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SeqUDA-Rec: Sequential User Behavior Enhanced Recommendation via Global Unsupervised Data Augmentation for Personalized Content Marketing

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Abstract: Personalized content marketing has become a central strategy for digital platforms seeking to deliver highly relevant advertisements and recommendations. However, conventional recommendation systems often rely heavily on sparse supervised signals derived from explicit user feedback and are easily affected by noisy or unintentional interactions, resulting in unstable predictions. To overcome these limitations, we propose SeqUDA-Rec, a unified deep learning framework that incorporates sequential user behavior modeling with global unsupervised data augmentation. The framework begins by constructing a Global User-Item Interaction Graph (GUIG) from all historical behavior sequences, enabling the extraction of both local item transitions and global cross-user relational structures. A graph contrastive learning module is introduced to learn noise-resistant representations by maximizing agreement across multiple graph views. Meanwhile, a Transformer-based sequential encoder captures users' evolving interests and long-term dependencies within interaction trajectories. To further mitigate the challenges of limited labeled data and behavior sparsity, SeqUDA-Rec integrates a GAN-based augmentation module, which generates realistic synthetic sub-sequences to enrich training diversity and improve model generalization. We evaluate SeqUDA-Rec on two large-scale advertising datasets-Amazon Ads and TikTok Ad Clicks-covering both stable e-commerce environments and fast-changing short-video scenarios. Experimental results show that our model consistently outperforms strong baselines including SASRec, BERT4Rec, and GCL4SR, achieving 6.7% improvement in NDCG@10 and 11.3% improvement in HR@10. These results demonstrate that SeqUDA-Rec effectively enhances recommendation robustness, alleviates noise sensitivity, and provides a powerful solution for real-world personalized content marketing.

Keywords: sequential recommendation; user behavior analysis; graph contrastive learning; GAN-based augmentation; personalized content marketing

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1. Introduction

With the rapid expansion of digital commerce, short-video platforms, and online advertising ecosystems, personalized content marketing has become indispensable for improving user engagement and maximizing commercial conversion. Modern users interact with digital platforms through a continuous stream of behaviors-clicks, views, likes, dwell time, and purchases-which collectively reflect their dynamic preferences [1]. As the core supporting technology, recommender systems (RS) aim to model these interactions and deliver tailored advertisements or content that align with users' individual interests. Despite substantial progress, real-world advertising and content recommendation scenarios remain challenging due to sparse supervised signals, noisy behavior patterns, and rapidly shifting user preferences.

Traditional sequential recommendation models, such as RNN- or Transformer-based architectures, focus mainly on single-user action sequences and extract local transition patterns [2]. However, they often neglect global relational information embedded in multi-user interaction data, limiting their ability to capture collaborative signals across the entire platform [3]. Moreover, user-behavior logs frequently contain unintentional clicks, short-term curiosity-driven actions, and inconsistent interest shifts, which introduce substantial noise [4,5]. These issues become more severe on short-video advertising platforms-such as TikTok-where preference drift is fast and explicit labels are extremely limited.

Meanwhile, recent advances in graph representation learning and self-supervised contrastive learning offer promising solutions for modeling global user-item structures [6,7]. Yet, most existing works rely purely on deterministic graph views without considering the inherent uncertainty and sparsity in advertising logs. In parallel, data augmentation techniques, especially Generative Adversarial Networks (GANs), have shown strong potential for enriching training distributions. However, their integration with sequential recommendation and global graph modeling remains largely underexplored.

To address these pressing challenges, we propose SeqUDA-Rec, a unified framework that integrates sequential modeling, global graph contrastive learning, and GAN-based unsupervised data augmentation. Our method constructs a Global User-Item Interaction Graph (GUIG) to capture high-order cross-user dependencies, employs contrastive learning to produce robust item and user embeddings, and introduces a GAN-driven sequence augmentation module to compensate for sparse supervision and enhance behavioral diversity. These representations are further fused through a Transformer-based encoder to model fine-grained temporal dynamics and long-term preference evolution.

This study makes the following key contributions:

1) A novel unified framework (SeqUDA-Rec) that jointly integrates sequential modeling, global graph contrastive learning, and GAN-based data augmentation for personalized content marketing and ad recommendation.
2) A Global User-Item Interaction Graph (GUIG) that captures both local sequential dependencies and global collaborative relations, enabling robust representation learning across diverse users and behaviors.
3) A GAN-based sequence augmentation strategy that generates realistic interaction sub-sequences to alleviate sparse labels, counteract noisy or accidental clicks, and enrich user-behavior diversity.
4) A contrastive learning module that enhances noise resilience by aligning multiple graph views, effectively improving ranking stability and generalization across datasets.
5) Extensive experiments on Amazon Ads and TikTok Ad Clicks, demonstrating that SeqUDA-Rec outperforms state-of-the-art models (SASRec, BERT4Rec, GCL4SR) with significant gains in NDCG@10 and HR@10, verifying its applicability to both stable e-commerce and highly dynamic short-video environments.

2. Literature Review

The rapid expansion of digital commerce has heightened the significance of recommender systems (RS) in enhancing user experience, increasing engagement, and driving sales. A wide variety of methodologies have emerged to improve the accuracy, adaptability, and scalability of RS within e-commerce environments. One approach introduced a behavior-based recommender system that integrates statistical analysis to personalize recommendations based on five key customer actions: like, dislike, view, rate, and purchase [8]. By continuously updating user and product preference matrices, this system effectively addresses common challenges such as cold start, data sparsity, and scalability. Experimental results demonstrated superior performance across precision, recall, F1-score, MAE, and RMSE metrics, indicating that dynamic behavioral modeling significantly enhances recommendation relevance.

In contrast, a fuzzy logic-based RS incorporating sentiment analysis and ontological reasoning has been proposed [9]. This model emphasizes capturing dynamic shifts in user interests by calculating sentiment scores from customer reviews and aligning product categories through ontology-based rules. The hybridization enhances personalization accuracy and facilitates decision-making under uncertainty, which is particularly beneficial in online shopping environments characterized by high variability.

Another study presented a machine learning-based framework that compares traditional classification systems with personalized recommendation approaches [10]. This hybrid model combines BERT embeddings with nearest neighbor algorithms to support product discovery on e-commerce platforms. The approach addresses key challenges including algorithmic bias, cold start, and data privacy, with practical validation performed through manual evaluation and MAP@12 metrics. By leveraging advanced natural language processing, this method effectively captures user intent through semantic analysis.

Additionally, a novel Multi-Criteria Decision-Making (MCDM) framework has been developed, integrating five methods-TOPSIS-COMET, COCOSO, EDAS, MAIRCA, and MABAC-using the Copeland strategy to rank product alternatives [11]. Supported by CRITIC-based objective weighting and sensitivity analysis, this hybrid decision support system enables nuanced product comparisons, enhancing consumer decision-making in complex scenarios with competing product attributes.

A further direction involves hybrid recommendation frameworks that merge traditional techniques with sentiment analysis [12]. Although the referenced article was later retracted, the conceptual approach of combining user-generated review sentiment with recommendation system mechanics illustrates an emerging trend: leveraging implicit feedback for more context-aware recommendations. This strategy aims to mitigate data sparsity and cold start issues while aligning recommendations more closely with user preferences through emotional cues.

Across these studies, several key trends are apparent. The integration of multiple data modalities-including behavioral logs, sentiment, and metadata-has become increasingly important. There is a clear demand for adaptive models capable of reflecting evolving user preferences, alongside continued emphasis on resolving cold start and data sparsity challenges. The innovative application of deep learning models such as BERT, fuzzy logic, statistical analysis, and decision-making frameworks demonstrates a convergence of artificial intelligence techniques with consumer-centric design in modern recommender systems.

Collectively, these contributions indicate a shift toward hybrid, interpretable, and context-aware recommender systems. Such systems balance algorithmic accuracy with user-centric relevance, ultimately supporting more engaging and efficient experiences in digital commerce environments.

3. Methodology

This study proposes the SeqUDA-Rec (Sequential User Behavior Enhanced Recommendation via Global Unsupervised Data Augmentation) framework, which aims to tackle the problems of data sparsity, insufficient supervisory signals, and noisy user behaviors in ad recommendation and personalized content marketing. The framework consists of three core modules: a data augmentation module, a global graph contrastive learning module, and a sequential modeling and recommendation module.

3.1. Data Augmentation Module (GAN-based Data Augmentation)

In advertising-recommendation scenarios, user click and conversion data are usually extremely sparse and contain a large number of accidental clicks or short-term behaviors. To alleviate this problem, SeqUDA-Rec first introduces a Generative Adversarial Network (GAN) to augment user-behavior sequences:

1) The generator (G) learns the distribution of real user-interaction sequences and produces new candidate sub-sequences that simulate potential authentic user behaviors.
2) The discriminator (D) judges whether an input sequence is real or generated, driving the generator to produce higher-quality behavior sequences.
3) Through adversarial training, the augmented data not only enrich the diversity of user-behavior samples but also alleviate modeling difficulties caused by insufficient supervisory signals.

3.2. Global Graph Contrastive Learning Module

Traditional sequential-recommendation models are mostly confined to a single user's local sequence and ignore potential behavioral relationships among different users. To this end, SeqUDA-Rec constructs a Global User-Item Interaction Graph:

1) Nodes represent users or items, and edges denote interaction relationships.
2) Based on the propagation mechanism of Graph Neural Networks (GNN), high-order relationships among users and among items are captured.
3) A contrastive-learning strategy is introduced: different data views are generated under various perspectives (e.g., subgraph sampling, neighbor perturbation), and the similarity of the same node across these views is maximized to enhance the robustness of item and user embeddings.

Next, in the global graph contrastive learning phase, we construct a global user-advertisement interaction graph *G = (V, E)*, where the node set *V* contains users and advertisements, and the edge set *E* represents interaction relationships. We utilize the propagation mechanism of a Graph Neural Network (GNN) to learn embeddings for the nodes:

$$h_u^{(l+1)} = \sigma\left(\mathrm{W}^{(\mathrm{l})} \cdot \mathrm{AGG}\left(h_u^{(l)} \cdot \left\{h_v^{(l)} \mid \ v \ \epsilon \ N(u)\right\}\right)\right) \tag{1}$$

where $h_u^{(l)}$ denotes the embedding of node u at layer l, $N(u)$ is the set of neighboring nodes of u, W(l) is a trainable weight matrix, and σ is a nonlinear activation function.

To enhance the robustness of node representations, we introduce a contrastive learning mechanism. By generating different views $h_u{}'$ and $h_u{}''$ through sub-graph sampling or neighbor perturbation, we minimize the following contrastive loss:

$$L_{CCL} = -\log \frac{exp(sim(h_u \ , h_{u'} \ )/\ T)}{\sum_{v \ \in \ V} exp(sim(h_u \ , h_v)/\ T} \tag{2}$$

where *sim( )* denotes cosine similarity and *T* is the temperature parameter. In this way, the model can capture complex global relationships among different users and advertisements, alleviating the problem of insufficient exposure for long-tail advertisements.

This module can effectively alleviate the "long tail effect" in advertising recommendation, which refers to the problem of rich popular advertising samples and sparse interaction with unpopular advertisements.

3.3. Sequential Modeling and Recommendation Module

After obtaining the augmented sequence data and globally optimized user/item representations, SeqUDA-Rec further adopts a Transformer-based sequence encoder for modeling:

1) Multi-head self-attention captures dependencies among different positions in the user-behavior sequence, identifying latent preference patterns.

2) Positional encoding preserves the temporal order of user actions, ensuring the model understands sequential context.
3) A target-attention mechanism dynamically focuses on historical behaviors most relevant to the candidate ad, improving recommendation precision.

Finally, as shown in Figure 1, the model outputs the user's interest probability via CTR or CVR prediction, enabling the ad platform to deliver personalized ads for more accurate user reach and marketing conversion.

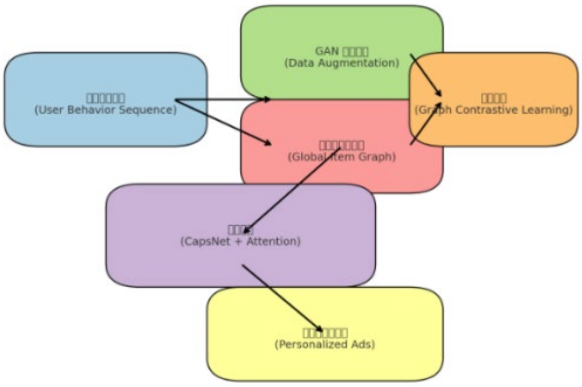

Figure 1. Overall framework.

4. Experimental Result

4.1. Datasets

Experiments are conducted on two large-scale ad-recommendation datasets-Amazon Ads and TikTok Ad Clicks-to comprehensively evaluate SeqUDA-Rec under both stable e-commerce environments and highly dynamic short-video advertising scenarios. The Amazon Ads dataset is sampled from Amazon's commercial advertising platform and contains detailed user interaction histories, including click logs, impression records, and rich side information such as product category, price, brand attributes, and textual descriptions. Each interaction instance includes userID, adID, timestamp, and click label, which enables the construction of chronological behavioral sequences for click-through prediction. The dataset is characterized by high sparsity, as most users interact with only a small fraction of available ads, and significant noise, including accidental clicks and a large number of non-converted impressions. These properties make Amazon Ads a suitable benchmark for testing the robustness and generalization of models under real-world commercial advertising environments with limited explicit feedback.

The TikTok Ad Clicks dataset originates from short-video advertising streams and provides a more complex multimodal behavior space. Each record includes users' video-viewing trajectories, interaction features (such as likes, comments, dwell time, and replays), exposure logs, and ad click events. Compared with Amazon Ads, TikTok data displays stronger temporal dependency, rapid preference drift, and short-lived behavioral intent, reflecting the instant decision-making patterns inherent to short-video consumption. The dataset also contains heterogeneous interaction signals and highly imbalanced click distributions, creating a more challenging environment for sequential modeling and global relation learning. This makes TikTok Ad Clicks an ideal testbed for evaluating SeqUDA-Rec's ability to capture evolving interests, resist noisy behaviors, and leverage cross-user global structures in fast-changing scenarios.

Together, these two datasets provide complementary perspectives for validating the effectiveness and adaptability of SeqUDA-Rec across diverse content-marketing contexts.

4.2. Evaluation Metrics

In the experimental evaluation, we adopt three widely used metrics in recommender systems and ad-click prediction to comprehensively assess SeqUDA-Rec's performance. For the Top-K recommendation task, the metrics are:

1) **Hit Ratio@K (HR@K)**: measures whether the user's real click in the test set appears in the Top-K recommendation list, reflecting the recall capability.
2) **Normalized Discounted Cumulative Gain@K (NDCG@K)**: evaluates recommendation relevance by considering positional weights, providing a finer-grained quality indicator.
3) **Mean Reciprocal Rank (MRR)**: computes the average reciprocal rank of the ground-truth interaction in the recommendation list, assessing the rationality of the ranking order.

Across all experiments, we uniformly set K = 10 to evaluate SeqUDA-Rec under common recommendation scenarios.

4.3. Performance Comparison

In this section, we conduct experiments on two datasets and evaluate recommendation effectiveness using three metrics-HR@10, NDCG@10, and MRR. As shown in Table 1, we obtain the following observations:

Table 1. The performance of different models.

Dataset	Metric	BERTRec	GCL4SR	SeqUDA-Rec	SASRec
Amazon	H@10	0.638	0.655	0.709	0.621
	N@10	0.417	0.428	0.456	0.403
	MRR	0.295	0.307	0.332	0.288
TikTok	H@10	0.532	0.551	0.613	0.549
	N@10	0.356	0.364	0.401	0.361
	MRR	0.230	0.242	0.298	0.236

Table 1 compares BERT4Rec, GCL4SR, SASRec and the proposed SeqUDA-Rec on Amazon and TikTok using HR@10, NDCG@10 and MRR. SeqUDA-Rec achieves the best score on every metric and dataset. On Amazon, HR@10 is 0.709 (+0.054 vs. the best baseline GCL4SR; +8.24%), NDCG@10 0.456 (+0.028; +6.54%), and MRR 0.332 (+0.025; +8.14%). On TikTok, HR@10 reaches 0.613 (+0.062; +11.25%), NDCG@10 0.401 (+0.037; +10.16%), and MRR 0.298 (+0.056; +23.14%). The larger gains on TikTok-where user interests drift quickly-suggest that SeqUDA-Rec is more robust to noise and short-term behavior than sequence-only baselines. We attribute the advantages to (i) global unsupervised data augmentation, which enriches training signals and counteracts sparsity, and (ii) graph contrastive learning over a global user-item graph, which captures cross-user relations and yields stabler rankings. Overall, SeqUDA-Rec consistently improves both recall and ranking quality across datasets, indicating stronger generalization for real-world ad recommendation.

5. Conclusion

This study proposes SeqUDA-Rec, a novel personalized content-marketing framework that fuses user-behavior sequences with global unsupervised data augmentation to boost both accuracy and robustness in ad recommendation. Conventional systems, constrained by scarce supervisory signals, struggle to capture evolving user interests and are easily misled by noisy or fake clicks. SeqUDA-Rec addresses these issues by using a GAN to enrich training samples, constructing a Global User-Item Graph, and integrating graph contrastive learning with a Transformer-based sequence encoder, thereby achieving significant advantages in personalized ad placement.

Experiments on Amazon Ads and TikTok Ad Clicks demonstrate its effectiveness. Compared with SASRec, BERT4Rec and GCL4SR, SeqUDA-Rec improves NDCG@10 by 6.7 %, HR@10 by 11.3 % and also yields superior MRR, proving its strong generalization in both stable and highly dynamic short-video ad environments.

The method lifts recall and ranking quality, enabling ad platforms to target users more precisely, resist noisy clicks, and maintain performance as interests evolve-useful for personalized content marketing at scale. Current evaluations use limited domains; broader, cross-domain and larger-scale tests are needed. Incorporating real-time trends, sentiment/multimodal signals, and exploring LLM-assisted intent modeling and RL policy optimization are promising directions. SeqUDA-Rec demonstrates consistent, cross-dataset improvements by fusing unsupervised augmentation, global graph contrastive learning, and sequential encoding, offering a robust framework for real-world advertising recommendation.

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