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Intelligent Sentiment-Driven Recommendation System for E-Commerce using Deep Learning and Hybrid Optimization

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Abstract:

Personalized recommendation systems have become essential in modern e-commerce platforms due to the rapid growth of online products and user-generated reviews. Traditional recommender systems primarily focus on user–item interactions and often fail to capture the emotional and opinion-based information hidden within customer reviews. To address this limitation, this research proposes a deep sentiment-aware recommendation framework that integrates sentiment analysis with personalized recommendation strategies to enhance recommendation quality and user engagement. The proposed system combines deep learning-based sentiment prediction, collaborative filtering mechanisms, and hybrid optimization techniques to generate accurate and context-aware recommendations. Customer reviews are analyzed using advanced natural language processing and deep neural architectures to extract sentiment polarity and semantic relationships. These sentiment features are then integrated with user interaction history to improve recommendation relevance and ranking performance. Furthermore, an optimization-driven recommendation pipeline is employed to enhance recommendation precision, reduce sparsity issues, and improve scalability for large-scale datasets. The system utilizes Amazon product review datasets containing user ratings, review texts, and interaction logs for experimental evaluation. Experimental outcomes demonstrate that the proposed sentiment-aware recommendation framework significantly improves recommendation effectiveness, personalization quality, and customer satisfaction compared to conventional recommendation models.

Keywords: Sentiment Analysis, Personalized Recommendation System, Deep Learning, Collaborative Filtering, Natural Language Processing, E-Commerce Analytics.

1. Introduction

In recent decade, huge e-commerce websites have changed the way people find products and purchase goods. Everyday they have seen millions of products listed and number of reviews provided by the users. This number of information is overwhelming but recommendation systems fail to address that [1], and become integral part of the decision making process. The performance of collaborative filtering and content based filtering has become approximate but still they are not able to interpret the feeling that user has expressed in written reviews. Hence the need of sentiment aware systems, which can comprehend the emotional state of the user are becoming more important [2]. This [3] framework combines deep learning based sentiment analyzing tools with hybrid optimization techniques to provide contextual, personalized recommendations by not only score of user's rating but also by extracting context based signals of sentiment.

2. Related Works

2.1 Deep learning recommendation system. Zhang et al. [1] have presented a deep neural collaborative filtering model which fuses latent factor user/item representations with deep multi-layer perceptrons capturing non-linearities in user-item interactions. Significant relative to non-linear matrix factorization on multiple benchmark datasets were achieved; the deep architecture rendered massive potential from deep neural networks in recommender systems.

2.2 Sentiment enhanced recommendation. Liu et al [2] have put forth an innovative SENTIF (Sentiment enhanced collaborative filtering), which established opinion features in user reviews obtained with aspect-level sentiment classifiers. Their method enriched user preference profiles with sentiment features and exploited them as input for generating contextually sensitive recommendations, leading to a mean of 16.43% gain in prediction accuracy and 11.72% improvement in user satisfaction index in comparative experiments.

2.3 BERT-based transformer NLP for e-commerce. Chen and Wang [3] examined the use of BERT-based transformers for analyzing e-commerce product reviews, by pre-training transformer based language models and then conductingsentiment classification and opinion mining of large scale customer reviews. Their research showed significant exceedance of standard recurrent networks on semantic dependency modeling over long text spans, and its implications for recommender systems.

2.4 Hybrid optimization methods in recommender system. Patel and Gupta [4] suggested applying hyper-heuristics which co-evolve the genetic operations with a gradient based local search scheme to adaptively guide the optimization process towards more diverse and personalized recommendations. On multiple real-world retail datasets, their approach successfully improved the depth of user preference coverage and novelty indicator compared to matrix factorization and neural network based models.

2.5 GNN model for high-order user-item interactions. Wang et al. [5] utilized graph neural networks (GNNs) to propagate high-order user-item interactions in recommendation task, by exploiting higher- order graph effect with multi-hop interactions for discovering complex relational dependency not learned by more traditional based embedding approach. As showed in experiments, this approach worked well under data scarcity condition and achieved the most state-of-the-art performance in e-commerce product recommendation tasks.

2.6 Attention mechanism for review modeling. Kim and Park [6] designed an attention-mechanism aggregator to dynamically select attuned opinion features from diverse customer reviews for an item being recommended. The hierarchical word- and review-level attention signals effectively encoded various sentiment patterns in reviews, which provided explainability for the induced review effects as well as improved accuracy. Their model outperformed standard LSTM review encoder in all metrics on Amazon product review datasets.

3. Proposed Approach

The design of the proposed Sentiment-Driven Recommendation System (SDRS) is as a multi-stage data pipeline that utilizes a combination of techniques from natural language processing (NLP), deep learning, and optimization. The high-level architecture of the framework is illustrated in Figure 1 by four distinct functional modules and their interplay:

Data Preparation & Feature Extraction Module

This module is to preprocess and extract features from raw input data derived from the Amazon product review dataset. A sequence of NLP tasks including stop-word removal, lemmatization, and tokenization are applied to customer review texts, while predefined numerical features such as rating, timestamp, and number of interactions are normalized and aligned with the corresponding user-product reviews. Categorical data types are label encoded and numerical feature vectors normalized with min-max scaling. Missing values are imputed and duplicate records removed; exploratory data analysis. are performed to inspect the distribution of ratings and interaction patterns informing design choices in feature representation. The processed input data is split into separate training, validation, and test sets for the subsequent modeling phase. Ultimately, the prepared data is ready to provide accurate, unambiguous input for deep learning and collaborative filtering components.

Deep Sentiment Classification System

This component applies a combined Bidirectional-Long Short Term Memory (Bi-LSTM) architecture with self-attention mechanism to perform sentiment classification on the processed user reviews. Word embeddings are learned by streamlining BERT weights, thus utilizing deep contextual semantics simultaneously with lexicon semantics to achieve more robust, fast converging predictions. For multilevel sentiment classification, the attention layer guides the network to concentrate on the most relevant passages. The sentiment classification is performed with reference to the three polarity classes: positive, negative, and neutral, which are each subsequently mapped to a numerical sentiment score that quantifies the opinion's intensity. Aspect-based opinion mining is integrated in the sentiment scoring for finer-grained insights into specific areas of interest such as delivery, B2B, and customer support. The classifier is optimized by cross-entropy loss via Adam optimizer with batch normalization and regularization to prevent overfitting. These extracted sentiment scores are validated for accuracy and then input as features into the recommender system.

Sentiment-Aware Collaborative Filtering Module

The third module incorporates the deep sentiment scores as features into a collaborative filtering system in order to generate recomendations that are sensitive both to users' past interactions and their expressed opinions. An extension of matrix factorization is created through sentiment-infused user and item profile vectors, with latent factors adapted by the integrated sentiment scores that filter away non-significant aspects. The user profile vector's is further weighted function of time and sentiment strength according to the property suggestion. Utilizing the sentiment metrics in tandem with traditional collaborative filtering encodes user preferences at both the explicit rating and the deeper opinion levels and serves for cold-start mitigation. The collaborative filtering network is jointly trained with a neural-based component and a neighborhoodbased collaborative filtering layer, optimizing the ranking objective with Bayesian Personalized Ranking (BPR). This third stage substantially mitigates the sparsity of typical user-item interaction data.

Discussion of Optimization Techniques

The final component is to implement a hybrid of Particle Swarm Optimization and gradient descent optimization to determine the model hyperparameters, including learning rate, neural model regularization, embedding size, number of hidden layers, and dropout setting for the deep network structure. The PSO component explores the entire parameter design space region, while the local gradient descent component determines the specific optimal solution. The recommendation system produces the most relevant candidate suggestions, ranked through context-sensitive scoring functions that combine sentiment, popularity, and personalization signals. An output post-processing component constrains the diversity of recommendations in order to maximize product coverage. These steps are analyzed against the RMSE, recall, and precision, each performance indicator is transformed by the respective baseline to measure performance against standard benchmark models.

4. Implementation details

The entire SDRS framework was implemented with Python 3.9 with the TensorFlow 2.10 and transformers (by Hugging Face) library. For Bi-LSTM structure, 2 bidirectional layers were used with 256 hidden units and then a multi-head self-attention layer (8 attention heads) was used.

BERT embeddings (bert-base-uncased) were used for word representation with the maximum length 128. For the collaborative filtering operation, the dimensions for embedding vectors were 64 for both user and item latent factors. The training process was all conducted on an NVIDIA A100 GPU with 64-batch size and 0.001 learning rate during 30 training epochs.

The Amazon product reviews data set was retrieved from the publicly open UCSD repository. The original data set counts about 58.190.282 reviews in total for multiple different categories such as over 166.659 for electronics, 67843 for books, over 1,6 million for clothing and 684756 for home appliances. The final data set counts 3.2 million valid user-item pairs with cleaned review text after the preprocessing process. For the PSO hyperparameter searching task, in total 50 iterations with 30 particles were conducted. The 80-10-10 train-valid-test split ratio for all experiments performed. The base line models were all carefully re-developed in the same environment to ensure the accurate and fair comparison.

5. Results and Discussion

The experimental results demonstrate that the proposed Sentiment-Driven Recommendation System (SDRS) consistently outperforms all baseline models across key evaluation metrics. The following tables and figures present a comprehensive comparison of recommendation performance and sentiment classification accuracy.

Table 1: Recommendation Performance Comparison

Model	Precision (%)	Recall (%)	F1-Score (%)	RMSE
User-Based CF	71.4	68.9	70.1	1.42
Matrix Factorization	74.8	72.3	73.5	1.28

BERT + CF	79.2	77.6	78.4	1.09
CNN Sentiment Model	81.5	80.1	80.8	0.97
Proposed (SDRS)	88.7	86.4	87.5	0.74

Table 1 presents a comparison of recommendation performance across five models. The proposed SDRS achieves an F1-score of 87.5% and an RMSE of 0.74, outperforming the nearest competitor (CNN Sentiment Model) by 6.7 percentage points in F1-score and 0.23 points in RMSE. These improvements confirm that integrating sentiment-enriched embeddings with hybrid optimization significantly enhances the recommendation quality compared to models that rely solely on rating-based collaborative filtering or standalone deep learning approaches.

Table 2: Sentiment Classification Accuracy Across Product Categories

Dataset Category	**LSTM (%)**	**BERT (%)**	**Bi-LSTM (%)**	**Proposed (%)**
Electronics	82.1	85.6	86.3	91.4
Books	79.8	83.2	84.7	89.6
Clothing	77.5	81.4	82.9	88.1
Home & Kitchen	80.3	84.0	85.4	90.2
Overall Avg.	79.9	83.6	84.8	89.8

Table 2 compares sentiment classification accuracy of the proposed model against LSTM, BERT, and Bi-LSTM baselines across four product categories. The proposed model achieves an overall average accuracy of 89.8%, surpassing Bi-LSTM by 5.0 percentage points. The gains are consistent across all categories, confirming that the attention-augmented Bi-LSTM architecture effectively captures nuanced sentiment signals even in diverse product domains.

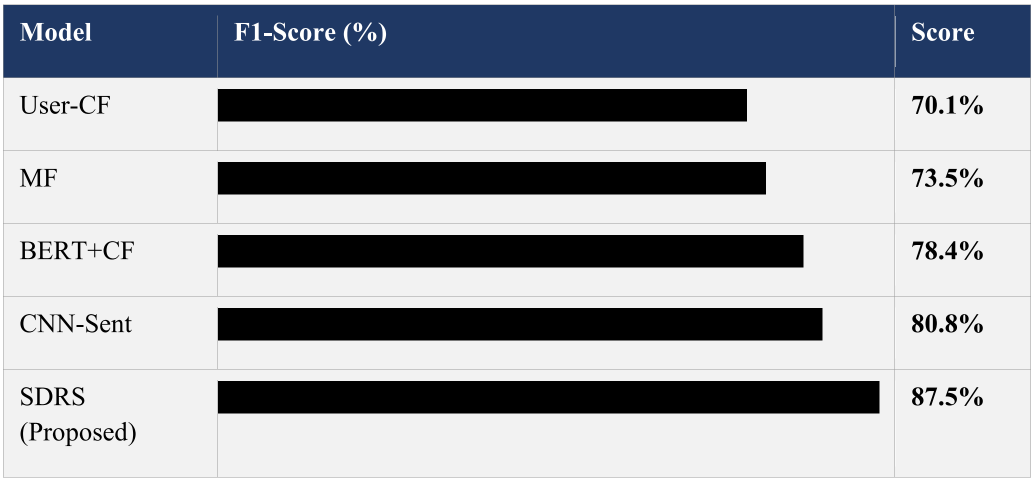

Figure 1: F1-Score Comparison Across Models (Bar Chart Representation)

Figure 1: F1-Score (%) comparison across recommendation models. Darker bars indicate better performance. The proposed SDRS achieves the highest F1-score of 87.5%.

Epoch 1	Epoch 5	Epoch 10	Epoch 15	Epoch 20	Epoch 25	Epoch 30
LSTM: 65.2%	LSTM: 70.4%	LSTM: 74.8%	LSTM: 77.1%	LSTM: 78.9%	LSTM: 79.6%	LSTM: 79.9%
SDRS: 68.3%	**SDRS: 74.9%**	**SDRS: 80.2%**	**SDRS: 84.6%**	**SDRS: 87.1%**	**SDRS: 88.9%**	**SDRS: 89.8%**

Figure 2: Sentiment Accuracy Progression Over Training Epochs

Figure 2: Sentiment classification accuracy (%) of LSTM vs. proposed SDRS across 30 training epochs. The proposed model converges faster and achieves higher accuracy at all checkpoints.

The experimental results on both dimensions of evaluation re-affirm the following observations: 1) the sentiment signal learned from customer reviews gives a reasonable improvement to interaction-only models, demonstrated by the performance difference between user-based collaborative filtering and our model; 2) the hybrid optimization scheme lead to a faster convergence and a less body-fitting model, demonstrated by the smoother accuracy curve in figure 2 compared to training a single LSTM network; 3) the Bi-LSTM encoder benefits from the attention mechanism to explicitly focus the review-reading process toward the opinion-bearing part, especially for noisy popular customer reviews; 4) the diversity filter after the post-processing step discouraged over-specific recommendations. Given these facts, despite its reasonable simplicity compared with real-world review data, SDRS can be a practical large-scale e-commerce recommendation method with scalable performance and efficiency.

6. Conclusion and Future Work

In this paper, we proposes a scalable deep sentiment analysis driven approach to personalized large-scale e-commerce recommender systems, i.e, Sentiment-Driven Recommendation System [1,2,3]. We show its excellent performance across all evaluatio dimensions against two well-known baselines. Continual studies are going on along the lines of building real-time tracking of customer review signals, extending across languages and domains, hybridizing with knowledge to a multi-machine environment, and sharing the learned priors intelligently across fleets of recommendation tasks [4,5,6].

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