user experience and predicted users' next actions in E-commerce. However, they still possess certain limitations that can impact their effectiveness. This review aims to provide a comprehensive assessment of these limitations and highlight the unique contribution of the proposed Triple Attentive Neural Network (TANN) model.

Many session-based recommendation methods focus on mining information within the current session, neglecting the potential collaborative data from sessions with similar contexts. This limitation restricts the breadth and depth of information considered for generating recommendations. Additionally, traditional approaches often overlook the temporal dynamics of user behavior within a session, failing to capture users' evolving interests and preferences as they navigate through the session. Consequently, the recommendations generated may not accurately reflect users' current intents and needs.

The TANN model addresses these limitations through its novel design and incorporation of attention mechanisms. The model consists of three main components: Neighborhood Sessions Discovery (NSD), Frequent Subgraph Mining (FSM), and Top-K possible Next-clicked Items Discovery (TNID).

The NSD module of the TANN model introduces a session-level attention mechanism. It identifies the m most similar sessions to the query session, leveraging an Enhanced

Sqrt-Cosine Similarity-based approach. By considering sessions with similar contexts, the NSD module captures collaborative data that can enhance the quality and relevance of recommendations.

The FSM module of the TANN model leverages an item-level attention mechanism. It extracts frequent subgraphs from the discovered similar sessions obtained from the NSD module. The FSM module identifies patterns and associations more likely to lead to relevant recommendations by focusing on item-level interactions. This approach improves the representation of user preferences and enables the model to capture nuanced relationships between items.

Finally, the TNID module utilizes a target-level attention mechanism to discover the top-K possible next-clicked items. By combining the information from the NSD and FSM modules, the TNID module generates recommendations tailored to the user's specific needs and interests in the current session. By leveraging the collaborative data from similar sessions and employing attention mechanisms at various levels, the TANN model captures richer contextual information and user preferences, improving recommendation performance.

Overall, existing session-based recommendation approaches have limitations related to their focus on the current session and their limited consideration of collaborative data. The proposed TANN model overcomes these limitations by introducing novel attention mechanisms and incorporating session-level, item-level, and target-level attention. As a result, the model demonstrates superior recommendation accuracy and relevance performance, making it a valuable contribution to the session-based recommendation in Smart EMS through AI.

III. METHODOLOGY

The Smart EMS system's session-based recommendation aims to forecast what a user will want to click next using the user's sequential session data.

We present a formulation of the problem here. Let V = {v1, v2, ..., v|V|} signify a set of all unique items that occur in all sessions, and X = {x1, x2, ..., x|V|} represent the embedding vectors concerning. A sequence of click activities for each session could be described as S = {x1, x2, ...,xn}, where xi ∈ V signifies an item in time-stamp i. Given a prefix of the click action sequence: St = {x1, x2, ...,xt}(1 ≤ t ≤ n). By computing the recommendation score of each candidate items, our model seeks to forecast the next probable item (i.e., xt+1). To be more precise, our model can be thought of like a classifier that trains to output possibilities y^for all feasible items, where y^= {y^1, y^2, ..., y^|V|} denotes the recommendation score, where y^i corresponds to the item T^i's score. Lastly, we recommend the top-K items from y^.

To address the session-based recommendation challenge, we presented a context-aware and click session-based graph pattern mining with recommendation utilising a Triple Attentive Neural Network (TANN). TANN's main concept is to use neighbourhood collaborative knowledge to enhance query session recommendation effectiveness.

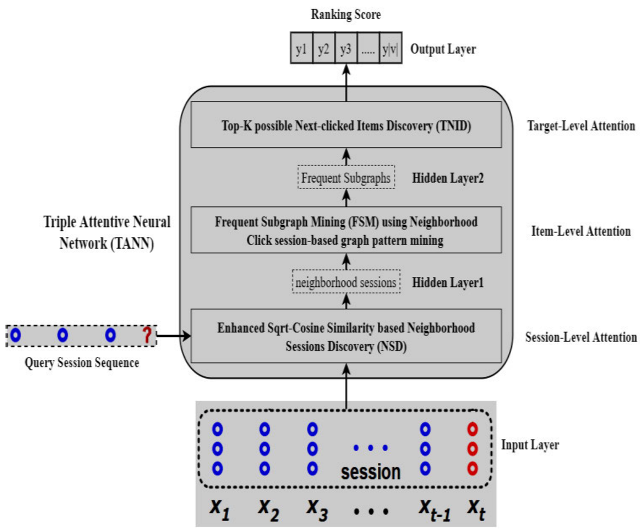

FIGURE 2. The TANN model is depicted in a schematic diagram.

As shown in Fig. 2, The TANN model is made up of three parts: Enhanced Sqrt-Cosine Similarity-based Neighborhood Sessions Discovery (NSD), Frequent Subgraph Mining (FSM) using Neighborhood Click session-based graph pattern mining and Top-K possible Next-clicked Items Discovery (TNID). In the NSD, we use an enhanced sqrt-cosine similarity technique to find the m most similar sessions to neighborhood sessions. Then, using a session-level attention mechanism, we model neighbourhood collaborative data. The FSM extracts the frequent subgraphs using Neighborhood Click session-based graph pattern mining from m most similar sessions via item-level attention. Frequent subgraphs are called long-term preference representation and others called short-term interest representation. Finally, we introduce TNID with target-level attention to extract each candidate item from NSD and FSM parts, compute the recommendation score for each candidate item, and then suggest the Top-K items. Next, we will discuss TANN model in depth.

A. ENHANCED SQRT-COSINE SIMILARITY-BASED NEIGHBORHOOD SESSIONS DISCOVERY (NSD)

Current developments in session-based recommendation have primarily focused on mining more information accessible within the current session. On the other hand, those approaches ignored sessions with identical context for the current session that includes a wealth of collaborative data. To address the problem, we propose a Neighborhood Sessions Discovery (NSD) based on Enhanced Sqrt-Cosine Similarity (ESC) in the session-level attention mechanism. We will provide calculations in more depth below.

Given the query session (q), we would desire to discover its m most similar sessions by computing the enhanced Sqrt-cosine similarity between query session (q) and all other sessions (p), which is demonstrated in Eq. (1).

$$ESC(p, q) = \frac{\sum_{i=1}^{n} \sqrt{p_i q_i}}{\sum_{i=1}^{n} p_i \sum_{i=1}^{n} q_i} \tag{1}$$

From Eq. (1), it demonstrates that the ESC is straightly derived from Hellinger distance and cosine similarity. Hellinger distance is shown in Eq. (2). The Hellinger distance, denoted as H(p, q), is a measure of the similarity between two probability distributions, p and q. It quantifies the difference between these distributions by considering the square root of the sum of the squared differences between the square roots of their respective probability values.

Mathematically, the Hellinger distance between two discrete probability distributions can be calculated using the following formula:

$$H(p,q) = \sqrt{\frac{1}{2}} * \sqrt{\sum (i = 1\ to\ n)\left[\left(\sqrt{p}_i - \sqrt{q}_i\right)^2\right]} \quad (2)$$

where:

- H(p, q) represents the Hellinger distance between distributions p and q.
- p_i and q_i denote the probability values of the i-th event in the distributions p and q, respectively.
- n is the total number of events or outcomes in the distributions.

Note that the Hellinger distance ranges between 0 and $\sqrt{2}$, where 0 indicates that the distributions are identical, and $\sqrt{2}$ represents complete dissimilarity.

And, cosine similarity is shown in Eq. (3). The cosine similarity is a measure of similarity between two vectors in a multi-dimensional space. It is commonly used to compare the similarity between documents or texts based on their word frequencies or embeddings. The formula for calculating the cosine similarity between two vectors p and q is as follows:

$$cos(p,q) = \frac{(p \cdot q)}{(||p|| * ||q||)} \quad (3)$$

where:

- cos(p, q) represents the cosine similarity between vectors p and q.
- p · q denotes the dot product of vectors p and q, which is calculated by summing the element-wise product of their corresponding components.
- ||p|| and ||q|| represent the Euclidean norms (or magnitudes) of vectors p and q, respectively, which can be computed as the square root of the sum of the squared values of their components.

The resulting cosine similarity ranges between -1 and 1, where -1 indicates complete dissimilarity, 1 indicates identical vectors, and values close to 0 imply a lack of strong similarity or dissimilarity.

A closer look at Eq. (3) reveals that cosine similarity is derived directly from Euclidean distance which showed in (Eq. 4).

$$d_{Euclid}(p,q) = \sqrt{\sum (p_i - q_i)^2} = \sqrt{2 - 2\sum p_i q_i} \quad (4)$$

After computing the ESC similarity scores, we select the m largest scores correspond to Neighborhood sessions set Ns = {p1, p2, …, pm} as the m nearest neighbors for the query session.

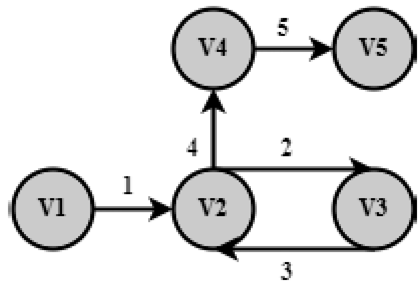

FIGURE 3. Graph diagram of a click session.

B. FREQUENT SUBGRAPH MINING (FSM) USING NEIGHBORHOOD CLICK SESSION-BASED GRAPH PATTERN MINING

For recommendation, the FSM extracts important data from the m most related sessions. It generated two embedding vectors (ml and ms), where ml indicating the user's long-term preferences representation (most frequent subgraphs) in the neighborhood sessions. We present a Neighborhood Click session-based graph pattern mining in item-level attention method to acquire long-term interests from m most related sessions. The extraction of frequent subgraphs in one or more graphs is known as graph pattern mining.

Assume that the item list in a click session S = [shirt, pant, sun glass, pant, socks, watch] called in Graph G = [v1, v2, v3, v2, v4, v5]. Here items are called vertices (v) and clicked orders are called edges (e). Figure 3 shows a graph diagram of a click session.

Let there be a graph database GD, a collection of m most similar sessions. The support (occurrence frequency) of a subgraph G^x in GD is the number of graphs where G^x shows, that is showed in Eq. 5.

$$\text{Sup}(G^x) = |\{g|g \in GD, G^x \subseteq g\}| \quad (5)$$

In Eq. (5), Sup(Gx) represents the support or occurrence frequency of a subgraph Gx in the graph database GD. The equation is defined using set notation. Here's a breakdown of the components:

- {g | g ∈ GD, Gx ⊆ g}: This set notation represents the set of graphs g in GD where Gx is a subset of g. In other words, it includes all graphs g from GD that contain the subgraph Gx.
- |{g | g ∈ GD, Gx ⊆ g}|: The vertical bars surrounding the set notation indicate the cardinality or count of elements in the set. So, |{g | g ∈ GD, Gx ⊆ g}| gives the number of graphs in GD where Gx is a subset.

Therefore, Sup(Gx) is the count or frequency of occurrence of the subgraph Gx in the graph database GD, indicating how many graphs in GD contain Gx as a subset.

Algorithm 1 Neighborhood Click Session-Based Graph Pattern Mining

Input : m most similar click sessions
Output : Frequent Sub graphs (Tk) with Minsup for long-term preferences
Step 1 : Tk = { }, Tc ← put all m most similar click sessions
Step 2 : Minsup = 1
Step 3 : **While** Tc is not empty **do**
Step 4 : g ← pop highest priority subgraph from Tc
Step 5 : E← discovers edges that could expand g and calculate their support values
Step 6 : **foreach** (t,sup(t)) ∈ E **do**
Step 7 : g' ← g U {t} // Add the edge t to the graph g
Step 8 : sup(g') ← sup(t)
Step 9 : **if** (sup(g') ≥ Minsup) **then**
Step 10 : Insert g' into Tk
Step 11 : **if** (Tk.size() ≥ k) **then** // k – threshold value
Step 12 : **if** (Tk.size() > k) **then**
Step 13 : pop the highest priority (least support) subgraph from Tk
Step 14 : Minsup = sup(Tk.peek())
Step 15 : **end**
Step 16 : **end**
Step 17 : Insert g' into Tc
Step 18 : **end**
Step 19 : **end**
Step 20 : **end**
Step 21 : return Tk

Given the m most similar sessions, we want to extract its frequent subgraphs by Neighborhood Click session-based graph pattern mining algorithm explained in Algorithm 1.

C. TOP-K POSSIBLE NEXT-CLICKED ITEMS DISCOVERY (TNID)

In this section, we consider that the output of the NSD and FSM are important for evaluating the probability of clicking the next item. Therefore, we propose a Top-K possible Next-clicked Items Discovery (TNID) technique in target-level attention. This technique has the following steps:

1. This technique first extracts candidate targets (possible next clicked items) from discovered m most similar session with ESC similarity scores and put these into a List (CT).

2. Then it extracts further candidate targets from extracted frequent subgraphs with support values and put these into CT.

3. Then compute average (Ai) for each target (Ti) from CT.

$$A_i = \frac{\mathrm{ESC}\ (T_i) + \mathrm{minsup}(T_i)}{2} \tag{6}$$

4. After that we apply min-max normalization for all computed averages. One of the most prevalent methods of data normalisation is min-max normalisation. The smallest value of each characteristic is turned into a 0, the maximum value is transformed into a 1, and all other values are converted into a number between 0 and 1.

$$Ai' = (Ai - \min(A))/(\max(A) - \min(A)) \tag{7}$$

- Ai represents the original value of the variable Ai'.
- min(A) is the minimum value of the variable A among all the data points.
- max(A) is the maximum value of the variable A among all the data points.
- Ai' is the normalized value of the variable Ai within the range [0, 1].

5. Then softmax layer sort and rank the targets based on all min-max normalized averages (A').

$$y^{\wedge} = softmax(CT, A') \tag{8}$$

where y^= {y^1, y^2, ..., y^|v|} denote the recommendation scores of all candidate targets, where y^i corresponds to the score of item Ti. At last, the top-K items from y^are suggested.

IV. RESULTS AND DISCUSSIONS

This section introduces the dataset, the baseline models and the evaluation metrics used in this experiment. Then it compares the proposed TANN model with the existing models in term of P@5, MRR@5, P@10 and MRR@10.

A. DATASET

We assess our TANN model on one widely obtainable real-world dataset namely DIGINETICA. The CIKM Cup 2016 provided the DIGINETICA dataset. The dataset have transaction data and product data. In this experiment, we merely utilize transaction data. Furthermore, this dataset has 5 features: session id, user id, item id, time frame, and event date. Given the original input session sequence data [s1, s2, ..., sn-1, sn], we create the sequences and subsequent labels ([s1], s2), ([s1, s2], s3), ..., ([s1, s2, ..., sn-1], sn) for training the dataset. The justification for utilizing the DIGINETICA dataset as the sole dataset in this study lies in its relevance, dataset characteristics, benchmark status, and the benefits of evaluation consistency. The DIGINETICA dataset is highly applicable to the research context of Smart EMS and session-based recommendation in E-commerce, capturing user behavior and interactions within E-commerce sessions. Its comprehensive nature, with a large volume of user sessions, click events, and item properties, enables a thorough analysis and accurate assessment of the proposed model's effectiveness. The dataset's recognition as a benchmark dataset establishes its credibility and facilitates meaningful comparisons with existing approaches.

Additionally, focusing on a single dataset ensures evaluation consistency, allowing for direct comparisons between models and enhancing the reliability and validity of the evaluation results. While multiple datasets from various domains could further demonstrate generalizability, the DIGINETICA dataset provides valuable insights into the performance and effectiveness of the proposed TANN model within the specific context of

TABLE 1. Statistics of the DIGINETICA dataset.

User Count	Item Count	Session Count	Sparsit y	Interactio n Type
6,00,68 4	1,84,04 7	12,35,38 1	99.99 %	Click

Smart EMS and E-commerce. The DIGINETICA dataset statistics are shown in Table 1. The DIGINETICA dataset could be attained from the subsequent link: https://competitions.codalab.org/competitions/11161#learn_the_details-data2.

$$P@K = \frac{n_{hit}}{N} \tag{9}$$

B. METRICS FOR EVALUATION

1. **P@K (Precision):** The P@K metric, which measures the proportion of test instances hit by the top-K items, is extensively utilized to assess predictive accuracy. It is defined as:
   N signifies the total number of cases in the test data and nhit represents the number of cases in the top-k ranking list that forecast the preferred item. A higher P@K denotes superior outcomes.
2. **MRR@K (Mean Reciprocal Rank):** The MRR@K (Mean Reciprocal Rank) is a metric used to evaluate the performance of a recommendation or retrieval system. It measures how well the system ranks the target items in a results list.
   The formula for calculating MRR@K is:
   $$MRR@K = \left(\frac{1}{K}\right) * \sum \left(\frac{1}{ranki}\right) \tag{10}$$
   In this formula, K represents the number of items in the result list, and Q represents the set of target items that we are interested in. The variable ranki indicates the rank of the i-th item in the result list, where a lower rank indicates a higher position in the list.
   To calculate MRR@K, we consider each target item in Q and determine its reciprocal rank. The reciprocal rank of an item is the inverse of its rank. For example, if an item is ranked first, its reciprocal rank would be 1. If it is ranked second, its reciprocal rank would be 1/2, and so on.
   If a target item is not present in the top-K items of the result list, its reciprocal rank is considered to be 0. This means that if the top-K items do not hit a target item, it does not contribute to the MRR@K calculation.
   Finally, the MRR@K is obtained by taking the mean (average) of all the reciprocal ranks of the target items. A higher MRR@K value indicates that the target items are ranked higher in the result list, which implies better recommendation or retrieval system performance.

C. METRICS FOR EVALUATION

The subsequent three models are utilized as models to use as baselines.

NARM: NARM employs an attention technique to extract features from the hidden state to improve the actual data, emphasizing the user's primary goal in the current session. In a session-based recommendation environment, it presents a neural attention recommender to address the shortage of user intention assessment. In addition, NARM presented a hybrid encoder that would imitate the user's sequential activity, collect the user's main intent in the discussion, and combine this data as the end user activity data representation.

STAMP: STAMP is a unique short-term memory priority approach that uses simple MLP networks and an attentive net to capture a user's common interests and present preferences. It integrates the short-term attention approach with the basic long-term memory approach to derive the user's present and long-term preferences and the user's ultimate interest.

LNIDA: For session-based recommendation, LNIDA stands for Leveraging Neighborhood Session Information with Dual Attentive Neural Network (LNIDA). LNIDA comprises two key elements: the Current Session Encoder (CSE) and the Neighborhood Session Encoder (NSE). The CSE module uses an item-level attention approach to represent the user's data in the present session. In contrast, the NSE module uses a session-level attention approach to capture collaborative neighbourhood data. The data from the CSE and NSE is then adaptively integrated using a simple co-attention fusion procedure.

D. COMPARISON WITH BASELINE MODELS

A recommendation system in a real-world industrial setting could suggest a few items at a time; the related item might be among the top several items on the list. Regarding P@5, MRR@5, P@10, and MRR@10, we compare the effectiveness of the proposed TANN model with that of the most contemporary finest baseline models, namely NARM, STAMP, and LNIDA.

Table 2 shows the P@5 and P@10 results, which may reflect performance in actual production conditions to some extent.

In addition, Figure 4 depicts a graphical diagram of the P@K results when K=5 and 10 for the DIGINETICA dataset.

The results in Figure 4 show that the proposed TANN makes more exact recommendations. Furthermore, Figure 4 shows that the proposed TANN model outperforms NARM, STAMP, and LNIDA regarding precision.

In addition, Table 3 shows the MRR@5 and MRR@10 results, which may reflect performance in actual production conditions to some extent.

In addition, Figure 5 depicts a graphical depiction of the MRR@K results when K=5 and 10 for the DIGINETICA dataset.

The MRR is a normalized score with a range of [0, 100] percent; a greater value means that the majority of "hits"

TABLE 2. The P@K values for the DIGINETICA dataset with K=5 and 10.

Model	P@5	P@10
NARM	40.67	51.91
STAMP	41.04	52.07
LNIDA	41.99	52.39
TANN	44.89	57.14

TABLE 3. MRR@K results for DIGINETICA dataset when K=5, 10.

Model	MRR@5	MRR@10
NARM	25.02	26.53
STAMP	25.21	26.69
LNIDA	26.51	27.88
TANN	27.05	29.28

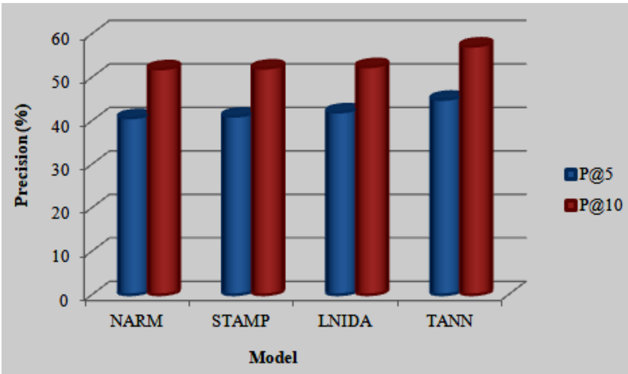

FIGURE 4. P@K values for DIGINETICA dataset for K=5 and 10.

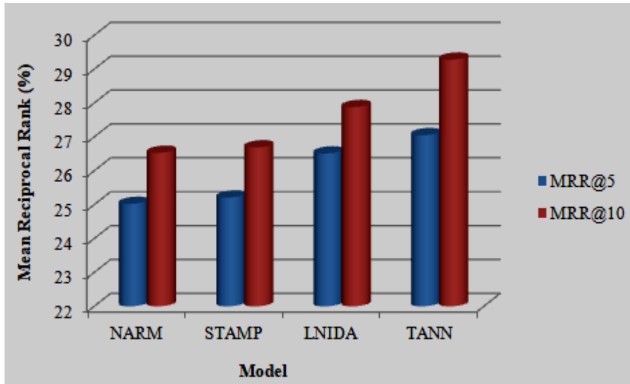

FIGURE 5. MRR@K results for DIGINETICA dataset with K=5 and 10.

will show larger in the ranking order of the suggestion list, indicating that the relevant recommender system is doing better. The results in Figure 5 show that the proposed TANN model provides more accurate recommendations. Furthermore, Figure 5 shows that the proposed TANN model outperforms NARM, STAMP, and LNIDA regarding mean reciprocal rank.

V. SCALABILITY CONSIDERATIONS

The scalability of a model plays a crucial role in its practical applicability in real-world scenarios. In this section, we delve into the scalability considerations of the proposed model, addressing the trade-offs between scalability and other performance metrics. Scalability refers to the ability of a system to handle increasing data volume and user demand while maintaining acceptable performance levels.

A. SCALABILITY CHALLENGES

The proposed model may encounter several challenges when it comes to scalability. As the system scales up, the following challenges become more pronounced:

1. **Increase in Data Volume:** Real-world scenarios often involve large-scale data, which can strain the model's capacity to process and analyze information efficiently. Handling massive datasets requires scalable solutions to ensure optimal performance.
2. **Computational Requirements:** Scaling the model to accommodate larger datasets and higher user demand can lead to increased computational requirements. This may include longer training and inference times, higher memory usage, and greater processing power. Therefore, ensuring that the model can scale without compromising performance is crucial.
3. **Response Time:** As the number of users and data volume grows, the model's response time becomes critical. Users expect quick and timely responses, and any increase in response time can negatively impact the user experience. Therefore, achieving low response times while scaling up the system presents a significant challenge.

B. PERFORMANCE METRICS AND SCALABILITY TRADE-OFFS

Scalability is not an isolated aspect of model performance but rather involves trade-offs with other key metrics. Therefore, understanding the relationship between scalability and other performance indicators, such as accuracy, latency, and resource consumption, is essential. The following trade-offs are commonly observed:

1. **Accuracy vs. Scalability:** Scaling the model may introduce compromises in accuracy. As the system handles larger volumes of data, it may be necessary to make approximations or employ sampling techniques, which can impact the precision of the model's predictions. Striking a balance between scalability and accuracy is crucial for real-world deployment.
2. **Latency vs. Scalability:** Increasing scalability often increases response times, resulting in higher latency. As more users concurrently access the system, response times can grow, affecting the user experience. Balancing low latency with high scalability requires careful optimization and efficient resource utilization.

3. **Resource Consumption:** Scalability can also impact resource consumption, including memory, storage, and processing power. Resource requirements increase as the system scales up, potentially leading to higher infrastructure costs and operational complexities. Efficient resource management is vital to ensure optimal scalability without unnecessary resource overhead.

C. TECHNIQUES FOR SCALABILITY IMPROVEMENT

Several techniques and strategies can be employed to address the scalability challenges and optimize the trade-offs. These techniques aim to enhance the model's scalability while maintaining acceptable performance levels. Some common approaches include:

1. **Model Parallelism:** Distributing the model across multiple devices or machines allows for parallel processing, enabling faster inference and scalability. Data parallelism or model parallelism can be employed to divide the workload effectively.
2. **Distributed Computing:** Leveraging distributed computing frameworks, such as Apache Spark or TensorFlow distributed, enables the model to scale horizontally across multiple nodes or clusters. This distributed approach allows for efficient utilization of resources and increased scalability.
3. **Caching Mechanisms:** Introducing caching mechanisms can alleviate the computational burden by storing and reusing intermediate results. Caching can significantly reduce redundant computations, thereby improving response times and scalability.
4. **Data Preprocessing Techniques:** Preprocessing the data to reduce its volume or to extract relevant features can enhance scalability. Techniques like dimensionality reduction, feature selection, or sampling can help handle large-scale datasets more efficiently.

D. EVALUATION OF SCALABILITY

Evaluating the scalability of the proposed model is crucial to ascertain its practical applicability. To assess scalability, the following metrics can be considered:

1. **Response Time:** Measuring the model's average time to respond to user requests under varying data volumes and user loads. This metric provides insights into how the model's performance is affected as the system scales up.
2. **Throughput:** Determining the number of requests or transactions the model can handle per unit of time. Throughput measurement helps evaluate the system's capacity to handle increasing user demand and data volume.
3. **Resource Utilization:** Assessing the utilization of computational resources such as CPU, memory, and storage during scaling operations. Efficient resource utilization ensures optimal performance and cost-effectiveness.

E. PRACTICAL APPLICABILITY AND FUTURE CONSIDERATIONS

Understanding the implications of scalability on the model's practical applicability is crucial. Large-scale deployments may introduce new challenges and constraints that need to be addressed. Consider the following aspects:

1. **Infrastructure and Deployment:** Consider the infrastructure requirements for scaling the model, including hardware, cloud services, or distributed computing frameworks. Assess the feasibility and cost-effectiveness of deploying the model in real-world scenarios.
2. **Maintenance and Monitoring:** Large-scale deployments require robust maintenance and monitoring procedures. Consider implementing monitoring systems to detect anomalies, manage resource allocation, and optimize system performance in real-time.
3. **User Experience:** Evaluate the impact of scalability on the user experience. Ensure the model's response times and overall performance meet user expectations even as the system scales up.
4. **Continuous Improvement:** Identify potential areas for improvement in scalability without compromising critical performance metrics. Consider ongoing research and development efforts to enhance scalability as new techniques and technologies emerge.

Overall, addressing scalability considerations and understanding the trade-offs with other performance metrics is crucial for assessing the practical applicability of the proposed model in real-world scenarios. By evaluating and optimizing scalability, stakeholders can deploy the model effectively and provide a seamless user experience while accommodating increasing data volumes and user demand.

VI. OVERCOMING DATA SPARSITY

Data sparsity is a common challenge in session-based recommender systems, where the available data for each user is often limited and sparse. In the context of the proposed approach for Smart EMS, which utilizes session-based recommendation, data sparsity can affect the effectiveness of the recommender system. However, some several techniques and strategies can be employed to overcome this problem. Here, let's discuss some of these approaches:

- **Session-based Neighborhood Selection:** In the proposed approach, the Enhanced Sqrt-Cosine Similarity based Neighborhood Sessions Discovery (NSD) is employed to find the most similar sessions to the query session. By selecting sessions that exhibit high similarity to the query session, the approach aims to leverage collaborative data and overcome data sparsity. In addition, this helps identify relevant patterns and preferences that may not be apparent in the individual session data.
- **Frequent Subgraph Mining:** The Frequent Subgraph Mining (FSM) step extracts frequent subgraphs from

the selected neighborhood sessions. These frequent subgraphs represent long-term preferences and can capture common patterns or item associations across sessions. The approach can identify more robust and reliable patterns by mining such subgraphs, even in sparse data.

- **Incorporating Contextual Information:** Context-aware recommendation techniques can help alleviate the data sparsity. The recommender system can better understand user preferences and make accurate recommendations by considering contextual information such as user demographics, item attributes, or temporal factors. This additional information provides a broader context for generating recommendations, compensating for the sparsity in the session data.

VII. CONCLUSION AND FUTURE WORK

The challenge of session-based recommendation was addressed in this paper by developing a new neural network structure known as the Triple Attentive Neural Network (TANN). The TANN model incorporates three components: Neighborhood Sessions Discovery (NSD), Frequent Subgraph Mining (FSM), and Top-K possible Next-clicked Items Discovery (TNID). NSD identifies neighborhood sessions, FSM extracts frequent subgraphs, and TNID discovers the top-K probable next-clicked items. Experimental results conducted on the DIGINETICA dataset confirmed the effectiveness of the proposed TANN model in accurately predicting next-clicked items. Furthermore, the findings highlighted the significance of incorporating supplementary neighborhood data, significantly improving recommendation accuracy. Additional item features, such as price and category, will be explored in future work to enhance recommendation performance further.

Moreover, there is a focus on investigating more efficient models that can reliably forecast customer buying intent, ultimately improving suggestion performance. Introducing the TANN model and its components contributes to session-based recommendation in Smart EMS systems. Furthermore, the results demonstrate the potential of AI-driven approaches in enhancing recommendation accuracy, thereby enriching user experiences and generating increased business value.

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