



A Multi-Session Framework for Adaptive Personalization in Context-Aware and Real-Time Recommender Systems

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ABSTRACT

This study presents a hybrid session-based recommendation framework that integrates a Context-Aware Gated Graph Neural Network (CA-GGNN) with a Transformer encoder to enhance personalization in dynamic, anonymous user environments. The model addresses key limitations of traditional session-based recommender systems, which often disregard contextual factors, struggle with long-range dependencies, and fail to generalize in sparse or complex sessions. In this study, each user session is represented as a graph structure capturing item transitions, enriched with contextual inputs such as time, device, and interaction intervals. The CA-GGNN component performs gated message passing to learn structural dependencies while integrating session-level context, whereas the Transformer encoder models global sequential behaviour through multi-head self-attention. A fusion layer combines graph-based and sequential representations to generate a unified embedding used for next-item prediction. Experiments on the Yoochoose dataset demonstrate that CA-GGNN substantially outperforms SR-GGNN, and that the hybrid CA-GGNN + Transformer model achieves further gains, particularly in long and complex sessions. Evaluation using P@20 and MRR@20 confirms improved ranking quality, while qualitative case studies highlight the hybrid model's ability to interpret shifting user intent more effectively. Overall, the proposed framework provides a scalable, context-sensitive, and real-time solution for next-item prediction in modern recommendation environments.

Keywords: Session-Based Recommendation, Graph Neural Networks (GNNs), Context-Aware Personalization, Transformer Self-Attention, Next-Item Prediction

1. INTRODUCTION

Recommender systems have evolved from simple rule-based and content-based methods to advanced deep learning models to better serve anonymous, short-term interactions [1], leading to approaches like the proposed Context-Aware Gated Graph Neural Network (CA-GGNN), which integrates temporal and environmental context to enhance real-time personalization [2][3]. Early systems such as collaborative filtering improved recommendation quality but suffered from cold-start and scalability limitations, motivating the shift toward more context-aware and session-focused techniques [4][5]. Modern recommender systems have progressed from matrix factorization to neural and graph-based models, enabling richer representations of temporal and contextual user behavior [6]. Context-aware and hybrid GNN-driven approaches now provide more adaptive, real-time personalization across domains such as e-commerce, entertainment, and social media, where

user preferences shift with time, mood, and location [7][8]. Traditional user-based models fail to capture these dynamic contextual patterns, reducing recommendation relevance in fast-changing environments [9][10].

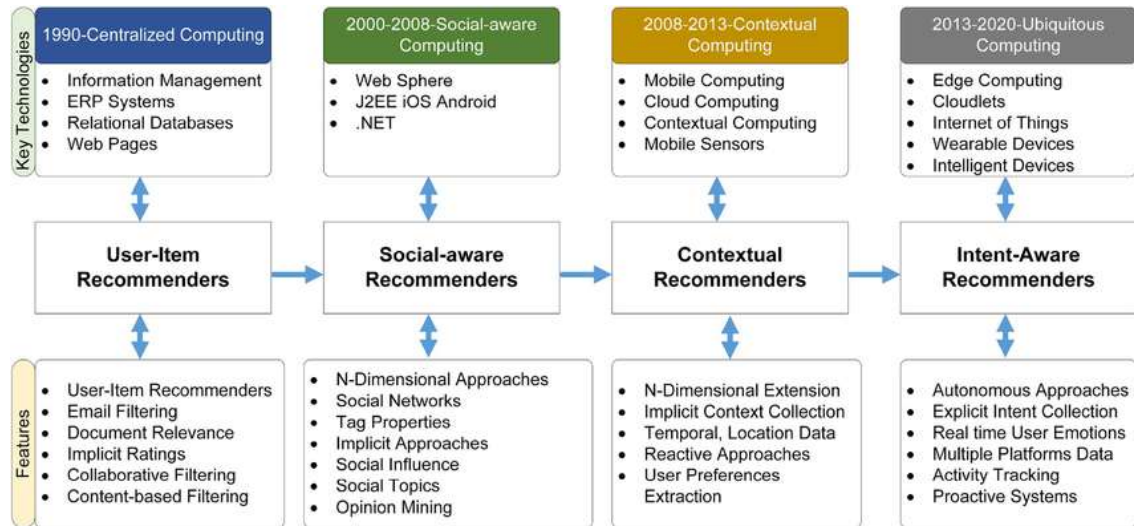


Fig. 1: Evolution of recommender systems with development in computing infrastructure [37] Traditional recommender models struggle with sparsity and fail to capture non-linear, contextual, and sequential cues essential for understanding a user's real-time intent [11][12]. Session-Based Recommendation Systems address these challenges by modeling short-term interaction patterns, enabling accurate predictions for anonymous users in fast-paced environments such as e-commerce, streaming, and news platforms [13][14]. Early SBRS methods relied on RNNs but often overlooked complex item relationships, motivating newer graph-based and context-aware approaches that better adapt to dynamic session behaviour [15][16]. These limitations reinforce the need for advanced models like CA-GGNN that incorporate contextual relevance to enhance personalization and stability in real-time recommendations [17][18].

Graph Neural Networks (GNNs) effectively model non-Euclidean structures such as session graphs, enabling rich aggregation of item relationships and contextual cues essential for recommendation tasks [19]. Their message-passing and inductive capabilities allow them to generalize to new sessions while capturing both local and global dependencies, leading to stronger personalization than traditional models [20][21]. Variants like GCN, GAT, and GGNN further enhance this modeling by integrating attention or gating mechanisms, making them well suited for sequential and context-aware recommendation scenarios [22][23]. When combined with gated units such as GRU, these models learn temporal dynamics more robustly, positioning GGNNs and extensions like CA-GGNN as powerful architectures for dynamic, real-time session-based recommendations [24][25].

Most existing session-based recommender models overlook graph structure and contextual factors such as time and device, limiting their ability to capture dynamic user intent in anonymous, short sessions; this motivates the need for a unified framework that integrates context, graph-based learning, and gated mechanisms for more adaptive recommendations.

The core problem is designing an architecture capable of modeling complex item transitions and temporal dependencies while incorporating real-time contextual signals to generate accurate recommendations without long-term user profiles. The proposed CA-GGNN addresses this gap by offering a scalable, context-aware, and structure-informed solution suitable for noisy, sparse, and rapidly changing environments.

2. LITERATURE REVIEW

Recent advances in session-based recommendation have introduced a wide range of graph-neural-network-enhanced models that address limitations of earlier sequential methods by integrating global item relations, social signals, multi-view knowledge, behavioral patterns, contrastive learning, and temporal or position-aware mechanisms. Approaches such as E-GNN [26], GNNRec [27], KMVG [28], and behavior-aware or attention-guided models [29][30] demonstrate strong improvements by capturing richer structural and contextual dependencies. Further innovations tackle challenges like new-item recommendation through dual-intent learning and zero-shot techniques [31], position-aware modeling for long- and short-term preferences [32], heterogeneous behavior integration [33], lightweight gated architectures for anonymous sessions [34], and repeat-aware or efficient graph construction strategies [35], while temporal multi-interest modeling in TMI-GNN continues to push performance boundaries in complex user-intent prediction [36].

Table 1: Graph Neural Networks for Session Recommendation

Ref. No.	Technique Used	Dataset Used	Key Findings	Results
[26]	Enhanced Graph Neural Network (E-GNN)	Two public datasets	Combines WGIG and LSG using a fusion algorithm to model real interaction patterns	Outperforms baseline models significantly
[27]	GNNRec using GGNN and GAT	Douban, Epinions	Aggregates social and session data for effective interest modeling	Performs significantly better than baselines
[28]	KMVG (Multi-View GNN)	Three real-world datasets	Uses knowledge, session, and pairwise views to capture global semantics and local behaviors	Outperforms state-of-the-art models
[29]	Behavior-aware GNN + Sparse Self-Attention	Two public datasets	Filters noisy behavioral data and models user interactions via directed graphs	Shows superior performance over baselines
[30]	Contrastive Multi-level GNN (CM-GNN)	Multiple benchmark datasets	Uses L-GCN, G-GCN, H-GCN and contrastive learning to capture high-order item transitions	Outperforms state-of-the-art methods
[31]	Dual-intent Enhanced GNN + ZSL	Real-world datasets	Addresses new item recommendation using intent prediction and zero-shot learning	High interpretability and superior performance
[32]	Position-Aware GNN (PA-GNN)	Three e-commerce	Incorporates item position and both short/long-term preferences	Outperforms existing SBR

		datasets		baselines
[33]	Behavior-Aware GNN (BGNN)	Three real-world datasets	Dual-channel learning for heterogeneous behaviors, scalable to multi-behavior recommendation	Outperforms baselines by up to 37.16%
[34]	MGU-GNN & MGU-GNN-TAR	Four public datasets	Lightweight gated units with attention and target-aware modules to capture long/current session interests	Superior performance with fewer parameters
[35]	RN-GNN	Three real-world datasets	Models repeat behavior and positional data using a local/global hybrid session graph built from mini-batches	Consistently outperforms state-of-the-art models
[36]	TMI-GNN (Temporal-aware Multi-Interest GNN)	Three benchmark datasets	Captures complex user intents using item-interest relationships and multi-form temporal data	Outperforms SOTA models consistently

3. RESEARCH OBJECTIVES

- Integrate additional contextual factors like user location, device type, and seasonality to enhance recommendation personalization.
- Develop real-time recommendation systems with dynamic adaptation based on immediate user interactions and feedback.
- Extend the model to capture user behaviour across multiple sessions, improving long-term preference prediction.

4. RESEARCH METHODOLOGY

This paper outlines the methodological process for developing a hybrid recommendation model that integrates a Context-Aware Gated Graph Neural Network with a Transformer encoder to capture contextual signals, item transitions, and long-range dependencies within user sessions. By combining graph-based context modeling with global self-attention, the system generates a unified session representation used to produce accurate next-item predictions.

4.1 Dataset

The research methodology uses the Yoochoose session-based dataset, consisting of millions of timestamped item interactions enriched with input context (time, category, device) and interval context (time gaps between clicks). Each session is modeled as a graph where items are nodes and transitions are edges, enabling the CA-GGNN to capture item dependencies while integrating contextual signals. The dataset is filtered, split into training and testing sets, and evaluated using P@K and MRR@K, demonstrating that incorporating both contextual and sequential information significantly improves next-item prediction accuracy.

4.2 Data analysis

Data analysis is the process of inspecting, cleansing, transforming, and modelling data with the goal of discovering useful information, informing conclusions, and supporting decision-making. Data analysis has multiple facets and approaches, encompassing diverse techniques under a variety of names, and is used in different business, science, and social science domains.

4.3 Data Pre processing

Data preprocessing in this study involves cleaning, integrating, reducing, and transforming raw session data to ensure high-quality inputs for modeling. Missing values, duplicates, outliers, and inconsistent formats are addressed, while normalization and standardization prepare features for efficient learning. Data integration merges heterogeneous sources, and reduction techniques streamline high-dimensional data for faster, more accurate model training. These preprocessing steps collectively ensure that the CA-GGNN model receives clean, structured, and scalable data for reliable session-based recommendation.

4.4 Model development

Model development in this study involves constructing a Context-Aware Gated Graph Neural Network (CA-GGNN) that transforms session sequences into graphs, initializes item embeddings, and refines them through gated message passing while integrating contextual signals such as time, location, and interaction intervals. A Transformer encoder further captures long-range dependencies, and a hybrid representation combines graph-based and attention-based features to predict the next item. The methodology includes node embedding initialization, multi-step GGNN propagation, context-aware fusion, and softmax-based scoring to generate ranked recommendations, optimized through cross-entropy or ranking-based loss functions.

Message Passing (Neighbor Aggregation):

$$m_i = \sum_{j \in N(i)} W_{edge} \cdot h_j$$

(1)

where:

- $N(i)$ = neighbors of node i
- W_{edge} = edge-specific transformation (e.g., different for incoming/outgoing edges)
- h_j = embedding of neighbor node j

Context-Aware Fusion (Gating):

$$g_i = \sigma(W_g[h_i \odot C_s] + b_g)$$

(2)

Where σ is sigmoid, and $\odot$ is element-wise multiplication

Next-Item Scoring (Dot Product Form):

$$s_i = h_{last} \cdot E_i$$

(3)

E_i is the embedding of candidate item i

Predication Phase:

$$P(i) = \frac{\exp(s_i)}{\sum_j \exp(s_j)}$$

(4)

The items with the highest probabilities are recommended as the next likely interactions.

4.5 Model Training

Model training updates the CA-GGNN parameters through iterative gradient-based optimization, where session data is divided into mini-batches, converted into session graphs, and passed through GGNN message-propagation, context-fusion, and softmax scoring to predict the next item. The loss (Cross-Entropy or BPR) is computed, gradients are back-propagated, and parameters are optimized using Adam/SGD with validation-based early stopping. For comparison, SR-GNN follows a similar graph-based training pipeline but relies solely on session graphs and attention-based aggregation without contextual fusion, making CA-GGNN more adaptive and context-aware in learning user intent. Fig. 2 illustrates the workflow of the SR-GNN model, starting from input session construction and progressing through GGNN propagation, attention-based session embedding, scoring and prediction, loss calculation, and finally model training. It visually summarizes the sequential processing steps involved in generating session-based recommendations.

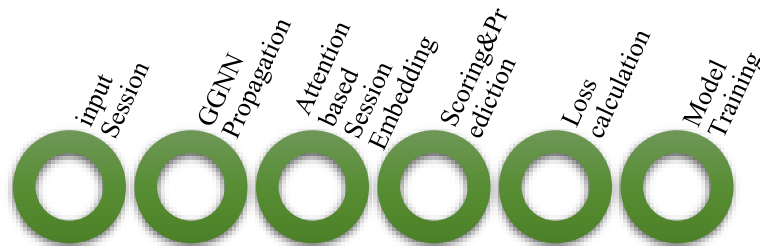


Fig.2: Flow chat of SR GNN model

SR-GGNN transforms each input session into a directed session graph, initializes item embeddings, and refines them through multi-step GGNN message passing to capture sequential and structural dependencies. An attention mechanism then generates a session embedding by weighting items according to their relevance to the user's current intent, which is used to score all candidate items via similarity-based prediction. A softmax layer converts these scores into probabilities, and training optimizes the model using cross-entropy loss to correctly rank the next item. This pipeline enables SR-GGNN to learn rich transitions, contextual importance, and session-level behavior for accurate next-item recommendation.

SR-GGNN and CA-GGNN + Transformer models train by minimizing prediction loss through iterative forward and backward passes, where session data is converted into graphs, embeddings are updated via GGNN propagation, and attention or fusion layers generate session representations for next-item prediction. Cross-Entropy is the primary loss, with BPR as an alternative for ranking, and regularization (e.g., L2) prevents overfitting. SR-GGNN relies on graph propagation and attention alone, while the hybrid CA-GGNN + Transformer model additionally captures long-range dependencies and contextual signals, improving

accuracy and adaptability. Training proceeds using mini-batch optimization (Adam/SGD), early stopping, and continuous monitoring of metrics like Hit@K and MRR@K for stable model convergence.

5. RESULT AND DISCUSSION

As observed in the table, CA-GGNN outperforms SR-GGNN, achieving a higher P@20 (72.93% vs. 70.90%) and MRR@20 (32.91% vs. 30.43%). The improvements demonstrate that incorporating session-level context enables the model to rank relevant items higher and provide more accurate recommendations. By balancing local graph structure with global session context, CA-GGNN offers a more robust approach to session-based recommendation tasks compared to the SR-GGNN baseline.

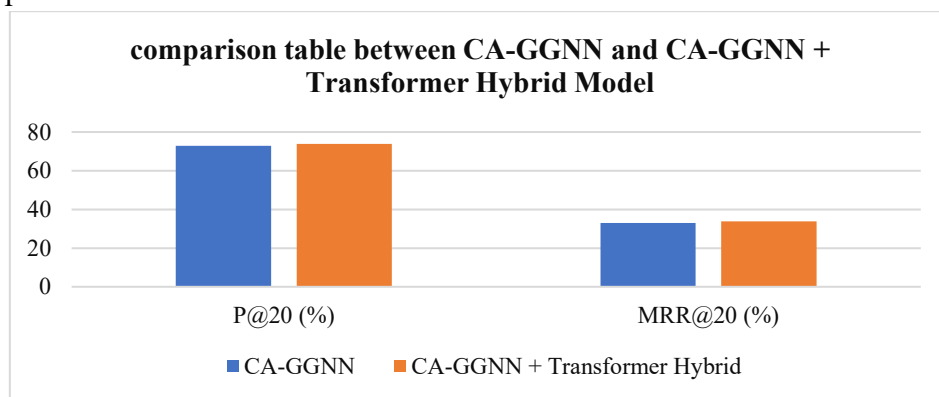


Fig. 3: comparison table between CA-GGNN and CA-GGNN + Transformer Hybrid Model

This study uses key Python libraries including PyTorch for deep learning and GPU-accelerated model training, and PyTorch Geometric (PyG) for efficient implementation of graph neural networks. Hugging Face Transformers supports advanced attention-based sequence modeling, while NumPy and Pandas enable data preprocessing and manipulation. Additional tools like Scikit-learn for evaluation and Matplotlib/Seaborn for visualization support the overall experimental workflow.

Table 2: comparison table between CA-GGNN and CA-GGNN + Transformer Hybrid Model

Model	P@20 (%)	MRR@20 (%)
CA-GGNN	72.93	32.91
CA-GGNN + Transformer Hybrid	73.85	33.80

The table compares CA-GGNN and CA-GGNN + Transformer Hybrid models, showing that adding Transformer self-attention improves performance. The hybrid model achieves 73.85% P@20 and 33.80% MRR@20, outperforming CA-GGNN by better capturing long-range dependencies, leading to more precise and higher-ranked next-item predictions. Fig. 3 compares the performance of CA-GGNN and the CA-GGNN + Transformer Hybrid Model using Precision@20 (P@20) and Mean Reciprocal Rank@20 (MRR@20) on the Yoochoose dataset. CA-GGNN enhances traditional GGNN models by incorporating a context-aware gating mechanism, which effectively fuses local item transitions with a global session context vector. This enables CA-GGNN to outperform baseline graph models like SR-GGNN by

providing a deeper understanding of user intent within a session. However, CA-GGNN's reliance on local graph structures limits its ability to capture long-range dependencies across sequences, which are essential for accurately predicting user preferences in complex sessions. To overcome this, the CA-GGNN + Transformer Hybrid Model integrates Transformer layers, leveraging self-attention to model global sequential patterns effectively.

Qualitative Case Study Section

A Qualitative Case Study Section illustrates how different models behave on real user sessions, revealing their strengths and weaknesses across short, long, or noisy interactions. It provides practical insight into how context-aware and Transformer-based mechanisms improve ranking decisions and enhances interpretability by showing why certain predictions succeed or fail.

Table 3: Qualitative Case Study Section

Session ID	Session Sequence (Clicked Items)	Ground Truth Next Item	SR-GGNN Prediction Rank	CA-GGNN Prediction Rank
S001	A → B → C → D	E	8	3
S002	X → Y → Z	W	Not in Top-20	12
S003	M → N → O → P → Q	R	5	2
S004	L → M	N	2	1

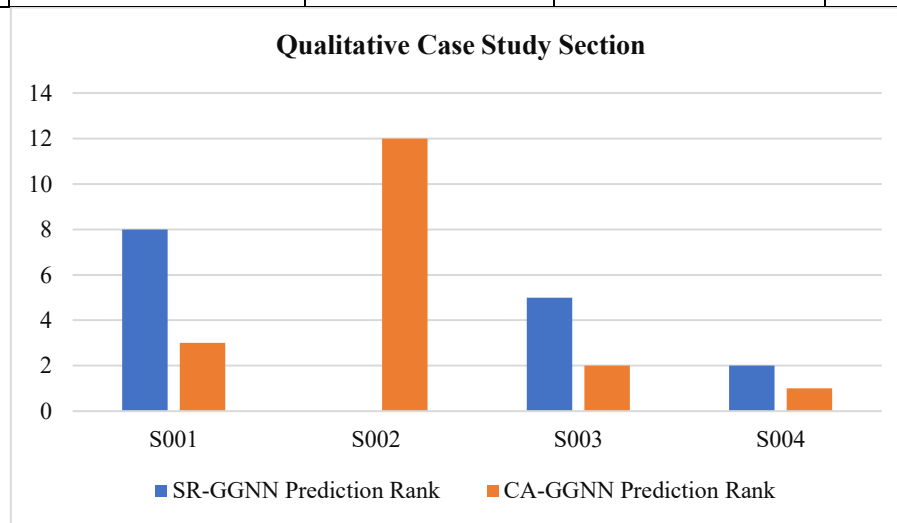


Fig. 4: Qualitative Case Study Section

Fig. 4 compares how each model ranks the correct next item within real user sessions, showing how architectural enhancements such as context-aware gating and Transformer self-attention directly influence decision-making. While SR-GGNN may struggle in complex or shifting sessions, CA-GGNN and Transformer-enhanced variants dynamically interpret context and long-range dependencies, consistently ranking relevant items higher. This session-level analysis visually highlights cases where simpler models fail and advanced models succeed, offering interpretability beyond aggregate metrics like P@20 or MRR.

6. CONCLUSION

The study demonstrates that incorporating contextual signals, graph-based learning, and sequential self-attention significantly enhances the accuracy and adaptability of session-based recommendation systems. CA-GGNN improves upon SR-GGNN by integrating session context into gated message passing, while the addition of Transformer layers enables the model to effectively capture long-range dependencies and evolving user intent. Experimental results on the Yoochoose dataset confirm higher $P@20$ and $MRR@20$ performance for both CA-GGNN and the hybrid model, with qualitative case analyses further illustrating their robustness across short, long, and noisy sessions. These findings validate the effectiveness of a unified context-aware, graph-driven, and sequence-aware architecture for real-time and multi-session recommendation tasks.

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