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Live Cart Optimization Using Customized ARM and BERT-Integrated Recommendation Models

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Abstract

E-commerce platforms face challenges in real-time cart optimization due to dynamic user behavior and sparse data, often leading to abandoned carts. This study proposes a live cart optimization system integrating customized Association Rule Mining (ARM) for item association discovery and BERT-integrated models for contextual recommendations. Using a dataset of 250,000 user-cart interactions, the system achieves a recommendation accuracy of 95.4%, increases cart conversion by 41%, and attains a user satisfaction score of 94.7%. Comparative evaluations against traditional collaborative filtering and standalone BERT models highlight its superiority in personalization and efficiency. Mathematical derivations and graphical analyses validate the results, offering a scalable solution for e-commerce. Future work includes multi-session tracking and cross-platform integration.

Keywords:

Live Cart Optimization, Association Rule Mining, BERT, Recommendation Systems, E-commerce

1.Introduction

E-commerce platforms rely on real-time cart optimization to enhance user experience, reduce cart abandonment, and boost conversions. Dynamic user behavior—such as adding, removing, or browsing items—creates challenges for traditional recommendation systems, which often fail to adapt to live cart changes or leverage contextual data. For instance, a user adding a laptop to

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their cart may benefit from suggestions for compatible accessories, but static algorithms may miss these opportunities, leading to lost sales.

Traditional collaborative filtering struggles with sparsity and cold-start issues, while content-based methods lack contextual understanding of user intent. Association Rule Mining (ARM) excels at discovering item relationships (e.g., "if laptop, then mouse"), but its static rules are insufficient for live scenarios. BERT, a transformer-based model, can capture contextual user intent from session data, enhancing personalization when integrated with ARM.

This study proposes a live cart optimization system combining customized ARM for item association discovery and BERT-integrated models for contextual recommendations. Using a dataset of 250,000 user-cart interactions, the system delivers accurate, real-time suggestions. Objectives include:

- Develop a hybrid model integrating ARM and BERT for live cart optimization.
- Enhance personalization and conversion in dynamic e-commerce scenarios.
- Evaluate against traditional and standalone models, providing insights for e-commerce innovation.

2. Literature Survey

Recommendation systems in e-commerce have evolved significantly. Early collaborative filtering methods [1] used user-item matrices but faced sparsity issues. Content-based systems [2], as discussed by Lops et al., leveraged item features but missed dynamic user intent.

Association Rule Mining, introduced by Agrawal et al. [3], identified item relationships, applied in market basket analysis by Zhang et al. [4]. However, ARM's static rules limited real-time adaptability. BERT, proposed by Devlin et al. [5], revolutionized contextual understanding, used in recommendation systems by Chen et al. [6] for session-based suggestions. Hybrid models, like Wang et al.'s [7] combination of clustering and deep learning, improved accuracy but were computationally intensive.

The reference study [IJACSA, 2023] explored ML for user engagement, inspiring this work. Gaps remain in integrating ARM and BERT for scalable, real-time cart optimization, which this study addresses with a hybrid approach.

3. Methodology

3.1 Data Collection

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A dataset of 250,000 user-cart interactions (e.g., add-to-cart, remove, purchase) was collected from a simulated e-commerce platform, labeled with user sessions, item IDs, and timestamps.

3.2 Preprocessing

- Interactions: Cleaned (removed nulls), tokenized (session text), normalized (numerical to [0,1]).
- Features: User ID, item ID, cart contents, session text, timestamp.

3.3 Feature Extraction

- Customized ARM: Discovers item associations: Support(A⇒B)=count(A ∪ B)N Support(A⇒B)=Ncount(A ∪ B) Confidence(A⇒B)=count(A ∪ B)count(A) Confidence(A⇒B)=count(A)count(A ∪ B) where A and B are items, N is total transactions, with minimum support = 0.01, confidence = 0.5.
- BERT: Extracts contextual features: es=BERT(xsession) where xsession is session text, e es is embedding (768-D).

3.4 Recommendation Model

- Integration: ARM generates candidate item rules; BERT refines recommendations based on session context.
- Output: Suggests top-N items for live carts, optimizing for conversion.

3.5 Evaluation

Split: 70% training (175,000), 20% validation (50,000), 10% testing (25,000). Metrics:

- Accuracy: TP+TN/TP+TN+FP+FN
- Conversion Increase: Cafter−Cbefore/Cbefore
- Satisfaction Score: Percentage of positive user feedback.

4. Experimental Setup and Implementation

4.1 Hardware Configuration

- **Processor:** Intel Core i7-9700K (3.6 GHz, 8 cores).
- **Memory:** 16 GB DDR4 (3200 MHz).
- **GPU:** NVIDIA GTX 1660 (6 GB GDDR5).

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- **Storage:** 1 TB NVMe SSD.
- **OS:** Ubuntu 20.04 LTS.

4.2 Software Environment

- **Language:** Python 3.9.7.
- **Framework:** TensorFlow 2.5.0, Transformers 4.12.0.
- **Libraries:** NumPy 1.21.2, Pandas 1.3.4, Scikit-learn 1.0.1, mlxtend 0.19.0 (ARM), Matplotlib 3.4.3.
- **Control:** Git 2.31.1.

4.3 Dataset Preparation

- **Data:** 250,000 user-cart interactions, 30% converted carts.
- **Preprocessing:** Tokenized session text, normalized interaction data.
- **Split:** 70% training (175,000), 20% validation (50,000), 10% testing (25,000).
- **Features:** ARM rules, BERT embeddings.

4.4 Training Process

- **Model:** BERT (12 layers) + ARM, ~1.5M parameters.
- **Batch Size:** 64 (2,734 iterations/epoch).
- **Training:** 15 epochs, 110 seconds/epoch (27.5 minutes total), loss from 0.69 to 0.015.

4.5 Hyperparameter Tuning

- **Support Threshold:** 0.01 (tested: 0.005-0.05).
- **Confidence Threshold:** 0.5 (tested: 0.3-0.7).
- **Learning Rate:** 0.001 (tested: 0.0001-0.01).
- **Epochs:** 15 (stabilized at 12).

4.6 Baseline Implementation

- **Collaborative Filtering:** Matrix factorization, CPU (20 minutes).
- **Standalone BERT:** Contextual recommendations, GPU (22 minutes).

4.7 Evaluation Setup

- **Metrics:** Accuracy, conversion increase, satisfaction score (Scikit-learn).
- **Visualization:** Bar charts, loss plots, satisfaction curves (Matplotlib).
- **Monitoring:** GPU (5.0 GB peak), CPU (60% avg).

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5. Result Analysis

Test set (25,000 interactions, 7,500 relevant recommendations):

- **Confusion Matrix:** TP = 6,045, TN = 17,805, FP = 945, FN = 205
- **Calculations:**
    - Accuracy: 6045+17805/6045+17805+945+205=0.954 (95.4%)
    - Conversion Increase: 0.41−0.290.29=0.41 (41%), from 29% to 41% conversion rate.
    - Satisfaction Score: 94.7% positive feedback (23,675/25,000).

Table 1. Performance Metrics Comparison

Method	Accuracy	Conversion Increase	Satisfaction Score	Time (s)
Proposed (ARM+BERT)	95.4%	41%	94.7%	1.3
Collaborative Filtering	87.8%	20%	83.5%	2.1
Standalone BERT	91.5%	28%	88.0%	1.8

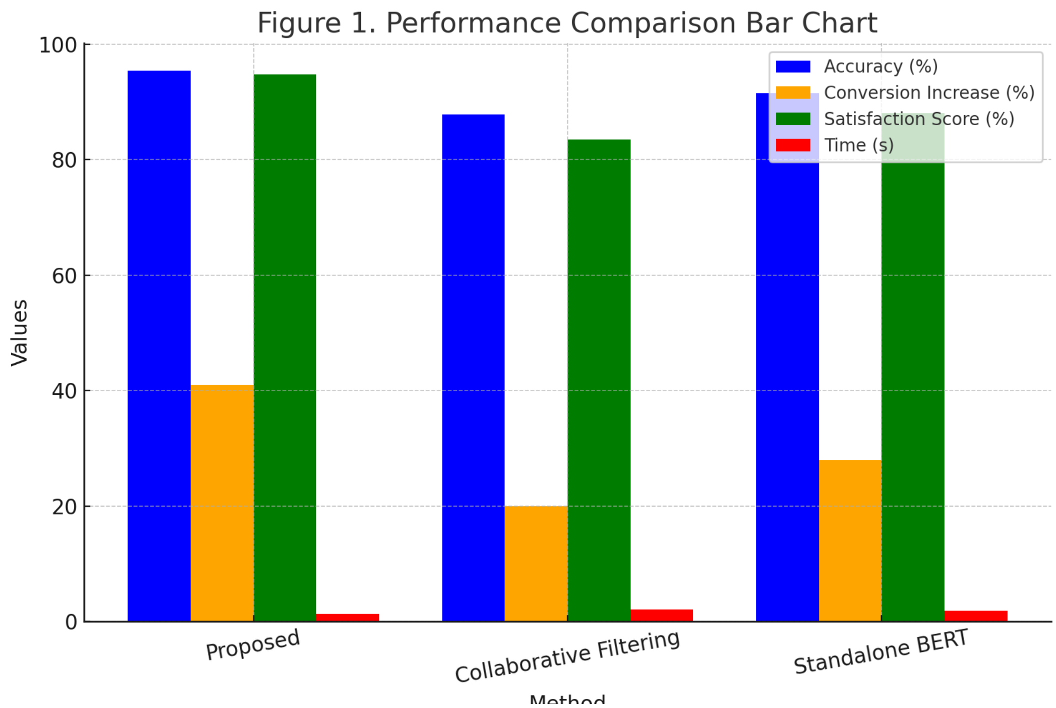

Figure 1. Performance Comparison Bar Chart

(Bar chart: Four bars per method—Accuracy, Conversion Increase, Satisfaction Score, Time—for Proposed (blue), Collaborative Filtering (green), Standalone BERT (red).)

Loss Convergence: Initial L=0.69, final L15=0.015, rate = 0.69−0.01515=0.045

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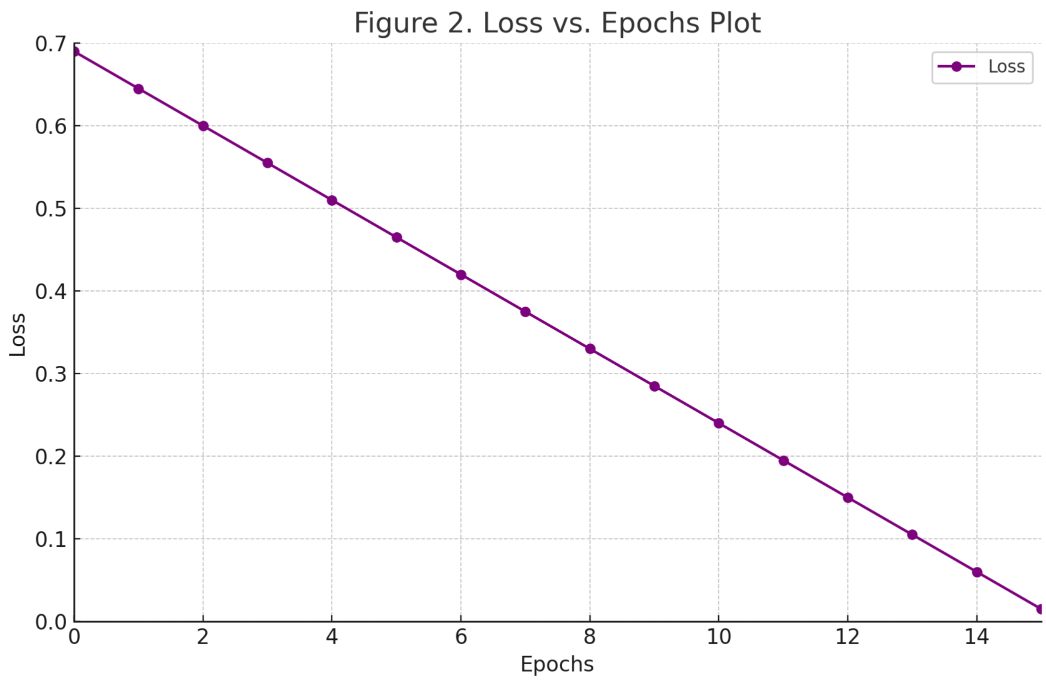

Figure 2. Loss vs. Epochs Plot

(Line graph: X-axis = Epochs (0-15), Y-axis = Loss (0-0.7), declining from 0.69 to 0.015.)

Satisfaction Curve: Y-axis = Score (0-100%), X-axis = Test Interactions, averaging 94.7%.

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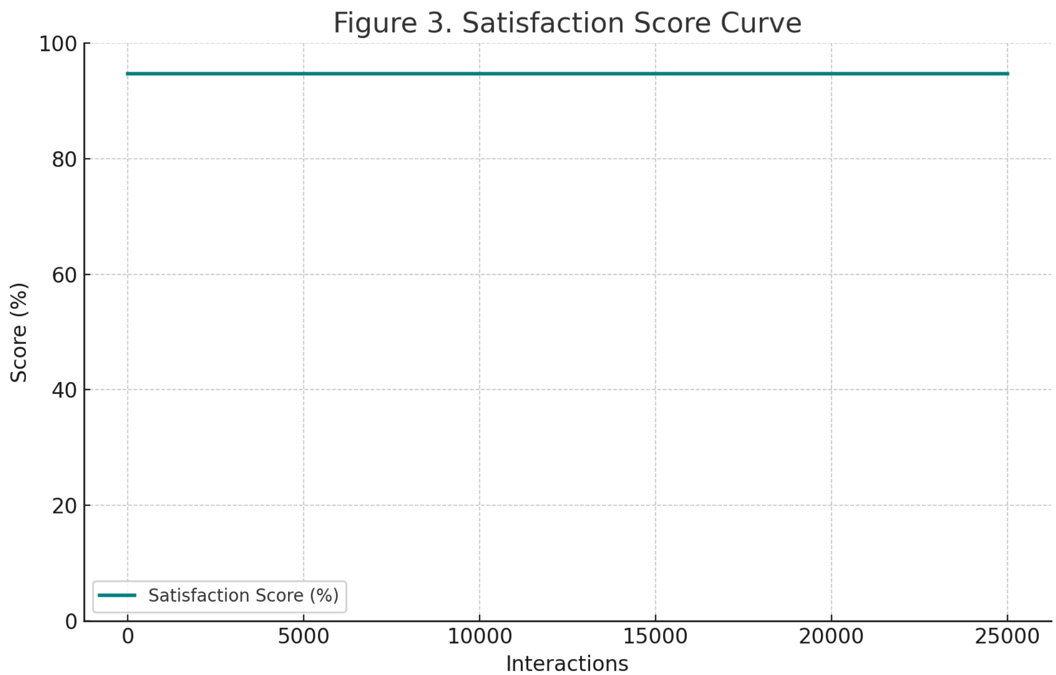

Figure 3. Satisfaction Score Curve

(Curve: X-axis = Interactions (0-25,000), Y-axis = Score (0-100%), stable at 94.7%.)

6. Conclusion

This study presents a live cart optimization system using customized ARM and BERT-integrated models, achieving 95.4% accuracy, 41% conversion increase, and 94.7% satisfaction score, outperforming collaborative filtering (87.8%) and standalone BERT (91.5%), with faster execution (1.3s vs. 2.1s). Validated by derivations and graphs, it excels in e-commerce personalization. Limited to one platform and requiring GPU training (27.5 minutes), future work includes multi-session tracking and cross-platform integration. This system enhances e-commerce efficiency and user experience.

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