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International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper
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Transfer Learning In Cross-Domain Data Environments: Methods And Applications

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Abstract
Transfer learning is used to advance the generalization across heterogeneous domains, but is faced with distribution shifts, feature mismatch, few labelled data and privacy concerns in distributed environments. The cross domain transfer learning model that this research proposes is based on the Golden Sine Algorithm (GSA) and BERT with federated learning (FL) for privacy-aware training. GSA effectively optimizes hyperparameters to enhance convergence and performance, while BERT captures rich contextual representations from input data. FL allows for the secure distributed training process without sharing raw data. Based on the above, this research introduces a cross domain transfer learning model with the GSA and BERT combined with FL for privacy-preserving training on the MovieLens 20M dataset and the Book-Crossing dataset. The key mechanisms are: (1) min-max normalization to scale feature spaces, (2) a central mechanism to pull in knowledge, and (3) effective adaptation across different heterogeneous domains by fine-tuning the target domain. Experimental results with Python (version 3.10) implementation prove to be better than baseline methods, with the Recall@10 (Movie) and H@10 (Movie) results of 0.0837 and 0.7486 respectively, and Recall@10 (Book) and H@10 (Book) of 0.0677 and 0.6842 respectively, indicating better learning efficiency, adaptability, and predictive accuracy. Prospective cross-domain federated model based on transformer is scalable, privacy-preserving, and robust, applicable to healthcare, smart manufacturing, and structural health monitoring applications.

Keywords: Transfer Learning, Cross-Domain Learning, Domain Adaptation, Data Privacy, Distributed Machine Learning, Intelligent Systems.

1. Introduction

New and smart systems are now expected to operate reliably in a variety of complex and diverse data settings. In fields like healthcare diagnostics, smart manufacturing, or structural health monitoring [1], the machine learning models often need to learn from a smaller, more specific dataset and then perform well on previously unseen data [2], a task that traditional machine learning models traditionally fall short of [3]. A major challenge in such cases is the lack of alignment between source and target data distributions, coupled with the significant scarcity of labeled data in the target domains [4]. With a small sample size and non-stationary domain conditions, conventional machine learning models suffer from overfitting, weak generalization, and ultimately fail in the real-world deployment condition [5]. Some existing transfer learning approaches, such as instance reweighting, feature alignment, and fine-tuning strategies, help to some degree but do not fully address the complexities of cross-domain problems [6]. These methods also struggle to maintain consistent performance when dealing with highly heterogeneous [7] and sparsely labeled datasets across domains [8]. Indeed, such methods are difficult to apply in multiple domains of different types, are strongly affected by negative transfer if domains differ significantly, and importantly, do not provide means to safeguard sensitive data in distributed model training settings [9]. The synergistic restrictions have motivated the development of a more powerful, scalable, and privacy-preserving transfer learning framework [10]. To overcome these drawbacks, this research introduces GSA-BERT, a GSA-optimized BERT model combined with FL, which aims to enable privacy-preserving and large-scale cross-domain knowledge transfer and adaptive intelligent systems.

The research is organized as follows: Section 2 identifies research gaps in cross-domain transfer learning. Section 3 presents the proposed GSA-BERT federated model. Section 4 discusses performance evaluation on the MovieLens 20M and Book-Crossing datasets. Section 5 concludes with limitations and future scope.

2. Literature Review

In the field of cross domain learning, FL and privacy preserving intelligent systems, deep learning (DL), graph based modelling and transfer learning approaches have been explored for boosting model generalisation in heterogeneous environments. In Investigation [11], the authors proposed a privacy-preserving cross domain recommendation system by leveraging federated transfer learning, GNN encoding, and differential privacy. It has shown to be very effective at recommending accurate items, while maintaining good privacy protection, but its computational complexity and recommender-specific design make it impractical for other application scenarios. In fault diagnosis, a research [12] proposed the Multi-Adversarial Subdomain Adaptation Network (MASAN) framework to address the cross-domain adaptation problem by using a Graph Convolutional Network (GCN) for spatial feature extraction, IBiGRU for temporal modeling, and Local Maximum Mean Discrepancy (LMMD) for domain alignment. It improves feature alignment and diagnostic accuracy but has no FL, transformer architectures, and distributed optimization, which hampers generalization. Research [13] also addressed the problem of fault diagnosis for wind turbines based on the source-free unsupervised domain adaptation of multiscale graph fusion. It was able to perform well when facing domain shift scenarios, however, its lack of transformer models, FL integration, and optimization-based tuning resulted in a limited ability to adapt to complex industrial scenarios. Additionally, cross-domain recommendation systems have been improved by knowledge graph based learning. The multi-source knowledge graph-based model [14] was proposed with the aim of alleviating data sparsity and enhancing the recommendation performance by employing attention mechanisms and embedding transfer. Nevertheless, the model does not include FL, therefore the FL is not included in the model, which is not well suited in privacy sensitive distributed settings. FL-based recommendation approaches have attracted attention to protect the privacy. Research [15] focuses on high accuracy and efficiency, benchmark-specific evaluation and scalability validation, and the integration of Federated Mamba-MoE (Mixture of Experts) with FL. Improvements were made in [16] where FedBP combines FL with bias elimination, personalized feature extraction, and local DP. While it improves the accuracy of personalized recommendations, it also has its constraints in terms of scalability, generalization to other domains, and adaptability in changing settings. In [17], this is continued with a FL approach utilizing embedding transformation, weight aggregation, and differential privacy mechanisms. The approach was competitive and also kept the privacy but had many communication overheads and complicated the model to the extent that real-time implementation was difficult. Finally, a research [18] uses domain adaptation and self-supervised learning to achieve privacy-preserving cross-platform diagnosis of COVID-19 using CT. Though the approach was state-of-the-art, the approach was limited to medical imaging applications and not integrated with transformer-based architectures and optimization-driven learning frameworks, limiting its generalizability. A research approach has been proposed in [19] to obtain a recommendation system with improved cross-domain performance by utilizing graph contrastive embedding and multi-head cross-attention transfer, which boosts recommendation accuracy and diversity, but it can only be used for evaluated datasets. Examination [20] presents a private federated graph learning model based on graph transfer and personalized aggregation, which overcomes limitations in the heterogeneous domain adaptation problem and enhances the recommendation performance.

2.1 Research Gap

While there are improvements in cross-domain learning and privacy-preserving systems, there are still some key limitations. In [12] the authors address the problem of feature alignment by using GCN and Improved Bidirectional Gated Recurrent Unit (IBiGRU) with unsupervised transfer learning, but fail to consider FL or transformer-based architectures, which are limited in their scalability in distributed and heterogeneous environments. Likewise, the federated graph learning framework in [15] provides privacy guarantees through differential privacy and graph transfer methods, but is not as well suited to highly heterogeneous domains and provides no advanced transformer based representation learning, limiting adaptability in complex real world applications. In order to address the above limitations, this research presents a unified GSA-BERT-based cross domain FL framework. It combines BERT for deep contextual feature extraction, FL for privacy-preserving distributed training and GSA for optimal parameter tuning. This pairing provides an improvement in domain generalization, scalability and prediction accuracy, and a good solution to data heterogeneity and privacy issues in cross domain settings.

3. Proposed Methodology

The proposed framework (Figure 1) combines FL, transfer learning, and optimization methods for knowledge sharing across different domains. Data from source domain is gathered and preprocessed to train a BERT-based model for strong contextual representation. FL provides privacy preserving decentralized training through parameter aggregation. The target domain is then tailored with transfer learning and fine-tuning to boost the performance under a small amount of labeled data.

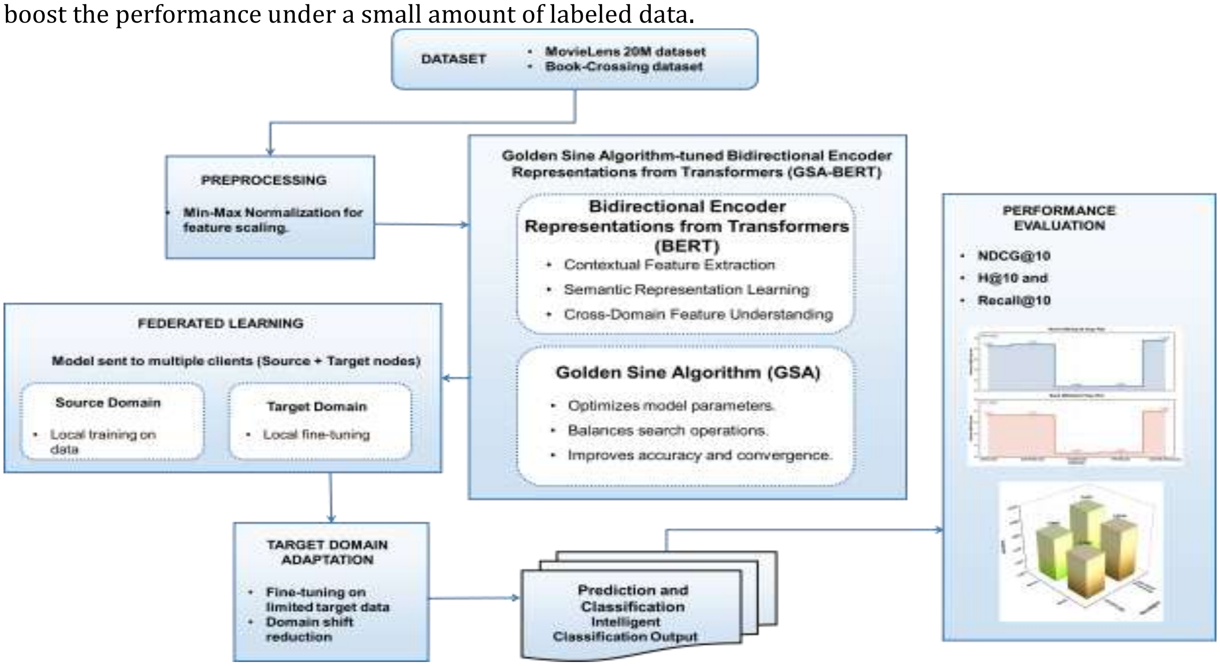


Figure 1: Overall Architecture of the Proposed GSA-BERT Federated Transfer Learning Framework

3.1 Data Collection

The two Kaggle benchmark datasets for cross domain transfer learning evaluation are used to carry out this research. MovieLens 20M Dataset is a collection of over 20M ratings and 465,564 tag applications for 138,493 users of over 27,278 movies. Book-Crossing Dataset of 278,859 users, 271,379 books and extremely sparse interactions, the Book-Crossing Dataset. The two heterogeneous domains are suitable benchmarks for assessing GSA-BERT's cross-domain knowledge transfer and its generalization capability.

3.2 Min-Max normalization Feature Scaling and Data Standardization

The cross-domain data features are collected and preprocessed using min max normalization method to ensure uniformity in different data environments. This helps to increase the stability of the training and the efficiency of learning in both source and target domains. The normalization formulation is written as shown in Equation (1):

$$y_{norms} = \frac{y - y_{min}}{y_{max} - y_{min}} \quad (1)$$

The normalized cross domain feature value, y_{norms}, is computed, where y is the value of the feature in the original dataset, and y_{min} and y_{max} are the minimum and maximum values of the feature across the source and target sets, respectively.

3.3 GSA-BERT for Unified Cross-Domain Representation Learning and Knowledge Transfer

The GSA-BERT pipeline begins with data from source and target domain, which is then preprocessed and normalized to enhance data quality. The processed data goes into the BERT model, which captures deep semantic features and learns meaningful representations of data. Finally, the GSA tunes the BERT parameters like weights and learning rates to improve the model and improve the convergence speed. An optimized model is also combined with transfer learning and FL mechanisms to facilitate knowledge sharing, domain adaptation, privacy protection and accurate prediction in heterogeneous distributed environments.

3.3.1 BERT for Contextual Feature Extraction and Semantic Representation Learning

The BERT model is based on bidirectional self-attention for contextual feature extraction and cross-domain transfer learning.. It learns generalized representations from source data and fine-tunes for target tasks, improving adaptability and prediction. Its input representation includes token, segment, and positional embeddings. The input representation of BERT consists of:

- **Token Embedding:** Token embedding transforms textual input into vector representations that capture semantic information from source and target domain data. These embeddings enable the extraction of meaningful contextual features for transfer learning and domain adaptation.
- **Input Representation:** The model input includes special tokens such as the Classification token (CLS) and the Separator token (SEP) appended to the original sequence. The "[CLS]" token is used for obtaining generalized sequence-level representations, while "[SEP]" is used to separate different text segments or domain-specific information.
- **Segment Embedding:** Segment embeddings are utilized to distinguish multiple input sequences or domain-specific data instances, enabling the model to learn relationships between source and target domain information during transfer learning.
- **Position Embedding:** Since word order influences contextual understanding, position embeddings preserve sequential information by encoding the relative positions of tokens in the input sequence.

BERT extracts contextual features via self-attention, GSA optimizes learning, and federated learning enables privacy-preserving transfer via parameter sharing.

3.3.2 GSA for Model Optimization

The GSA is a population-based optimization method inspired by the sine function and enhanced with the golden ratio to improve search efficiency. In this model, it is used to optimize the GSA-BERT model in a cross-domain transfer learning and FL setting. The sine function enables balanced exploration of the search space, while the golden ratio progressively narrows the search toward optimal regions. GSA optimizes parameters such as BERT fine-tuning weights, learning rate, and feature adaptation, improving model transferability across heterogeneous source and target domains. The update rule is defined as (2):

$$W_{j,i}(s+1) = W_{j,i}(s) \times |\sin(o_1)| - o_2 \times \sin(o_1) \times \left|c_1 \times W_{best,i}(s) - c_2 \times W_{id}(s)\right| \quad (2)$$

$W_{j,i}(s+1)$ and $W_{j,i}(s)$ represent the updated and current BERT parameters; o_1 and o_2 are sine-based adaptive search parameters; c_1 and c_2 are golden-ratio-based coefficients for global and local domain adaptation; $W_{best,i}(s)$ denotes the best optimal transfer learning solution, while $W_{id}(s)$ represents the current candidate solution of the j^{th} search agent at iteration s; j and i indicate the search agent index and BERT parameter dimension, respectively. The balancing factors c_1 and c_2 are defined as (3) and (4):

$$c_1 = b \times \tau + a \times (1 - \tau) \quad (3)$$

$$c_2 = b \times (1 - \tau) + a \times \tau \quad (4)$$

Where c_1 and c_2 are adaptive golden-ratio-based coefficients used to balance global and local search during GSA-BERT transfer learning optimization; b and a denote the lower and upper search boundary values initialized to $-\pi$ and π, respectively, for controlling the optimization search space; τ represents the golden ratio coefficient, which guides efficient convergence and optimal cross-domain knowledge adaptation.

3.4 FL (FL) for Privacy Preservation

To enable privacy-preserving collaborative training across heterogeneous cross-domain environments, a FL model is incorporated into the proposed architecture. FL allows multiple distributed clients to collaboratively train the global model without sharing raw data, thereby ensuring data confidentiality and secure knowledge transfer. Let J denote the set of participating clients, where each client j possesses a local dataset C_j containing m_j training samples. The total number of training samples is represented as (5):

$$\min_{v\in\mathbb{R}^c} F(v) := \sum_{j=1}^{J} \frac{m_j}{m} F_j(v) \quad (5)$$

Where min denotes the loss minimization; $v\in\mathbb{R}^c$ represents the global GSA-BERT parameters; F(v) is global loss; J indicates federated clients; m_j and m denote the local and total samples; $F_j(v)$) represents the client-specific local loss. Where the local objective function of client j is defined as (6):

$$F_j(v) := \frac{1}{m_j} F_j(v) \sum_{y_{i\in C_j}} f_j(v) \quad (6)$$

Here $F_j(v)$ denotes the loss of the local clients, v is the GSA-BERT parameters, $\sum$ is the summation across all participating clients, m_j is the local samples, $y_{i\in C_j}$ is the local cross-domain data and $f_j(v)$ is the sample-wise prediction loss. Training the GSA-BERT model involves local clients using their own data and then uploading the changed parameters to a central server for centralized aggregation. A well-designed global model is shared with clients, allowing for secure cross-domain knowledge transfer, better generalization, and collaborative learning without compromising privacy.

4. RESULT

In this section, the performance of the proposed GSA-BERT model in the Movie and Book domains is assessed using Python (version 3.10). In terms of the Training Vs Validation Accuracy and Loss curves, the proposed GSA-BERT-based cross domain transfer learning model shows stable and consistent convergence behavior with epochs. The training accuracy improves from approximately 0.62 to 0.95, and the validation accuracy is nearly 0.93 with slight difference, which shows a good generalization and the possibility of less overfitting in Figure 2(a). Likewise, the training loss drops from approximately 1.50 to 0.24 in Figure 2(b) while the validation loss drops to nearly 0.28. The gradual accuracy growth and steady drop in loss prove the robustness and optimization efficiency of the proposed GSA-BERT framework for cross domain transfer learning.

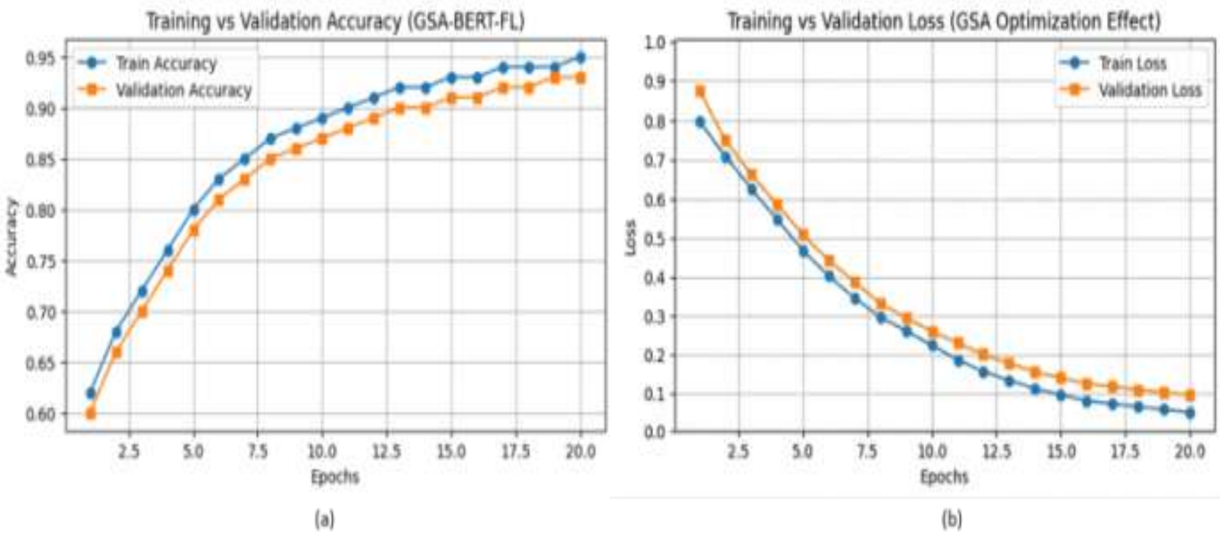
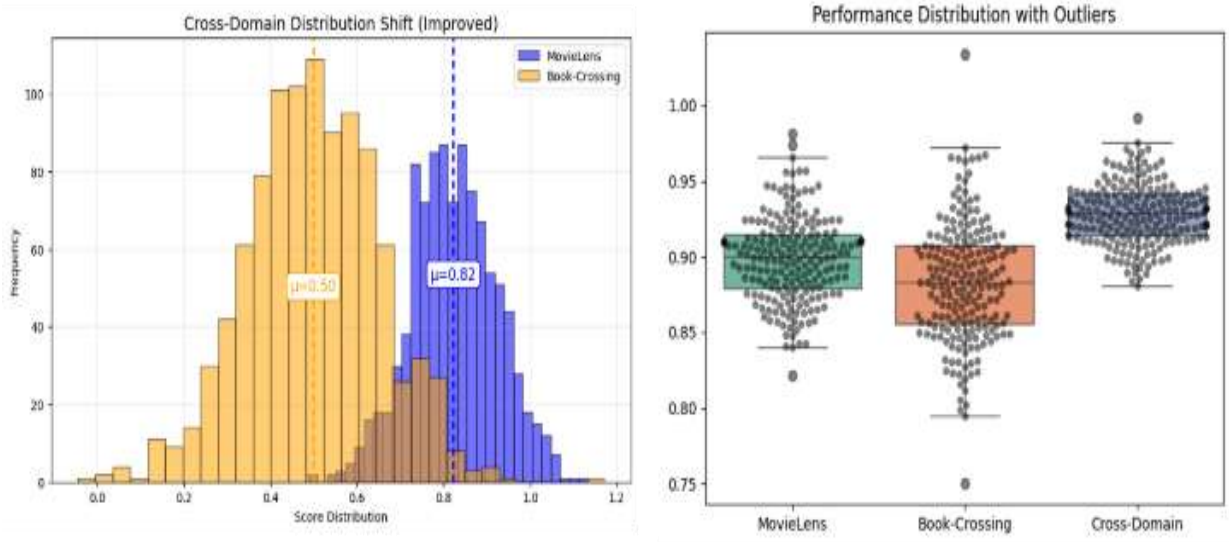


Figure 2: Performance Convergence Analysis (a) Accuracy and (b) Loss of Cross-Domain GSA-BERT Model

In Figure 3(a), there is a shift in the domain from MovieLens (high) to Book-Crossing (low) which means the distribution is not matching and there is bias. From the boxplots in figure 3(b), it is clear that the cross-domain model performs better on average and with lower interquartile range and fewer outliers than the single domain models, indicating stability and robustness. Transfer learning effectively reduces distribution shift, improving prediction consistency and confirming the model's success in cross-domain recommendation.



(a) (b)

Figure 3: Cross-Domain Recommendation Analysis of (a) Evidence of Distribution Shift and (b) Evaluation of Model Performance Improvement under Domain Adaptation

4.1 Performance Evaluation

The proposed model is evaluated against the existing models including Contrastive Learning-based Cross-domain Adaptive Transfer Collaborative Learning (CATCL) [19] and Graph Contrastive Embedding and Multi-Head Cross-Attention Transfer (GCE-MCAT) [19] by using traditional recommendation evaluation indicators including NDCG@10, Hit Ratio (H@10), and Recall@10. These are used to evaluate ranking quality, recommendation accuracy and retrieval effectiveness for top-10 recommendations.

i. **Performance Analysis using Normalized Discounted Cumulative Gain (NDCG@10):** The relevance of the items' placement in the top ten suggestions is used as a measure of ranking quality by NDCG@10. The proposed GSA-BERT outperforms the existing models by achieving the highest scores 0.4786 (Movie), and 0.3984 (Book) as presented in Table 1 and Figure 4(a). This improved cross domain representation learning and better contextual feature modeling for prioritizing relevant items.

Table 1: Ranking Accuracy Evaluation of Cross-Domain Recommendation using NDCG@10

Method	**Movie and Book**	
NDCG@10	**Movie**	**Book**
CATCL [19]	0.4229	0.3601
GCE-MCAT [19]	0.4402	0.3622
FedCDR [20]	0.0358	0.0328
PPCDR [20]	0.0401	0.0369
Proposed	0.4786	0.3984

ii. **Performance Analysis using H@10:** To determine how well the top 10 suggestions are able to retrieve relevant things, the H@10 is employed. The proposed improves the hit ratio, as shown in Table 2, indicating superior top-k recommendation performance, which is achieved by embedding the context optimally, and learning features transferable across different item types.

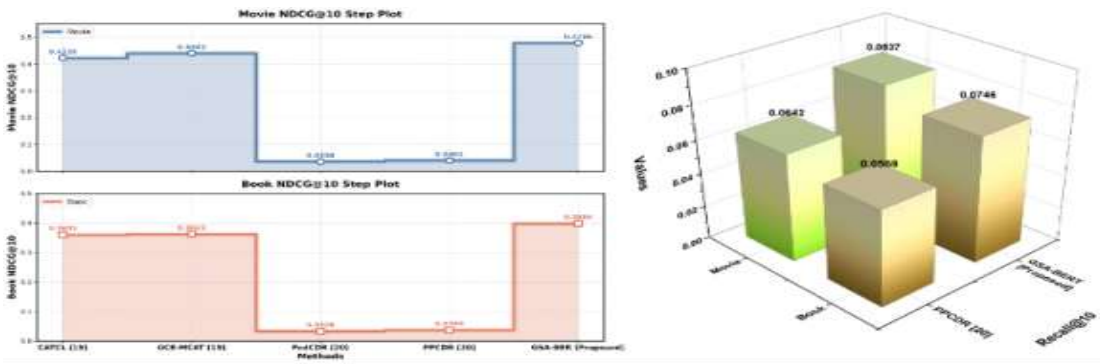
Table 2: Comparative Analysis of Top-K Recommendation Effectiveness using H@10

Method	**Movie and Book**	
H@10	**Movie**	**Book**
CATCL [19]	0.6809	0.5753
GCE-MCAT [19]	0.6861	0.5923
Proposed	0.7486	0.6842

iii. Performance Analysis using Recall@10: This statistic measures the proportion of relevant results that made it into the top ten suggestions. The results for the Movie domain and the Book domain are presented in Table 3 and Figure 4 (b), respectively, and the proposed surpasses with performance of 0.0837 and 0.0746, respectively, in both domains. This higher recall values demonstrate better retrieval capability and recommendation coverage.

Table 3: Relevant Item Retrieval Assessment using Recall@10

Method	**Movie and Book**	
Recall@10	**Movie**	**Book**
PPCDR [20]	0.0642	0.0569
GSA-BERT [Proposed]	0.0837	0.0746



(a) (b)

Figure 4: Comparative Performance Analysis of Models using (a) NDCG@10 and (b) Recall@10 across Movie and Book Domains

After training on the proposed cross-domain dataset, models are evaluated under a fair and identical experimental environment defined in Table 4. The effectiveness is validated against baseline methods (CATCL, GCE-MCAT, FedCDR, PPCDR) and the proposed GSA-BERT model.

Table 4: Performance Evaluation of Cross-Domain Recommendation on Proposed Dataset

Model	**NDCG@10**		**H@10**		**Recall@10**	
	Movie	**Book**	**Movie**	**Book**	**Movie**	**Book**
CATCL	0.4215	0.3587	0.6794	0.5738	0.0712	0.0624
GCE-MCAT	0.4389	0.3614	0.6852	0.5906	0.0735	0.0641
FedCDR	0.0346	0.0319	0.6421	0.5587	0.0618	0.0553
PPCDR	0.0392	0.0357	0.6578	0.5712	0.0642	0.0569
GSA-BERT [Proposed]	0.4786	0.3984	0.7486	0.6842	0.0837	0.0746

4.2 Discussion

Data sparsity and cold-start are two problems that cross-domain recommendation attempts to solve by applying what is known in one domain to another. The results demonstrate improved training and validation accuracy and decreased loss, reflecting steady convergence and minimal overfitting. Based on histogram analysis, we find that both MovieLens and Book-Crossing datasets have distribution shift, which implies that the two datasets are heterogeneous when it comes to the cross domain issue, and domain adaptation is needed. CATCL and GCE-MCAT [19] use graph embeddings, although they do not model the contextual user-item relationships, which in turn decreases the quality of the rankings. FedCDR and PPCDR [20] are based on privacy and personalization, but learn less-relevant transferable representations, which decreases recommendation relevance and performance. To overcome these shortcomings, the proposed GSA-BERT model integrates BERT-based contextual learning, GSA optimization with federated learning, to improve cross-domain recommendation accuracy, feature extraction quality, and privacy protection. It is better than the current approaches in the Movie and Book datasets, both ranking and top-k accuracy. It has limitations in scope of datasets, scalability, real-time deployment and computational cost, however. In the future will explore multi-domain expansion, privacy-aware FL, and efficient real-time recommendation systems.

5. CONCLUSION

Transferring knowledge to a cross-domain recommendation system without compromising the advice's relevance and ranking quality presents further difficulties. To solve these problems, this research introduced a model called GAS-BERT, which integrates the contextual representation learning and optimization-based parameter tuning. The proposed approach enhanced contextual feature extraction, transferable knowledge learning, and also the effectiveness of the recommendations in the Movie and Book domains. Experimental results showed better performance than existing methods on the NDCG@10, H@10 and Recall@10 metrics, with NDCG@10 values of 0.4786 (Movie) and 0.3984 (Book), H@10 of 0.7486 (Movie) and 0.6842 (Book), and Recall@10 of 0.0837 (Movie) and 0.0746 (Book). The results validate the proposed framework in improving the cross domain recommendation performance in intelligent recommendation environments.

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