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A Cross-Domain Recommender System for Literary Books Using Multi-Head Self-Attention Interaction and Knowledge Transfer Learning

Yuan Cui, Commerce Department, Shanxi Professional College of Finance, China & Lincoln University College, Malaysia*

Yuexing Duan, College of Information and Computer, Taiyuan University of Technology, China

Yueqin Zhang, College of Information and Computer, Taiyuan University of Technology, China

Li Pan, Zhengzhou Institute of Engineering and Technology, China & UCSI University, Malaysia

ABSTRACT

Existing book recommendation methods often overlook the rich information contained in the comment text, which can limit their effectiveness. Therefore, a cross-domain recommender system for literary books that leverages multi-head self-attention interaction and knowledge transfer learning is proposed. Firstly, the BERT model is employed to obtain word vectors, and CNN is used to extract user and project features. Then, higher-level features are captured through the fusion of multi-head self-attention and addition pooling. Finally, knowledge transfer learning is introduced to conduct joint modeling between different domains by simultaneously extracting domain-specific features and shared features between domains. On the Amazon dataset, the proposed model achieved MAE and MSE of 0.801 and 1.058 in the "movie-book" recommendation task and 0.787 and 0.805 in the "music-book" recommendation task, respectively. This performance is significantly superior to other advanced recommendation models. Moreover, the proposed model also has good universality on the Chinese dataset.

KEYWORDS

BERT Model, Comment Text, Cross-Domain Recommender System, Knowledge Transfer Learning, Literary Books, Multi-Head Self-Attention

INTRODUCTION

With the growing number of book resources, readers face increasing difficulty in finding books that align with their interests. To address this challenge, book recommendation technology has emerged (Moore et al., 2022). This technology utilizes user information, book information, and historical

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*Corresponding Author

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user behavior to predict books of potential interest, allowing users to quickly and accurately obtain relevant books and saving them significant time (Naghiaei et al., 2022; Zdravko, 2020). In addition, high-quality book recommendation methods can help book sales platforms improve their precision recommendation capabilities, thereby enhancing their core competitiveness (Lin, 2022; Shen et al., 2020).

Currently, literary books account for the highest proportion within the book industry. With the increasing sophistication of intelligence in the book industry, there is a growing emphasis on personalized recommendation of literary books. This, in turn, has become a significant area of research. However, the field of literary book recommendation faces several challenges (Behera & Nain, 2022; Choi et al., 2023; Herce et al., 2022):

1. The significant growth of data in the literary book domain has resulted in an enormous amount of information. This has led to the problem of data sparsity, which means the total number of books read by readers is only a small fraction of the available books. This makes it difficult to calculate the nearest neighbor of readers or books, leading to a sharp decline in the recommendation quality of the recommendation system.
2. The cold start problem refers to the challenge of recommending books to new readers or new books. This is due to the system having insufficient data on these users or items, hindering accurate recommendations.
3. Traditional book retrieval systems based on search engine technology struggle to properly reflect current user preferences. This limitation makes it difficult to achieve "truly personalized" recommendations, resulting in lower accuracy and recall of search results.

Cross-domain recommendation (CDR) aims to utilize information like user preferences and project features from other domains to help improve the accuracy of recommendations in the target domain (Zhou et al., 2023). This approach enables a more comprehensive modeling of users or projects in the target domain, effectively alleviating data sparsity and user cold start issues (Banik et al., 2023; Cao et al., 2022). Literature shows a significant correlation between users and projects across different fields (Liu et al., 2023). For example, users in different fields often share similar hobbies, such as those who love horror movies tend to purchase horror books, while those who love lyrical music tend to purchase romantic books.

To address the issues in the field of literary book recommendation, a CDR model is proposed, integrating multi-head self-attention interaction and knowledge transfer learning. The innovation of the proposed method lies in:

1. Existing single-domain book recommendation models often face problems related to data sparsity and user cold start. Therefore, a knowledge transfer strategy is adopted, extracting domain-specific features and shared features for joint modeling across domains. Large-scale training samples in the source domain are used to bridge the knowledge gap in the book review dataset, alleviating data sparsity and user cold start issues.
2. Adopting the pre-trained BERT model can effectively conserve time and computational resources required for model training. Encoding the word vector of comment text through a Transformer-encoder can effectively capture the bidirectional relationships within comment text statements. In addition, the use of a CNN to extract deep semantic information from comment text can improve the model's semantic representation capability.
3. A new approach to combining comment features is proposed, involving cross-combination followed by self-combination. In the feature extraction layer, cross combination can achieve a preliminary crossover of comment features between users and projects. In the feature self-combination layer, multi-head attention interaction is applied to achieve higher-order feature combinations (Huang et al., 2022), effectively improving the CDR performance of the model.

The remainder of this article is arranged as follows. Section 2 reviews the related works about book recommendation and CDR. The proposed CDR model is described in Section 3. The results of CDR experiments on the Amazon dataset and universal experiments on several other datasets are provided in Section 4. Section 5 presents the achievements, limitations, and future work.

RELATED WORKS

Single Domain Book Recommendation

Many existing single-domain book recommendation methods are based on collaborative filtering (CF) techniques (Jian et al., 2022). Ruchitha (2021) used victim filtering strategies to preprocess information and provided recommendations based on CF or matrix factorization (MF). Wang and Hou (2021) proposed a CF-based book recommendation method, considering the book's interest as an important measure, including factors like search frequency, borrowing time, borrowing frequency, borrowing interval, and renewal frequency. Guo et al. (2023) proposed a recommendation method based on multi-factor random walk (MFRW), where MFRW calculated the current user's comprehensive trust value toward other users based on common friends, enhancing recommendation accuracy. Yin et al. (2022) proposed a multimodal recommendation model that employed a dual attention mechanism to quantify investor preferences, used deep networks to learn project features, and combined CF mechanisms to model both aspects.

However, these methods only use information from the book field for recommendations, which requires a substantial number of training samples. This reliance results in data sparsity and user cold start issues, significantly affecting the effectiveness of these recommendation methods.

CDR

The purpose of CDR is to utilize sufficient data from the source domain to alleviate the scarcity of user behavior in the target domain. Most existing cross-domain personalized recommendation methods rely on CF, while others use transfer learning and knowledge-based approaches. In a new approach, Liu et al. (2021) designed a cross-domain recommendation framework using deep adversarial and attention network (DAAN), leveraging both domain-shared knowledge and cross-domain specific knowledge. This approach combines CF, based on matrix decomposition, with deep adversarial domains through attention networks to achieve project recommendations. Liu et al. (2022) designed a deep selective learning network (DSLN) utilizing comments to characterize user preferences and project features. At the same time, useful information was selected and shared through a denoising autoencoder (DAE).

Yu, T., et al. (2021) proposed a hybrid heterogeneous decomposition model for extracting and transferring shared knowledge between the auxiliary and target domains. The model captures shared knowledge and domain features based on adaptive tensor decomposition and biased matrix decomposition, respectively, and then accumulates and combines them to obtain recommendation results. Yu, X., et al. (2021) proposed a cross-domain recommendation model using CF and latent factor alignment (CDCFLFA), calculating the project potential vector of the target domain by solving a linear least squares problem and obtaining unknown ratings based on updated user and project potential vectors.

Xie et al. (2021) proposed a new contrastive cross-domain recommendation (CCDR) framework, building a diverse preference network to capture users' information and design an intra-domain and three inter-domain comparative learning tasks to construct different cross-domain interactions. Wang et al. (2022) proposed a link prediction model based on the graph bidirectional aggregation network (GBAN), which utilizes a reverse aggregation mechanism to reconstruct user node feature representations and combines the scores between nodes to complete link recommendations. Wang et al. (2021) proposed a recommendation system based on cross-domain personality, defining the problem of cross-domain personality feature classification and employing predictive text embedding as a transfer learning method to transfer personality information from the source domain to the target domain.

While these models can achieve good cross-domain recommendations, they do not effectively extract the association relationship between the source and the target domains. Thus, it is difficult to provide users with truly personalized recommendation results.

Cross-Domain Book Recommendation

Taushif and Uma (2019) used ontology to discover the semantic similarity of items, applied CF to find similar items and users, and used the PrefixSpan sequence pattern mining algorithm to generate frequent item sequences. The expand cross-domain recommendations, they applied the TopSeq rule mining algorithm to recommend user preference items. Despite its focus on book recommendation, the above model does not effectively utilize the rich information contained in the comment text, making it difficult to address data sparsity and user cold start problems in this field (Zhang et al., 2022).

Motivation

The above analysis highlights that only a few cross-domain personalized recommendation models focus on books. While some studies have explored cross-domain recommendations for Movie-Books and Music-Books, they have not specifically addressed the problems of data sparsity and user cold start in this field. Moreover, there is room for improvement in the performance of personalized book recommendations.

To address the data sparsity and user cold start issues in existing recommendation models, this article extracts features from user and project comment aggregation texts in the source and target domains, respectively. This approach enhances the modeling of cold start users and projects. The article also uses a multi-head self-attention mechanism to extract important information from word-level features in the comment text, thereby improving the model's attention to important information. In addition, a new CDR model is proposed, aiming to effectively transfer learned knowledge, improve recommendation performance, and alleviate data sparsity and user cold start issues.

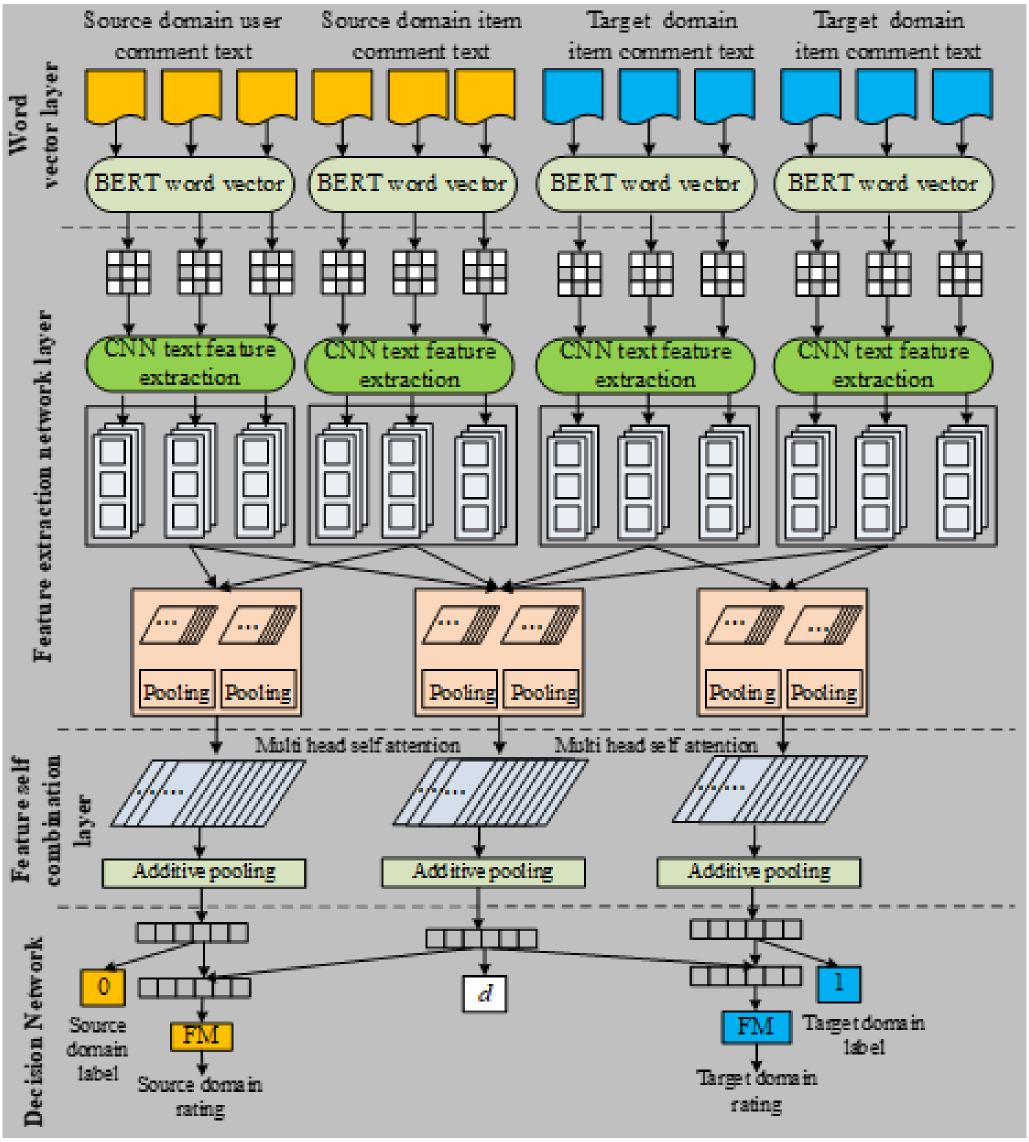
PROPOSED CDR MODEL

Overall Architecture of the Model

The proposed model aims to enrich the knowledge in the target domain by transferring insights from the source domain, achieving cross-domain knowledge transfer. It addresses the issues of sparse data and user cold start in the target domain by reasonably modeling and extracting effective information from the comment text, thereby improving the accuracy of target domain recommendations. The proposed model is constructed to jointly model three different domains: (1) source domain; (2) target domain; and (3) shared domain. It relies on a feature extraction network based on the dual attention mechanism, learning domain-specific features in the source and target domains, as well as shared features. Finally, the model incorporates the factorization dimension (FM) of the factorization machine to construct a cross-domain recommendation model. Figure 1 shows the architecture of the proposed model, including the word vector layer, feature extraction network, feature self-combination layer, and decision network.

1. **Word Vector Layer:** The embedded representation of text content is obtained through the pre-trained BERT model. The text features obtained from the BERT model are re-aggregated using a Transformer-encoder (He et al., 2022; Huang et al., 2023; Miyazawa & Nagai, 2023).
2. **Feature Extraction Network Layer:** First, CNN is used to simultaneously extract the source domain features, target domain features, and shared features from users' and items' comment texts (Li et al., 2023; Yang, 2023). Then, a cross-combination is performed, involving the source

Figure 1. Overall framework of the proposed method



domain (user & item), shared domain (source domain user & source domain item & target domain user & target domain item), and target domain (user & item), resulting in fused features.

3. **Feature Self-Combination Layer:** The multi-head self-attention mechanism is used to capture crucial information within the features, which is then fed into feedforward neural networks for analysis and output. Finally, adding and pooling techniques are used to obtain user and item vectors based on comments (Miao et al., 2022; Osei et al., 2022).
4. **Decision Network Layer:** Decision networks fuse knowledge from different fields (Li, et al., 2022) and use factor decomposition machines for scoring prediction (Chen et al., 2022).

Related Definitions

For the convenience of reading, the following definitions are used in the model.

Definition 1. Data Representation: The data representation of the input model can be described as a quad $\left\{U, I, G_I^U, S_I^U\right\}$, where *U* is the user, *I* is the item, G_I^U is the comment made by *U* on *I*, and S_I^U is the rating given by *U* on *I*.

Definition 2. Comment Aggregation Text. All comment texts written by a user *u* for *I* or all comment texts written by *U* owned by item *i*.

Definition 3. User Behavior. A user's behavior can be reflected in their project comments. This text can be described as a binary $\left\{u, \Psi^u\right\}$, where *u* represents the user, Ψ^u represents the set of comments written by user *u*, $\Psi^u = \left\{G_1, G_2, \cdots, G_m\right\}$ and *m* represents the number of comments written by the user.

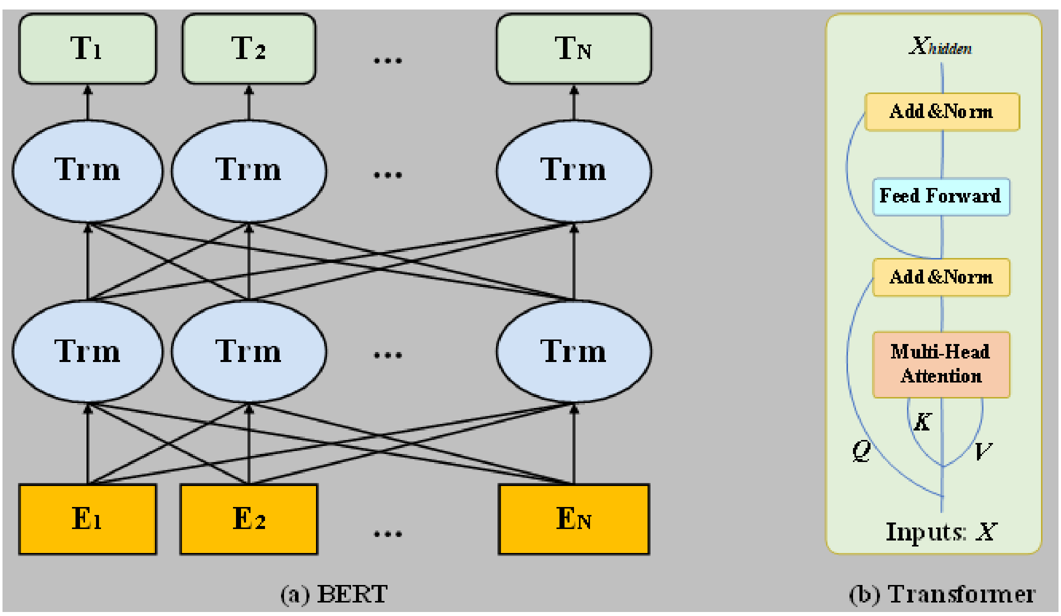
Definition 4. Item Properties. Item attributes can be reflected in the set of comments written by the user. This can be described as a binary $\left\{i, \Psi^i\right\}$, where *i* represents the item, Ψ^i represents the set of comments written by the user for item *i*, $\Psi^i = \left\{G_1, G_2, \cdots, G_k\right\}$, where *k* represents the number of comments the item has.

Comment Vector Representation

The BERT model can use pre-trained model parameters to generate dynamic contextual embedding representations from large corpora. Given the input text content $T = \left(t_1, t_2, \cdots, t_l\right)$, 1 represents the length of the text and an embedded representation of the text content $\vec{T} = \left(x_1, x_2, \cdots, x_l\right)$ is obtained through the BERT pre-trained model, where the vector of each word represents $t_i \in R^d$, and d represents the dimension of the vector.

The proposed model utilizes a Transformer-encoder to perform text re-aggregation on the text feature $\vec{T}$ obtained from the BERT model, enabling the text features to contain deeper semantic information (Manish et al., 2020; Wei & Nguyen, 2022). Figure 2 illustrates the structures of the BERT model and Transformer.

Figure 2. Structures of BERT and transformer



The feature of text re-aggregation is marked as $\hat{T}$, which is represented as follows:

$$\hat{T} = Transform - encoder\left(\vec{T}\right) \tag{1}$$

According to Definition 3, *m* comments written by user *u* are aggregated into a single document $\hat{T}^u_{1:m}$, denoted as:

$$\hat{T}^u_{1:m} = e_1 \oplus e_2 \oplus \cdots \oplus e_m \tag{2}$$

where, *e* is the sentence vector element of the comment.

According to Definition 4, the aggregated text of comments for item *i* is represented as a document $\hat{T}^i_{1,k}$, where k comments come from different users u. $\hat{T}^i_{l,k}$ is expressed as:

$$\hat{T}^i_{1:k} = e_1 \oplus e_2 \oplus \cdots \oplus e_k \tag{3}$$

Feature Extraction Network

CNN is used to extract deep features from text. The word vector document $\hat{T}^u_{1:m}$ of user u is first convolved. After each convolution operation, a feature map is generated. The resulting feature map f^u_j is as follows:

$$f^u_j = \delta\left(\hat{T}^u_{1,m} * K_j + b_j\right) \tag{4}$$

where $K_j \in \mathbb{R}^{c \times \kappa}$ represents the convolutional kernel, $\kappa\left(\kappa \in \left\{3,4,5\right\}\right)$ represents the window size of the convolutional kernel, $*$ represents convolution operation, b_j represents the offset amount and δ is the ReLU activation function.

Then, a maximum pooling operation is performed on each channel of the feature map to obtain the maximum value o_j in each channel:

$$o^u_j = \max\left\{f^u_1, f^u_2, \cdots, f^u_{\left(\Sigma_{i=1,\cdots,m} n_i - \kappa + 1\right)}\right\} \tag{5}$$

After maximum pooling, the convolutional features are reduced to a fixed-size vector with the same dimension and number of channels (Feng et al., 2023). The corresponding features of *q* neurons are spliced to obtain the features, denoted as:

$$O^u = \left\{o^u_1, o^u_2, \cdots, o^u_q\right\} \tag{6}$$

Subsequently, user and project features are concatenated to construct user-item features, resulting in feature O as follows:

$$O = O^{u} \oplus O^{i} \tag{7}$$

where O^i represents the feature extracted by the network for item i.

As the proposed model achieves knowledge transfer by simultaneously modeling three different domains, the feature extraction network is divided into three parts: (1) source domain; (2) target domain; and (3) shared domain (Ban et al., 2023; Huang et al., 2023). The network modules of the three domains use two parallel CNNs to extract user and project features, with the same network structure and no shared parameters. The source domain contains rich comment information, while the target domain has sparse or cold start data. By separately learning the unique features of each domain from both the source and target domains, the shared information between the two domains can be learned. User and item comments from the source domain are used as input to the source domain, while those from the target domain are input to the target domain. The comments from both source and target domains are fused and used as input to the shared domain. The specific process of feature extraction for the three different domains is outlined in Algorithm 1.

Feature Self-Combination Layer

The feature self-combination layer combines the comment features after intersecting the users and items, so that each comment feature vector can contain the feature information of all comments. This approach is employed because understanding a particular comment from a user (item) requires comprehensive inference based on all comments associated with that user (item).

In the feature self-combination layer, the corresponding comment feature vectors for users and items are calculated separately following the same process. Therefore, take the calculation of user comment feature vectors as an example (Li et al., 2023). First, the feature cross combination layer is connected to the comment feature vector before the cross, resulting in:

Algorithm 1. Feature extraction of the source, target, and shared domains

Input: User aggregated comment text document $\hat{T}^{u}_{1:m}$, item aggregated comment text document $\hat{T}^{i}_{1,k}$, window size of convolutional kernel K; Output: Source domain, target domain features O^{l}, shared domain features O^{c}
Begin
1. **For** EACH $j \in q$ **do** apply formula 6 to calculate the user features $\left(O^{u}\right)^{l}$ and item features $\left(O^{i}\right)^{l}$ of the target domain (or shared domain);
End for
2. Apply formula 7 to calculate the splicing features O^{l} of the target domain (or shared domain);
3. **For** EACH $j \in q$ **do** apply formula 6 to calculate user features $\left(O^{u}\right)^{c}$ and item features $\left(O^{i}\right)^{c}$ of the shared domain; **End for**
4. Apply formula 7 to calculate the splicing features O^{c} of the shared domain;
5. **Return** O^{l}, O^{c}
End

$$\begin{aligned}\phi^{u} &= \left\{o_0^{u},\cdots,o_q^{u},\hat{o}_0^{u},\cdots,\hat{o}_q^{u}\right\}\\ \hat{o}_i^{u} &= \sum_{j=1}^{n}\frac{\exp\left(a_{ij}\right)}{\sum_{k=1}^{n}\exp\left(a_{ik}\right)}\hat{o}_j^{u}\end{aligned}\tag{8}$$

where a_{ij} is the cross-attention matrix, calculated using the bilinear inner product method.

Then, multi-head self-attention is used to calculate the user's corresponding self-attention for all feature vectors, and self-combination is performed based on self-attention to obtain Z^u:

$$\begin{aligned}Q^{u} = \phi^{u}W_Q^{u}, K^{u} &= \phi^{u}W_K^{u}, V^{u} = \phi^{u}W_V^{u}\\ Z^{u} &= \text{softmax}\left(\frac{Q^{u}K^{uT}}{\sqrt{d_k}}\right)V^{u}\end{aligned}\tag{9}$$

where $W_Q^u, W_K^u, W_V^u \in \mathbb{R}^{d\times\left(n_h\times d_h\right)}$, n_h is the number of heads for multi-head self-attention, which is implicitly included in the second dimension of the parameter matrix. Input Z^u to the feedforward neural network layer to obtain:

$$FFN\left(Z^{u}\right) = \max\left(0, Z^{u}\omega_1^{u} + b_1^{u}\right)\omega_2^{u} + b_2^{u}\tag{10}$$

where ω and b are the weight and bias, respectively.

Then, the self-composed feature vectors are added and pooled to obtain the user vector u^{ψ} represented by comments:

$$u^{\Psi} = \sum_{i}^{2n} FFN\left(Z^{u}\right)_i\tag{11}$$

The calculation based on the item vector represented by comments is similar.

Knowledge Fusion and Rating Prediction

Features from the three domains are extracted using feature extraction networks, and, subsequently, knowledge from these domains is fused. The features from the source and shared domains are combined, while features from the target and shared domains are combined to achieve knowledge transfer (Wu et al., 2023; Zhao et al., 2023). The feature fusion process involves the features of the three domains are concatenated through fully connected layers, obtaining the final feature output $\hat{F}^{y}$:

$$\hat{F}^{y} = \begin{cases}\delta\left(\omega^{sc}h^{c} + \omega^{s}h^{s} + b^{s}\right), y = 0\\ \delta\left(\omega^{tc}h^{c} + \omega^{t}h^{t} + b^{t}\right), y = 1\end{cases}\tag{12}$$

where $y\left(y \in \left\{0,1\right\}\right)$ is the domain label, while 0 and 1 represent the source target domains, respectively. ω^{sc}, ω^{tc}, ω^{s}, and ω^{t} are the weights of the shared and source domains, shared and target domains, source domain, and target and shared domains, respectively. b^s and b^t are the biases of the source and target domains, respectively.

Subsequently, based on FM, the user's predicted rating for the project is obtained:

$$\hat{\Theta} = \hat{\omega}_0 + \sum_{i=1}^{\left|\hat{F}^y\right|} \hat{\omega}_i \hat{F}_i^y + \sum_{i=1}^{\left|\hat{F}^y\right|} \sum_{j=i+1}^{\left|\hat{F}^y\right|} \left\langle \hat{v}_i, \hat{v}_j \right\rangle \hat{F}_i^y \hat{F}_j^y \tag{13}$$

where $\hat{\omega}_0$ is the global offset, $\hat{\omega}_i$ is the weight value of the ith component in $\hat{F}_i^y$; $\left\langle \hat{v}_i, \hat{v}_j \right\rangle = \sum_{\zeta=1}^{\left|\hat{F}^y\right|} \hat{v}_{i,\zeta} \hat{v}_j$, and ζ represents the second-order interaction between each component.

Loss Function

To ensure that the domain-specific features remain independent, a domain discriminator is introduced after sharing features. This prevents the domain-specific features from entering the shared feature space, which could lead to data redundancy (Duan et al., 2022). A domain discriminator $p\left(d \middle| h^c\right)$ is used to predict the domain label d on the shared feature h^c, and distinguish whether the feature comes from the source domain or target domain. The definition is as follows:

$$p\left(d \middle| h^c\right) = soft\max\left(\omega^c h^c + b^c\right) \tag{14}$$

where ω^c and b^c represent the weight and offset of the shared domain, respectively.

The framework adds an adversarial loss to the shared feature space to eliminate noise features. This makes it difficult for the shared domain to distinguish whether the features come from the feature space of the source domain or the target domain, reduces the difference in probability distribution between different domains, and prevents domain-specific features from entering the shared space. The loss function is defined as:

$$L_{adv} = \frac{1}{n} \sum_{i=1}^{n} \sum_{k=0}^{l} p\left(d = k \middle| h_i^c\right) \log p\left(d = k \middle| h_i^c\right) \tag{15}$$

Subsequently, domain discrimination loss functions are added to the feature spaces of the source and target domains, respectively, allowing the domain-specific feature spaces to better distinguish different domains. The negative entropy loss functions of the source L_s and target domains L_t are defined as:

$$L\left\{s,t\right\} = -\frac{1}{n_{\left\{s,t\right\}}} \sum_{i=1}^{n_{\left\{s,t\right\}}} \sum_{k \in \left\{s,t\right\}} I^{\left(d_i = k\right)} \log p\left(d = k \middle| h_i^{\left\{s,t\right\}}\right) \tag{16}$$

The proposed model can be trained using the minimum mean square error (L2) and minimum absolute error (L1) loss functions. In the experiments, L2 performed slightly better than L1. Hence, the L2 loss function was used for training. The loss function of the model is ultimately defined as:

$$Loss = \sum_{k \in \{s,t\}} -\frac{1}{n_k} \sum_{j=1}^{n_k} \frac{1}{2} \left(\Theta_{u,i}^k - \hat{\Theta}_{u,i}^k\right)^2 + \frac{\gamma_1}{2} L_{adv} + \frac{\gamma_2}{2} L_s + \frac{\gamma_3}{2} L_t + \frac{\gamma_4}{2} \left\|\ell\right\|_F^2 \tag{17}$$

where γ is the regularization parameter of the loss function, ℓ represents the model parameters, and $\Theta_{u,i}^k$ and $\hat{\Theta}_{u,i}^k$ represent the true and predicted ratings of user *u* on item *i*, respectively.

Model Training

Algorithm 2 shows the specific process of training the proposed model. Joint training was performed and data from the source and target domains were sequentially fed into the network. Domain discriminators were used to determine the domain labels of features, and the loss values transmitted from different domains were added for backpropagation to update the parameters (Ji et al., 2023; Yang et al., 2023).

EXPERIMENTS

Experimental Environment and Dataset

The experiments were performed on a computer system with ubuntu16.04, 256GB memory, Intel (R) Xeon (R) Gold5218 CPU2.30GHz, a graphics processor consisting of two QuadroRTX4000 GPUs and a 4TB mechanical hard disk. The development framework was TensorFlow 2.2.

The experimental evaluation used the Amazon dataset, which contained user reviews and product metadata for website products, totaling 142.8 million comments with ratings ranging from 1 to 5. The dataset spans May 1996 to July 2001. To evaluate the proposed model, Movies, Books, and Music categories were chosen from the Amazon dataset. Two cross-domain combinations—Movie-Books and Music-Books—were created for experimental analysis.

The dataset underwent dense preprocessing, retaining users with more than 10 comments in each of the three categories, items with more than 120 comments in the Book and Movie categories, and items with more than 30 comments in the Music category. Then, interactive users from the Movie-Books and Music-Books cross-domain combinations were selected. Given the denser nature of the Movie category compared to the Book and Music categories, the Movie category was used as the source domain in cross-domain combinations, while Book and Music were used as the target domains.

Next, the comment text was preprocessed by performing word segmentation and removing stop words. The statistical information of the dataset is shown in Table 1.

Evaluating Indicator

Mean absolute error (MAE) and mean square error (MSE) were selected as evaluation indicators. The higher the recommendation accuracy, the closer the predicted score is to the true score. The MAE and MSE calculations are expressed as follows:

$$\begin{aligned} MAE &= \frac{1}{K} \sum_{k=1}^{K} \left|\Theta_{u,i}^k - \hat{\Theta}_{u,i}^k\right| \\ MSE &= \frac{1}{K} \sum_{k=1}^{K} \left(\Theta_{u,i}^k - \hat{\Theta}_{u,i}^k\right)^2 \end{aligned} \tag{18}$$

where K represents the number of test data.

Algorithm 2. Training pseudocode of the proposed model

Input: Training data from the source domain D_s ({data d_s, label l_s}), and training data for the target domain D_t ({data d_t, label l_t}), model δ, loss function *L*, Learning rate ε, attenuation rate ρ_1, ρ_2, stability coefficient τ; Output: Decision layer parameters $\omega^{sc}, \omega^{tc}, \omega^{s}, \omega^{t}, \omega^{c}, b^{sc}, b^{tc}, b^{s}, b^{t}, b^{c}$, and network parameters of the feature layer ℓ_s, ℓ_t, ℓ_c.
Begin
1. Orthogonal initialization parameters $\ell = \{\omega^{sc}, \omega^{tc}, \omega^{s}, \omega^{t}, \omega^{c}, b^{sc}, b^{tc}, b^{s}, b^{t}, b^{c}, \ell_s, \ell_t, \ell_c\}$;
2. iterations epoch=0 3. First and second moment variables: $\alpha = 0, \beta = 0$
4. Time step $t = 0$
5. **While** epoch≤Max epoch **Do** **For** EACH $\left(d^s, l^s\right) \in D^s$ **Do** Randomly select a target domain training data d_t, l_t from D_t, Calculate gradient: $g \leftarrow \frac{1}{m} \nabla_{\ell} L\left(\delta\left(d^s, d^t, \ell\right), l^s, l^t\right)$;
6. Update parameters: $\ell \leftarrow \ell - \varepsilon \frac{\frac{\rho_1 \alpha + \left(1-\rho\right) g}{1-\rho_1^t}}{\sqrt{\frac{\rho_1 \beta + \left(1-\rho_1\right) g^2}{1-\rho_1^t}} + \tau}$ $\alpha \leftarrow \rho_1 \alpha + \left(1-\rho_1\right) g, \beta \leftarrow \rho_1 \beta + \left(1-\rho_1\right) g^2$
7. $t = t + 1$
8. **End for**
9. epoch= epoch+1
10. **End While**
11. **Return** ℓ
End

Contrast Model

To evaluate the performance of the proposed model, it was compared with the following models:

- **Single Domain Recommendation Model:** Ruchitha (2021) proposed a recommendation model, MF, based on CF or content-based filtering. Guo et al. (2023) proposed a CF recommendation model based on MFRW to improve recommendation accuracy.
- **Non-Comment-Based Cross-Domain Recommendation Model:** Liu et al. (2021) designed the DAAN framework, combining matrix decomposition-based CF with deep adversarial domains

Table 1. Cross-domain scenario statistical information

	D_s	D_t	D_s	D_t
Domain	Movie	Book	Music	Book
Reviews	1697533	8898041	1097592	8898041
Overlap users	6074		1705	
Overlap user ratio/%	21.83	4.80	15.43	1.35
Verification user	1214		1823	
Test user	340		512	

through attention networks. Yu, X., et al. (2021) proposed CDCFLFA, which calculates the project potential vector of the target domain by solving a linear least squares problem. The project recommendation was completed based on the updated user and project potential vectors.

- **Cross-Domain Recommendation Model Based on Comment Text:** The DSLN recommendation model designed by Liu et al. (2022) uses comments to characterize user preferences and project features. It also shares useful information through DAE. Wang et al. (2022) proposed a GBAN recommendation model that utilizes a reverse aggregation mechanism to reconstruct user node feature representations and combines the scores between nodes to complete link recommendations.

Experimental Setup

Training sets consist of all source domain data and 60% of the target domain data. Validation sets comprise 20% of the target domain data, and the remaining 20% target domain data is used as testing sets. The glove was used to vectorize the comment text, with a word vector dimension of 100 and a convolution kernel count of 150. Multiple convolution kernels were used for convolution operations, with window sizes of 3, 4, and 5. A dropout of 0.5 was applied to the fully connected layer of the decision network to alleviate overfitting. The parameter settings for the loss function were $\gamma_1 = \gamma_2 = \gamma_3 = 0.04$ and $\gamma_4 = 0.00064$. The weight factor dimension of FM in the proposed model was set to 5, and the user feature dimension and project feature dimension of the input FM were set to 50. The Adam training model was optimized using adaptive moment estimation, which is a stochastic gradient-based optimizer with adaptive estimation. Its learning rate was set to 0.001, and the other parameter settings were the same as in TensorFlow.

Comparison Results and Analysis

To verify the recommendation accuracy of the proposed model, the model was compared with existing cross-domain recommendation models like DAAN (Liu et al., 2021), DSLN (Liu et al., 2022), CDCFLFA (Yu, X., et al., 2021), and GBAN (Wang et al., 2022) on the Movie-Book and Music-Book datasets. MAE and MSE were used as experimental evaluation indicators. The experimental results are shown in Table 2.

Table 2 shows that the proposed model outperforms the comparative models in terms of MAE and MSE on both the Movie-Book and Music-Book datasets. On the Movie-Book dataset, the proposed model achieves MAE and MES values of 0.801 and 1.058, respectively. These values are 7.61% and 5.87% higher than the comment-based GBAN model. On the Music-Book dataset, the proposed model achieves MAE and MSE values of 0.878 and 0.805, respectively. These values are 13.71% and 19.01% higher than the DAAN model and 4.84% and 10.65% higher than the DSLN

Table 2. Comparison of recommendation results of different cross-domain models on two datasets

$D_s \to D_t$	Movie→Book		Music→Book	
	MAE	MSE	MAE	MSE
DAAN	1.014	1.206	0.912	0.994
DSLN	0.875	1.131	0.827	0.901
CDCFLFA	0.983	1.159	0.895	0.976
GBAN	0.867	1.124	0.820	0.893
Proposed model	0.801	1.058	0.787	0.805

model, respectively. These results indicate that recommendation based on text comments has better performance, and the proposed model has higher recommendation accuracy due to the integration of multi-head attention interaction and knowledge transfer learning.

Effectiveness of Knowledge Transfer

To verify that knowledge transfer learning can improve the recommendation performance of the proposed model, it was compared with two single-domain recommendation models, MF (Ruchitha, 2021) and MFRW (Guo et al., 2023), using only the Movie and Book datasets. The experiment used MAE and MSE as evaluation indicators. The results are shown in Table 3.

Table 3 shows that the proposed model outperforms the comparative single-domain models. On the Movie-Book dataset, the proposed model outperforms the MFRW model by 26.45% and 16.76% in terms of MAE and MES, respectively. On the Music-Book dataset, the proposed model improves MAE and MES by 21.46% and 29.26%, respectively, compared to the MF model.

The superiority of the proposed model can be attributed to its effective utilization of auxiliary domain data to successfully fill the knowledge gap in the target domain. This results in significantly higher recommendation accuracy in the target domain compared to the single-domain recommendation models, showcasing the enhanced knowledge transfer performance of the proposed model.

Issues Related to Relieving Data Sparsity

Comparing the proposed model to single- and cross-domain models demonstrated that it could alleviate the problem of sparse data in the target domain. In the experiment, the sparsity of the data was adjusted by controlling the number of user comments in the test set. χ -fold comments were randomly selected from the user comments as the test set, with χ set to 20%, 40%, 60%, 80%, and 100%, respectively. The experiment tested different recommendation models using different χ , and the recommendation

Table 3. Comparison of the proposed model with two single-domain recommendation models

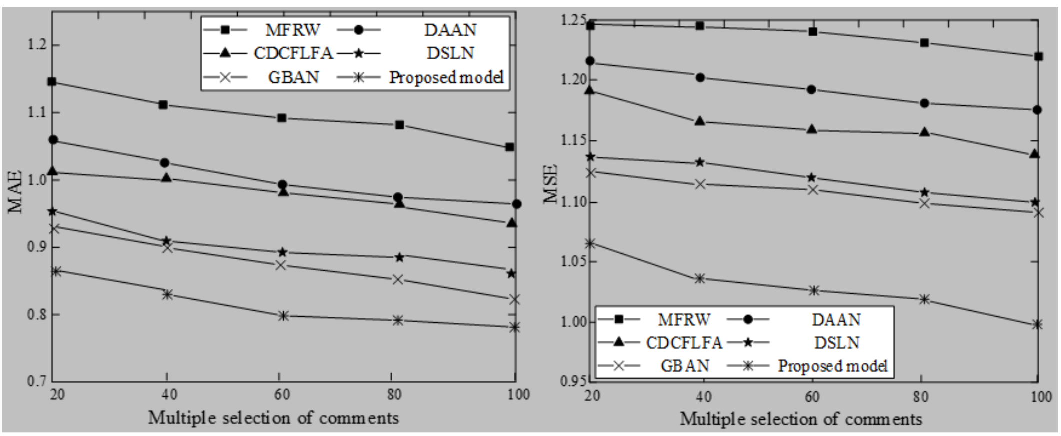
$D_s \to D_t$	Movie→Book		Music→Book	
	MAE	MSE	MAE	MSE
MF	1.206	1.425	1.002	1.138
MFRW	1.089	1.271	0.943	1.014
Proposed model	0.801	1.058	0.787	0.805

results on the Movie-Book and Music-Book datasets are shown in Figures 3 and 4, respectively. Among them, χ represents the sparsity of the data.

In Figures 3 and 4, the proposed model consistently achieves the lowest MAE and MSE values on both the Movie-Book and Music-Book datasets, regardless of the changes, demonstrating its ability to generate good recommendation results.

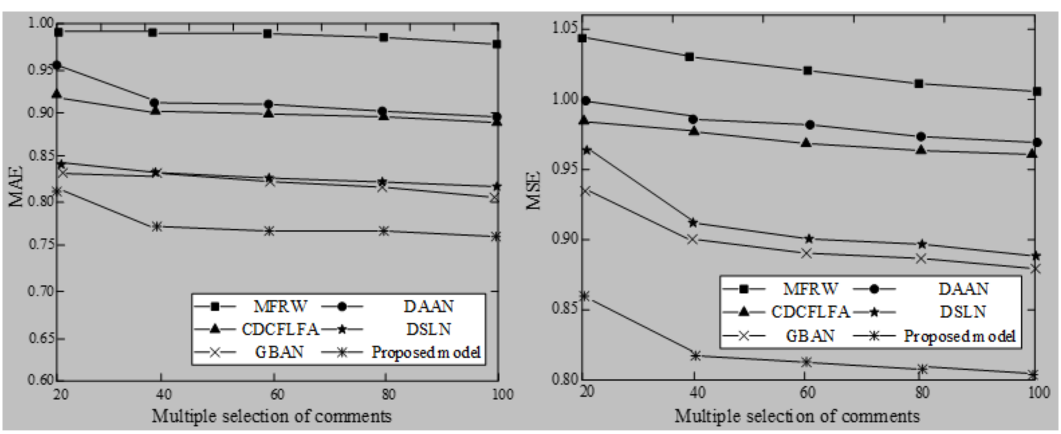
The recommendation results from the Movie-Book dataset in Figure 3 show that the recommendation performance of each model improves with the decrease in sparsity. For example, when the sparsity is reduced from 40% to 100%, the MAE values of MFRW, DAAN, DSLN, CDCFLFA, GBAN, and the proposed model decrease by 0.020, 0.018, 0.012, 0.021, 0.009, and 0.025, respectively. Similarly, the Music-Book recommendation results in Figure 4 show that the recommendation performance of each model improves as the number of comments increases. For example, when the number of comments is increased from 20% to 80%, the MSE values of MFRW, DAAN, DSLN, CDCFLFA, GBAN, and the proposed model decrease by 0.038, 0.013, 0.058, 0.009, 0.051, and 0.054, respectively.

Figure 3. Comparison of recommendation results by three models for the movie-book dataset: (a) MAE, (b) MSE



(a) (b)

Figure 4. Comparison of recommendation results by three model for the music-book dataset: (a) MAE, (b) MSE



(a) (b)

The above results reveal that, regardless of the value taken, the proposed model exhibits the lowest MAE and MSE, indicating its superior recommendation effectiveness. The MFRW model, being a single-domain recommendation model, has low accuracy when applied to cross-domain datasets. Both the DAAN and CDCFLFA models, although designed for cross-domain recommendation, fall short due to their lack of consideration for the important information of text comments, resulting in unsatisfactory recommendation results. The DSLN and GBAN models, while making cross-domain recommendations based on text comments, exhibit lower recommendation errors compared to single-domain or non-text-centric recommendation models but are impacted by data sparsity.

In contrast, the proposed model adopts a knowledge transfer strategy that simultaneously extracts domain-specific and shared features between domains for joint modeling. The proposed model leverages large-scale training samples in the source domain to fill the knowledge gap in the book review dataset, overcoming the problem of data sparsity. Moreover, through knowledge transfer learning, the proposed model fully mines essential information embedded in comment texts. This enables the model to obtain more user and project information compared to other comparative models, which is conducive to predicting ratings. Therefore, the proposed model can achieve the best recommendation effect.

Issues Related to Alleviating User Cold Start

User cold start poses a significant challenge in recommendation systems, particularly when new users have limited interactions with the system, making it difficult to discern their preferences and generate accurate recommendations. Cross-domain recommendations can alleviate this problem. To verify that the proposed model can address the cold start issue for users in the target domain, two sets of comparative experiments were conducted. The proposed model and a comparative model were evaluated on the Movie-Book and Music-Book datasets, respectively. Five hundred new users were selected from the Book datasets, ensuring no overlap with the training set users. The number of new user comments was controlled at 1, 2, 3, 4, and 5 for testing. The MAE and MSE results obtained by several recommendation models are shown in Figures 5 and 6, respectively.

Figures 5 and 6 show that the recommendation performance of all models gradually improves with an increasing number of comments. The proposed model consistently outperforms other comparative models, delivering the most favorable recommendation results under both evaluation indicators. This superior performance is especially more pronounced in situations with fewer comments, where the challenge of user cold start is more obvious. The proposed model excels in addressing user cold start

Figure 5. Comparison of recommendation results of different models on the movie-book dataset: (a) MAE, (b) MSE

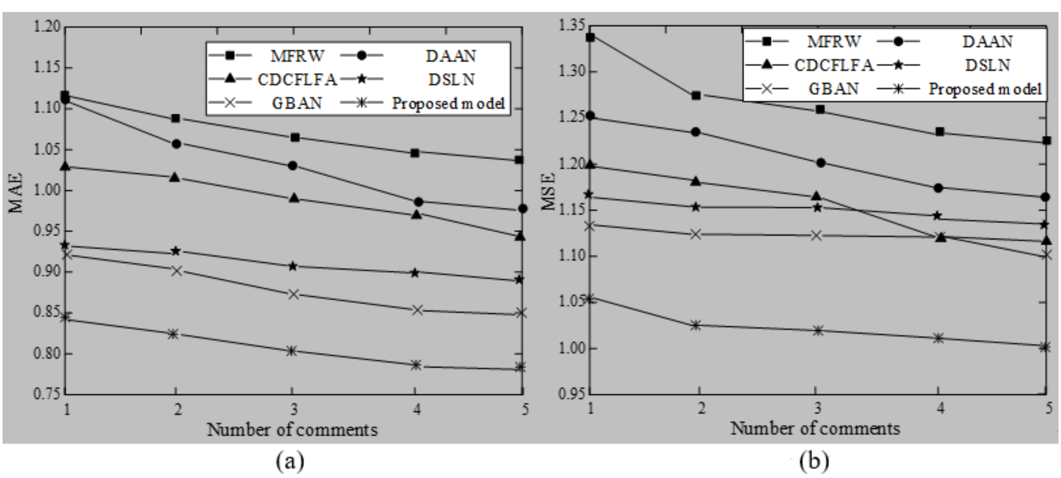
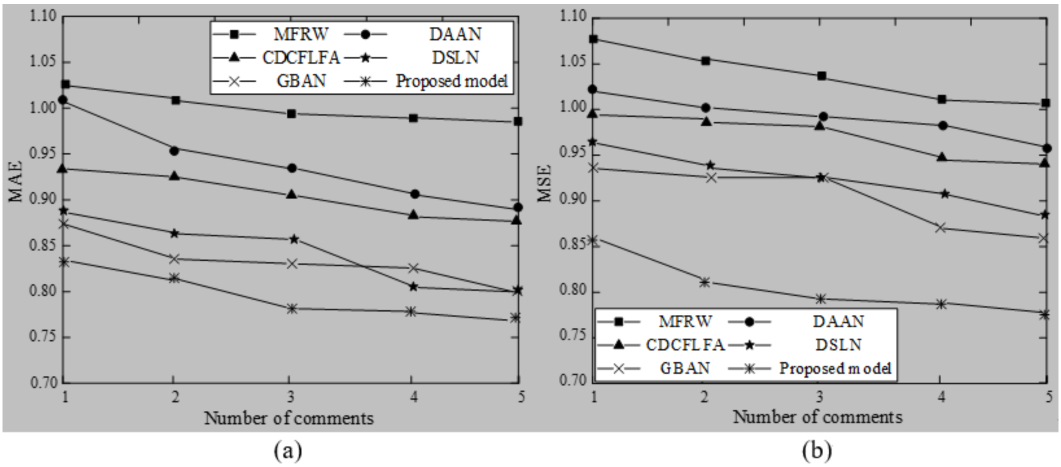


Figure 6. Comparison of recommendation results of different models on the music-book dataset: (a) MAE, (b) MSE



issues by extracting domain-specific features and shared features between domains for joint modeling, utilizing large-scale training samples from the source domain.

Ablation Experiment

The proposed model significantly outperformed other newer recommended models. To better understand its strengths and weaknesses, ablation experiments were conducted, comparing it with the following variants. The results are shown in Table 4.

1. **BERT:** Deleted the BERT model from the proposed model.
2. **Feature Self-Combination Layer:** Deleted the feature self-combination layer module from the proposed model.
3. **Addition and Pooling:** Deleted the addition-pooling module from the proposed model.

Table 4 shows that the removal of any module from the proposed recommendation model decreases MAE and MSE indicators. However, the difference between addition and pooling and the proposed model is not significant, about 0.02. The removal of BERT or the feature self-combination layer has a significant impact on the recommendation performance of the proposed model. On the Movie-Book dataset, the proposed model reduces MAE by 0.038 and 0.041, and MSE by 0.044 and 0.047, respectively, compared to the models without BERT and the feature self-combination layer. These results demonstrate that the BERT model and feature self-combination layer enhance

Table 4. Results of the ablation experiment

Model	Movie-Book		Music-Book	
	MAE	MSE	MAE	MSE
- BERT	0.839	1.102	0.819	0.848
- Feature self-combination layer	0.842	1.105	0.823	0.851
- Addition and pooling	0.803	1.061	0.790	0.807
Proposed model	0.801	1.058	0.787	0.805

the performance of the proposed recommendation model. Specifically, the BERT model completely captures the bidirectional relationship between comment text statements. In addition, the feature self-combination layer achieves higher-order feature combinations based on multi-head attention interaction, further improving the cross-domain recommendation performance of the proposed model.

Research on Model Universality

To demonstrate the model's universality, three large publicly available Chinese rating datasets were used as the source domain datasets, while the Chinese rating dataset for Literary Book served as the target domain dataset. Three sets of cross-domain recommendation experiments were conducted, namely Movie-Literary Book, Restaurant-Literary Book, and Commodity-Literary Book. The specific datasets are as follows:

- **Source Domain Dataset 1:** Douban Movie Dataset ez_ Douban. Dataset introduction: see https://github.com/SophonPlus/ChineseNlpCorpus/blob/master/datasets/ez_douban/intro.ipynb.
- **Source Domain Dataset 2:** Restaurant Rating Dataset yf_ Dianping. Dataset introduction: see https://github.com/SophonPlus/ChineseNlpCorpus/blob/master/datasets/yf_dianping/intro.ipynb.
- **Source Domain Dataset 3:** Product Rating Dataset yf_ Amazon. See https://github.com/SophonPlus/ChineseNlpCorpus/blob/master/datasets/yf_amazon/intro.ipynb.
- **Target domain dataset:** Douban Literary Book dataset. See: https://doi.org/10.18170/DVN/X20PS1. Douban Reading's top 250 literary book information, as well as the top 500 popular short reviews per book.

As all four datasets are in Chinese, they underwent pre-processing. During the experiment, Tencent word vectors were used for text processing, while other aspects remained consistent with the English Amazon dataset scenario, with the word vector dimension set to 100. The GBAN model was also compared with the proposed model for cross-domain recommendation analysis, and the results are shown in Table 5.

Table 5 shows that the proposed model achieved excellent results across all datasets. On the three cross-domain datasets—Movie-Literary Book, Restaurant-Literary Book, and Commodity-Literary Book—the proposed model achieves MAE values of 0.848, 0.869, and 0.851, respectively. These values are 0.047, 0.045, and 0.056 lower than those achieved by the GBAN model. While both MAE and MSE values increase slightly compared to the Amazon dataset, the recommendation performance remains ideal. In addition, the Restaurant-Literary Book dataset exhibits a slightly higher MAE value in the recommendation results due to the low correlation between the two domains. Overall, the proposed model achieves good recommendation results for both Chinese and English texts, indicating its broad applicability.

Table 5. Model universality experimental results

Model		GBAN	Proposed Model
Movie-Literary Books	MAE	0.895	0.848
	MSE	1.168	1.073
Restaurant-Literary Books	MAE	0.914	0.869
	MSE	1.191	1.102
Commodity-Literary Books	MAE	0.907	0.851
	MSE	1.176	1.095

CONCLUSION

Cross-domain recommendation can be used to solve the performance degradation problem of recommendation systems stemming from sparse data and user cold start. This article introduces a cross-domain literary book recommendation model that integrates multi-head self-attention interaction and knowledge transfer learning to better leverage comment text information. The proposed model uses the BERT model for word vector extraction and multi-head self-attention interaction, enabling a deeper understanding of comment text features.

On the Movie-Book dataset, the proposed model outperforms models without "BERT" and the "feature self-combination layer," resulting in a reduction of MAE by 0.038 and 0.041, and MSE by 0.044 and 0.047, respectively. This demonstrates the proposed model's ability to significantly reduce recommendation errors. By extracting domain-specific features and shared features between domains for joint modeling across different domains, the proposed model leverages large-scale training samples from the source domain to fill gaps in book text information, alleviating data sparsity and user cold start issues. On the Movie-Book and Music-Book datasets, the proposed model achieves MAE and MSE values of 0.801 and 1.058, and 0.787 and 0.805, respectively, outperforming other comparative recommendation models.

However, the analysis of the proposed model did not include differences in user rating scales. Therefore, in future research, more in-depth research will be conducted to address the issue of differences in user rating scales to further improve the recommendation performance of the model. The proposed model is relatively complex in terms of network structure. Therefore, in the future, some modules within the proposed model will be replaced with model pruning or the integration of lightweight networks. This approach seeks to improve recommendation efficiency while maintaining robust cross-domain recommendation results, making the model more practical and adaptable to Web 3.0 and the metaverse.

DATA AVAILABILITY

The data used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this paper.

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Cui Yuan, born in Taiyuan, Shanxi Province in 1978, PhD candidate at Lincoln University College,Malaysia. Now she teaches in Shanxi Professional College of Finance. The main research direction is ancient Chinese literature, higher vocational education.

Duan Yuexing, born in Taiyuan, Shanxi Province in 1964.Now he teaches in College of Information and Computer, Taiyuan University of Technology. The main research direction is Knowledge graphs, dialogue systems.

Zhang Yueqin, born in Taiyuan, Shanxi Province in 1963. Now she teaches in College of Information and Computer, Taiyuan University of Technology. The main research direction is Data mining, intelligent information processing, software development techniques and applications.