Information Resources Management Journal
Volume 37 • Issue 1 • January-December 2024

A Comment Aspect-Level User Preference Transfer Model for Cross-Domain Recommendations

Wumei Zhang
Zhejiang Tongji Vocational College of Technology, China

Jianping Zhang
Zhejiang Tongji Vocational College of Technology, China

Yongzhen Zhang
Zhejiang Tongji Vocational College of Technology, China

ABSTRACT

Traditional cross-domain recommendation models make it difficult to deeply mine users' aspect-level preferences from comment information due to existing problems such as polysemy of comment text, sparse comment data, and user cold start. A Cross-Domain Recommender (CDR) model that integrates comment knowledge enhancement and aspect-level user preference transfer (C-KE-AUT) was proposed to address the above issues. Firstly, an aspect-level user preference extraction model was constructed by combining the RoBERTa word embedding model, high-level feature representation based on Transformer, and aspect-level attention-learning methods. Then, a user aspect-level preference cross-domain transfer model was constructed based on a two-stage generative adversarial network that can transfer the aspect-level interest preferences of users in the source domain to the target domain with sparse data. The experimental results on the Amazon 2018 comment dataset indicated that the recommendation performance of the proposed C-KE-AUT model was significantly superior to other advanced comparative models.

KEYWORDS

Aspect Level, Cross-Domain Recommendation, Knowledge Enhancement, RoBERTa, Transformer, User Preference Transfer

Personalized recommendations have been integrated into various industries in today's society (Da'u & Salim, 2019; Lv et al., 2023). Such recommendations can improve users' experience, making it easier for them to find products or content that interest them based on their historical behavior (Xu et al., 2023). By providing personalized recommendation services to users, merchants can ensure users trust and rely on the recommendation system, thereby increasing user engagement and stickiness and improving user satisfaction. (Wang et al., 2021; Zang, 2021). In addition, analyzing user behavior and preferences can more accurately predict user needs and interests and improve the efficiency and accuracy of data analysis. (Liu, F., et al., 2020; Nie et al., 2021; Jeong et al., 2020).

Currently, the application of personalized recommendations is mainly limited to a single field, which is to obtain user interests and preferences based on user data in a certain field and carry out personalized recommendations for that field accordingly. However, in traditional recommendation systems, data sparsity and cold start issues have always plagued the accuracy and efficiency of

DOI: 10.4018/IRMJ.345360

recommendation systems (Bernardis & Cremonesi, 2021; Fernández-Tobías et al., 2019). The problem of data sparsity is mainly due to insufficient interaction information between users and items, which makes it hard to accurately capture preferences. The cold start problem arises when new users or items have no interaction information in the system, resulting in inaccurate recommendation results. (Zhong et al., 2020; Zhu et al., 2021; Javed et al., 2021). In fact, many internet platforms involve diverse fields. Public websites may involve multiple fields simultaneously, resulting in user data from different fields. User data from different fields is not always random; for example, users who enjoy detective books may like detective movies (Sang et al., 2023; Huang et al., 2023). This potentially similar pattern in different fields makes cross-domain recommendation (CDR) possible to meet the needs of user preference migration between different fields in practical applications (Qian et al., 2020; Soydaner, 2022). If users' preferences in one domain can be transferred to another domain, it will help improve the accuracy and efficiency of recommendations. Therefore, the research on CDR models aims to solve the problems in traditional recommendation systems and improve the accuracy and efficiency of recommendations (Xie et al., 2022; Dong et al., 2021; Lai & Jie, 2023).

However, there are usually some significant problems in existing CDR methods, such as the problem of polysemy in comment text, sparse comment data, the user cold start problem, and difficulty in deep mining user aspect-level preferences from comment information (Li & Tuzhilin, 2020; Abdi et al., 2018; Zhang et al., 2019; Zuo et al., 2022; Ni et al., 2023; Nie et al., 2021). In order to better address these problems, a CDR model integrating knowledge enhancement and C-KE-AUT is proposed. Compared with traditional CDR models, the innovation of the proposed method lies in the following:

- We have designed a cross-domain transfer architecture for user aspect-level preferences based on a two-stage generative adversarial network. During the transfer learning process, strategies such as fixing the source domain (D_s) encoder parameters and introducing domain discriminators are used to solve data distribution differences between two domains. This effectively utilizes the rich data in the D_s to alleviate the user cold start problem caused by sparse data in the target domain (D_t).
- In the text embedding layer, the RoBERTa pre-trained language model is utilized to transform text into word vectors and conduct initial feature extraction. Furthermore, knowledge enhancement is achieved through the use of representation dictionaries to more effectively address the challenge of polysemy. The innovation of this approach lies in its ability to leverage the powerful language comprehension capabilities of the RoBERTa model for extracting deep semantic features, while also enhancing the model's understanding of word sense diversity through the incorporation of representation dictionaries. This combination of pre-trained language models and knowledge enhancement strategies offers a novel and effective solution for tackling the issue of polysemy in natural language processing, thereby enhancing the model's performance in complex language tasks.
- Leveraging the transformer architecture to capture high-level contextual features and integrating aspect-level representations with attention mechanisms enables the precise extraction of fine-grained, aspect-level user preferences. This method enhances the understanding of nuanced user interests through a sophisticated blend of advanced contextual analysis and focused attention on specific aspects, thereby significantly improving the precision of user profile representations in personalized systems.

RELATED RESEARCH

CDR

The traditional CDR method utilizes a scoring matrix from two perspectives—knowledge aggregation and knowledge transfer—to complete information transmission for cold start users. (Wu et al., 2020; Li et al., 2022). Existing work has integrated users' D_s and D_t product rating matrices into a unified joint matrix to share user factors, thus achieving cross-domain integration of knowledge. When different fields are considered as a whole, however, these collaborative filtering-based works can be plagued by serious data sparsity issues (Wei, 2021).

In order to solve the problem of difficult session modeling during the CDR process due to complex situations, Zhang, Hua, et al. (2023) proposed the multi-channel interaction model (DCMI), an interactive model for cross-domain personalized recommendation using dual cross-domain session information. This model has high recommendation performance and considerable accuracy. However, due to data sparsity issues, the model lacks sufficient user preference data for model training and prediction. Based on the parameter sharing method, some parameters of the D_s are shared in the D_t and jointly learned to update these parameters. Li and Tuzhilin (2020) suggested a CDR model: deep dual transfer cross-domain recommendation (DDTCDR). In this model, the core of CoNet is the cross connected unit of the hidden layer, which learns the weights of different layers in two domains to achieve parameter sharing. However, this method has difficulty to capturing dynamic changes in user preferences and cannot adapt to real-time changes in user preferences. By directly sharing the D_s data with the D_t, Hong et al. (2020) proposed a corresponding recommendation model called cross-domain deep neural network (CD-DNN) based on data sharing. This method can enrich the D_t data and thus achieve good recommendation performance. Due to the lack of sufficient interactive information in user preferences in new fields, though, this method has a cold start problem. Implementing CDR from a graph perspective, Yang et al. (2021) developed a deep multi-graph embedding (DMGE) recommendation model by constructing interactive heterogeneous graphs between two domains. This model can combine graph convolutional neural networks to transform recommendation tasks into graph link prediction tasks. Yet, the interpretability of this model is poor, making it difficult for users and domain experts to understand the model's recommendation results, which may lead to users' distrust of and dissatisfaction with the recommendation results. By utilizing auxiliary information to enhance user representation, Zhao et al. (2020) created a CDR framework via aspect transfer network for cold-start users (CATN), which performs cross-domain aspect-level feature matching during rating prediction, resulting in good recommendation results. However, this method requires a large amount of computational resources and time to train and predict; as a result, the model might be unable to respond to user requests in real-time, which undermines the user experience.

User Preference Mining Based on Comments

User profiles are the foundation for achieving personalized recommendations. In order to more accurately depict consumers' user profiles, e-commerce platforms provide users with various channels for evaluation and feedback. Scoring represents an explicit form of feedback in which users provide a comprehensive evaluation by rating multiple items within a certain numerical range. It has the characteristics of simplicity, efficiency, and ease of processing. Comments represent an implicit form of feedback that allows users to provide more detailed evaluations and preferences, which can, to some extent, alleviate the problem of data sparsity in recommendation systems. Mining user preferences implicit in comments can provide more accurate user profiles and promote personalized recommendations for e-commerce platforms.

By using Word2Vec to vector transform semantic information in comments and combining fine-grained sentiment analysis to match the emotions of comment responses, Li et al., (2019) developed a comment extension mining model to accurately identify and recommend user preferences. However, this method has certain applicability limitations and cannot be used in multiple fields. Comment text provides implicit feedback based on subjective evaluation and description of products by users. With the rapid development of deep learning technology, natural language processing methods combined with deep neural networks have also received widespread attention in the application of recommendation systems. However, this method makes it difficult to accurately understand user preferences, which in turn makes it difficult to provide personalized recommendation services. By

Table 1. Explanation of Relevant Symbols

Parameters	Meaning
D_c	Sigmoid classifier
$\oplus$	Concat
F	Fully connect
D_s	Source domain
D_t	Target domain
M_u	User Embedding Matrix
U_c	Cold Start User Collection
P_u	User aspect-level preferences
A	Domain Global Aspect Representation

conducting knowledge mining on user documents composed of users' historical comments, Du et al. (2023) modeled user profile features and proposed hierarchical attention cooperative neural networks (HACN), a personalized recommendation model based on hierarchical attention. However, in e-commerce platforms, not all comments are equally important, and irrelevant comments in this method can affect the model's accurate mining of user preferences. Further, this method cannot effectively transfer users' preferences from one domain to another, thereby reducing the accuracy and efficiency of recommendations. By utilizing attention mechanisms to assign different importance to different comments, Zhang, Chen, et al. (2023) conducted user profile mining by selecting representative relevant comments. Based on this, an equal comment level method was proposed for personalized recommendations. Yet, this method cannot capture real-time dynamic changes in user preferences, making it difficult to provide accurate recommendation services.

Based on the above analysis, existing CDR methods often face issues such as polysemy, sparse comment data, user cold start, and difficulty in deeply mining user aspect-level preferences from comment information. To this end, the proposed CDR method uses knowledge transfer learning to solve data sparsity and user cold start problems, utilizes a powerful pre-trained language model to solve polysemy problems, and utilizes the transformer architecture to deeply mine user fine-grained aspect-level preferences.

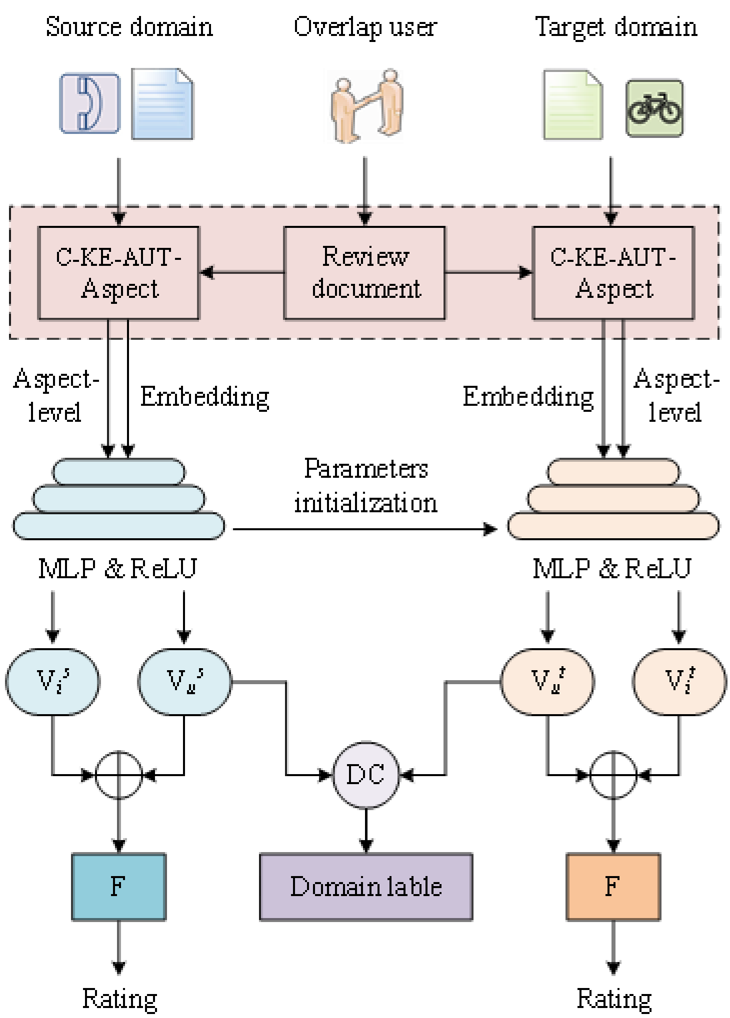
PROBLEM DEFINITION

Firstly, we provide a symbolic description of the problem; the meanings of the relevant symbols are shown in Table 1.

D_s and D_t represent the source domain and target domain, respectively. Shared domain users are a collection of users with historical interaction records in both D_s and D_t domains. Among them, cold start users refer to users who only interact with products in the D_s and have no interaction in the D_t. For a given cold start user $u \in U_c$, the goal is to predict their corresponding product rating in the D_t.

Further, D_u represents the set of comments given by user u; D_i is the set of comments received by product i. We use superscripts "s" and "t" to represent the D_s and D_t, respectively, where $D_u^{\ s}$ represents the set of comments from the user in the D_s. Similarly, users and products in the D_s and D_t can be represented. In the training of the model, the shared user is used as a bridge connecting the D_s and the D_t. For a given shared user u, it has two user documents, $D_u^{\ s}$ and $D_t^{\ s}$. The process of the CDR algorithm proposed in this paper is as follows:

Figure 1. The Framework of the C-KE-AUT

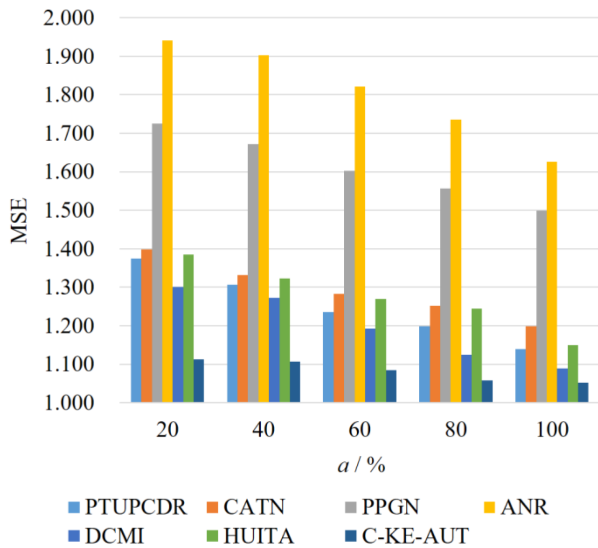


1. Mine P_u using D_u^s and D_t^s comment sets as inputs, obtain P_u^s and P_u^t as P_u in the D_s and D_t, respectively; similarly, obtain product features related to two fields.
2. Using P_u^s and P_u^t to train cross-domain transfer modules, P_u^s can learn to represent the user's aspect-level preferences P_u^t in the D_t after transfer.
3. For cold start users in the D_t, the user's D_s aspect-level preference P_u^s is utilized to obtain the D_t user aspect-level preference P_u^t and predict their corresponding product ratings in the D_t.

PROPOSED CDR MODEL

In this section, we present an overview of the CDR model integrating knowledge enhancement and C-KE-AUT, as well as a detailed introduction to each module based on this. The overall framework of the proposed C-KE-AUT model is shown in Figure 1.

Figure 2. Structure of C-KE-AUT-Aspect



In Figure 1, the overall structure of the proposed model includes an aspect-level user preference extraction module C-KE-AUT-Aspect and a user aspect-level preference cross-domain migration module.

Aspect-Level User Preference Modeling

Aspect can be defined as fine-grained, high-level semantic knowledge of the domain, which includes domain specific attributes. For example, in the field of electronic products, aspect can include information such as product functionality, battery performance, brand, and so on. In the proposed CDR method, the aspect-level user preference module (C-KE-AUT-Aspect) is the core module, and its architecture is shown in Figure 2.

The C-KE-AUT-Aspect includes a convolution module for extracting contextual features, an aspect-level word representation mapping module, and an aspect-level attention module. Users and products in both the D_s and D_t use the same process to extract aspect-level features.

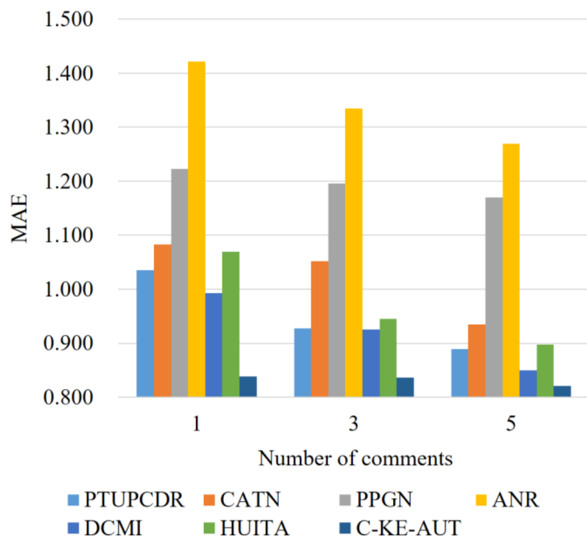
Aspect-level user preference modeling in the C-KE-AUT model enhances the precision of recommendations by focusing on the specific attributes of products or services that users mention in their reviews. This granular approach allows for highly personalized recommendations, addressing the nuances of individual preferences and improving the system's ability to predict user interests more accurately. By analyzing preferences at this detailed level, the model effectively deals with sparse data issues, especially in cross-domain scenarios, leading to a more refined recommendation process. This methodological advancement marks a significant leap towards achieving a deeper, more nuanced understanding of user preferences in recommendation systems.

Word Embedding

Word embedding transforms words into numerical vectors, capturing semantic relationships and context, thereby enhancing the ability of models like C-KE-AUT to process and understand textual data for more accurate and nuanced recommendations.

Word embedding is the mapping of each word in a sentence to a low dimensional, continuous, and dense vector. RoBERTa not only overcomes the problem of polysemy, but also fully considers the context of the word. Therefore, the RoBERTa pre-training model is used to initialize the vector

Figure 3. Word Vector Representation Using RoBERTa



representation of words, and knowledge enhancement is achieved through a representation dictionary. RoBERTa consists of two parts, namely embedder and encoder. The embedding layer converts words into words for embedding and then inputs them into the encoder layer for encoding to obtain text features. The word vector representation structure using RoBERTa is shown in Figure 3.

High-Level Feature Representation

In the C-KE-AUT model, the role of high-level feature representation is pivotal for capturing and representing richer, more complex contextual relationships and semantic information from text data, achieved through the transformer architecture. This process enhances the model's contextual awareness by leveraging the self-attention mechanism of transformers, which allows for considering the relationships between words across potentially large distances within the text, thus understanding context more effectively. High-level feature representation captures intricate semantic interactions between words, crucial for discerning subtle nuances in user comments. This capability is particularly important in understanding the varied meanings a word can have in different contexts, thereby improving the model's generalizability ability across unseen text or new domains. Such deep semantic understanding is essential for cross-domain recommendation systems, as it enables the extraction of refined and in-depth user preference information from textual data, facilitating more accurate and personalized recommendation outcomes across diverse domains.

The advantage of transformers in capturing contextual relationships to model low-level features of text is utilized in order to obtain richer high-level feature information. Taking user comment text as an example, the feature representation F_k^L of the k-th user's comment text is input into the transformer, as shown in Equations (1) and (2).

$$\begin{cases} Q_L = F_k^L \omega_Q \\ K_L = F_k^L \omega_K \\ V_L = F_k^L \omega_V \end{cases} \tag{1}$$

$$Att(Q_L, K_L, V_L) = softmax\left(\frac{Q_L K_L^D}{\sqrt{\lambda_k}}\right) V_L \tag{2}$$

In Equations (1) and (2), $\omega_Q \in R^{\lambda_k^L \times \lambda_k}$, $\omega_K \in R^{\lambda_k^L \times \lambda_k}$, $\omega_V \in R^{\lambda_k^L \times \lambda_v}$ are the linear transformation weight matrices of text features, respectively, $\lambda_k^L = \lambda_k = \lambda_v$ is the corresponding dimension size.

$$H_h = Att\left(Q_L \omega_h^Q, K_L \omega_h^K, V_L \omega_h^V\right) \tag{3}$$

$$MH(Q_L, K_L, V_L) = Co(H_1, H_2, \ldots, H_h)\omega_h^Z \tag{4}$$

In Equations (3) and (4), $\omega_h^Q \in R^{\lambda_k^L \times \lambda_k^h}$, $\omega_h^K \in R^{\lambda_k^L \times \lambda_k^h}$, $\omega_h^V \in R^{\lambda_k^L \times \lambda_v^h}$, $\omega_h^Z \in R^{\lambda_k^L \times h\lambda_v}$ are the linear transformation weight matrices of text features in multi-head attention, respectively, $\lambda_k^h = \lambda_v^h = \frac{\lambda_k^L}{h}$ is the dimension size of each head.

After the multi-head self-attention mechanism (Li et al., 2023), a vector representation of the internal relationship of user comment text is obtained through residual connection and layer normalization operation. Then, a feedforward neural network composed of two linear layers is formed, and, finally, the high-level text feature representation F_k^L of the k-th user is obtained through residual connection and layer normalization again. Similarly, the high-level text feature representation F_q^I of the *q*-th item can be obtained.

Aspect-Level Feature Representation

Aspect-level feature representation in models like C-KE-AUT captures the detailed attributes or facets of products or services mentioned in user reviews, enabling the model to understand and incorporate specific user preferences regarding these aspects into the recommendation process, thereby facilitating highly personalized and contextually relevant recommendations.

The process of aspect-level feature extraction is shown in Figure 4.

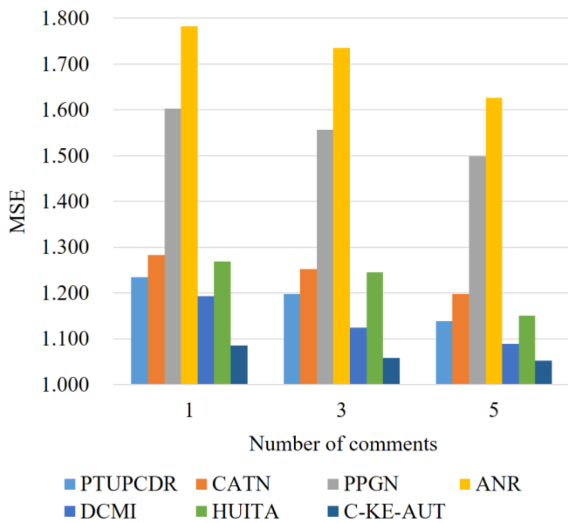
In the aspect-level feature extraction process, the context feature of *j*-th word is a combination of multiple semantic aspects. Here, we further utilize aspect-level feature-specific gating mechanisms to determine which features are related to aspect-level features. Specifically, for the *m* aspect-level features of user *u*, the extraction of aspect-level features $f_{m,j,u}$ specific to word w_j is shown in Equation (5).

$$f_{m,j,u} = \left(T_m F_u^L + b_m\right) \otimes \lambda\left(T_m{}^f F_u^L + b_m{}^f\right) \tag{5}$$

In Equation (5), λ is sigmoid, $\otimes$ is element product. $T_m, T_m{}^f \in R^{k \times n}$ and $b_m, b_m{}^f \in R^k$ represent the transformation matrix and bias vector of the *m*-th aspect-level feature, respectively. *k* is the potential dimension of aspect-level features. The second item on the right side of the above equation serves as a soft switch to control potential features related to aspect-level features. Therefore, the contextual features F_u of *M* words in specific aspects can be obtained, which can be used for further aspect-level feature extraction, as shown in Equation (6).

$$\begin{cases} F_u = \left[F_{1,u}, F_{2,u}, \ldots, F_{M,u}\right] \\ F_{m,u} = \left[f_{m,1,u}, f_{m,2,u}, \ldots, f_{m,l,u}\right] \end{cases} \tag{6}$$

Figure 4. Aspect-Level Feature Extraction



Aspect-Level Attention Learning

Aspect-level attention learning employs a mechanism to dynamically allocate significance to diverse product or service attributes within user-generated content, thereby optimizing recommendation systems to align with granular user preferences and enhancing the predictive accuracy of user satisfaction metrics through nuanced attention to detail.

Comments from different fields focus on different aspects. So, two globally shared aspect matrices were designed in D_s and D_t. They are defined as $A_s = [a_{1,s}, a_{2,s}, \ldots, a_{M,s}]$ and $A_t = [a_{1,t}, a_{2,t}, \ldots, a_{M,t}]$, corresponding to the D_s and D_t. A_s and A_t serve as queries to guide aspect feature extraction. Specifically, the m-th aspect extracted from $F_{m,u}$ represents the derivation of $\alpha_{m,u}$, as shown in Equations (7) and (8).

$$\alpha_{m,u} = \sum_{j=1}^{l} \eta_{m,j,u} f_{m,j,u} \tag{7}$$

$$\eta_{m,j,u} = \frac{\exp\left(f_{m,j,u}^{T} a_{m,s}\right)}{\sum_{j=1}^{l} \exp\left(f_{m,j,u}^{T} a_{m,s}\right)} \tag{8}$$

In Equations (7) and (8), $\eta_{m,j,u}$ represents importance of m-th aspect to w_j. Then, M aspect features get from D_u to aspect feature matrix $A_u = [a_{1,u}, a_{2,u}, \ldots, a_{M,u}]$. Similarly, M aspect feature matrices $A_i = [a_{1,i}, a_{2,i}, \ldots, a_{M,i}]$ were extracted from D_i. The aspect feature of D_u and D_i are shared in each flow. In addition, they were also used in every flow. The goal is to achieve cross-domain mapping of aspect features, A_s and A_t are shared in their respective domains.

Aspect-Level Knowledge Transfer

Aspect-level knowledge transfer operationalizes the cross-domain adaptation of granular, attribute-specific user preferences, leveraging inter-domain synergies to refine and personalize recommendation algorithms through the nuanced understanding of user interactions across heterogeneous data landscapes.

The comment document passes through the first three layers of the model to obtain the aspect matrices A_u and A_i for user u and project i. In the knowledge transfer layer, semantic matching is performed between the two aspects A_u and A_i to calculate the predicted score of user u on project i. The semantic matching between each aspect pair between A_u and A_i is calculated, as shown in Equation (9).

$$S_{p,q} = A_u^T \cdot M_a \cdot A_i \tag{9}$$

In Equation (9), M_a is an aspect matching mapping matrix that encodes the importance of preference transfer between each aspect in the D_s and each aspect in the D_t. $S_{p,q}$ reflects the degree of matching between the corresponding aspects and (p, q). Finally, each pair of semantic matches in $S_{p,q}$ is summed and their average value is taken, taking into account user and project biases, to calculate the final prediction score, as shown in Equation (10).

$$r_{u,i} = \frac{1}{M \cdot M} \sum_{p=1}^{M} \sum_{q=1}^{M} S_{p,q}(p, q) + b_u + b_i \tag{10}$$

In Equation (10), b_u is the user bias term, and b_i is the project bias term.

Optimization Strategy

The optimization strategy systematically refines model parameters to minimize error and improve recommendation accuracy by integrating aspect-level insights and cross-domain knowledge.

This article designs a user preference transfer model based on two-stage generative adversarial networks for cross-domain migration of aspect-level user preferences. Transferring user aspect-level interest preferences from D_s with rich interactive data to D_t with sparse data can effectively alleviate the cold start problem of users lacking interaction history in the D_t. Inspired by the method of generating adversarial networks, the aspect-level feature encoder E_s is trained and used as a generator in the data rich D_s. Combined with the constraints of domain discriminator D_c, the data distribution differences in different domains is solved by mapping the data from D_s and D_t to similar feature spaces. In the pre-training stage, A_u^s and A_i^s are used as inputs for E_s, combined with a multi-layer perceptron to predict the user's rating of the product and optimized using a square loss function, as shown in Equation (11).

$$Loss = \frac{1}{|O|} \sum_{(u,i)} \left(r_{u,i} - r'_{u,i} \right)^2 + \lambda_\theta \|\theta\|^2 \tag{11}$$

In the transfer learning stage, the goal is to transfer aspect-level features from the user's D_s to the D_t. Firstly, the pre-trained D_s feature encoder E_s is used to initialize the parameters of the D_t feature encoder E_t. The parameters of E_s are fixed and the parameters of E_t are updated, so that the aspect-level features encoded by E_t continuously approach the feature distribution in the D_s after encoding, while preserving the characteristics of the D_t data distribution. In order to constrain the similar feature distribution after encoding by two encoders, this article adopts two strategies: the parameters of the fixed D_s encoder do not participate in training, and, at the same time, a domain discriminator is designed to distinguish whether the encoded features come from the D_s or the D_t. When the distribution of the encoded features is sufficiently similar, the domain discriminator will not be able to correctly determine the domain to which the feature data belongs. On the one hand, the feature encoder can mine sufficiently effective domain-related features to achieve more accurate scoring prediction; on the other hand, domain-related features enable the domain discriminator to accurately determine the data source. Only when the feature distribution of the encoded data in the D_s and D_t is sufficiently similar can the domain discriminator fail to make accurate judgments. Therefore, in the transfer learning stage, the training process of domain discriminator and feature encoder is adversarial to each other.

The optimization goal of domain discriminator D_c is the classification task. This article sets the D_s as a positive class with a label of 1 and the D_t as a negative class with a label of 0. The optimization goal of the D_t feature encoder E_t is the regression task of scoring prediction. In adversarial learning, the optimization method of the D_t encoder E_t is shown in Equation (12), and the optimization of the domain discriminator D_c is the cross entropy loss function.

$$Loss' = -y \log D_c(x) - (1 - y)\log\left[1 - D_c(x)\right] \quad (12)$$

Remark 1

The proposed C-KE-AUT-based CDR strategy addresses the core challenges of polysemy, sparse data, user cold starts, and extracting nuanced user preferences by integrating a trio of advanced solutions. Knowledge transfer learning tackles data scarcity and the challenge of engaging new users by leveraging insights from related domains. To overcome the ambiguity of language, an advanced pre-trained language model interprets user comments with greater accuracy. Finally, the transformer architecture is employed to meticulously analyze user feedback, enabling the system to discern and cater to fine-grained, aspect-level preferences. This comprehensive approach not only mitigates existing limitations but also significantly enhances the precision and personalization of recommendations, promising a superior user experience.

Remark 2

Technically, the C-KE-AUT model introduces a two-stage generative adversarial network that facilitates the cross-domain transfer of user aspect-level preferences, effectively leveraging dense information in the source domain to address data sparsity and the cold start issue in the target domain. It incorporates the RoBERTa pre-trained language model for robust word embedding, enhancing the model's ability to handle the intricacies of language polysemy and contextual nuance within user comments. Further, the model employs the transformer architecture to deeply mine user preferences at an aspect level, capturing nuanced, fine-grained user preferences by focusing on the specific aspects of products or services that users care about. This technical synergy enables a more precise understanding and prediction of user preferences across different domains, paving the way for more accurate and personalized cross-domain recommendations.

EXPERIMENT

Environment and Parameter Settings

The experimental environment is shown in Table 2.

The model parameter settings are shown in Table 3.

Datasets and Evaluation Criteria

The experimental process was conducted based on the Amazon 2018 review dataset, which contains a large number of Amazon product reviews and related metadata, including review time, reviewer information, product information, ratings, and text comments. This dataset contains 233.1 million comments and was collected from May 1996 to October 2018, covering 29 product categories. In addition, the dataset also includes product metadata (such as description, category, price, brand, and image features) and link data (such as co view/co purchase relationship diagrams). This dataset can be used to study consumer perceptions and attitudes towards products, as well as to analyze the interrelationships between products. It has important application value for market research, product development, and sales strategy formulation. This article aims to use this dataset to achieve CDR.

Table 2. Experimental Environment

Project	Configuration
IDE Parameters	Anaconda3-Windows-x86_64
GPU	NVIDIA GeForce RTX 3090 Ti 24GB
Hard disk	1T
CPU	Intel CoreI i7-8750H@2.20GHz
Programming language	Python 3.10
Development Framework	TensorFlow 1.14.0

We selected three related categories as the domains (Books, Movies, and Music). Table 4 reports detailed statistical data for each field.

The data information for the three cross-domain scenarios is provided in Table 5.

The evaluation indicators are as follows.

(1) Mean absolute error (MAE) is represented in Equation (13).

$$MSE = \frac{1}{N}\sum_{(u,i)\in N}\left(r_{u,i} - r'_{u,i}\right)^2 \tag{13}$$

(2) Mean square error (MSE) is represented in Equation (14).

$$MAE = \frac{1}{N}\sum_{(u,i)\in N}\left|r_{u,i} - r'_{u,i}\right| \tag{14}$$

In Equations (13) and (14), N is the number of test data. $r_{u,i}$ represents the true score of the test data. $r'_{u,i}$ is the predicted score using the model.

Baseline Method

Several methods were selected as baseline methods for comparison, including a single-domain recommendation method based on comment user modeling and advanced CDR methods. The single-domain recommendation method based on comment user modeling is the aspect-based neural recommender (ANR) method (Chin, J., et al., 2018). This method is one of the most advanced single-domain recommendation methods and performs rating prediction by matching aspect-level information of users and products. Unlike attention-based methods, this method is based on deep neural networks to mine fine-grained aspect-level information of users.

The advanced CDR methods selected as baseline methods for comparison include the following:

- Personalized Transfer of User Preferences for Cross-domain Recommendation (PTUPCDR) (Zhu et al., 2021). This method proposes the concept of personalized transfer of user features for the first time. Based on the mapping method, meta learning is used to design and generate different personalized mapping parameters for each user, which is better than the method where all users share the same mapping model.
- Cold-start aspect transfer network (CATN) (Zhao et al., 2020). The leading aspect-level CDR method currently uses auxiliary information to enhance user documents, mine user aspect-level features, and use the matching degree of aspect-level features in CDR for rating prediction.

Table 3. Model Parameter Settings

Project	Configuration
Batch size	128
Regularization strategy	Dropout
Maintain probability	0.6
Hyperparameter optimization scheme	Grid search
Optimizer	Adam
Learning rate	0.001

Table 4. Detailed Statistical Data for Each Field

Dataset	Books	Movies	Music
User	126 666	27 822	11 053
Item	63 202	12 287	7 710
Score	3 494 976	779 376	296 188
Sparsity	0.044	0.228	0.348
Average user comments	27.6	28.0	26.8
Average item comments	55.3	63.4	38.4

Table 5. Data Information for Three Cross-Domain Scenarios

Scene	1		2		3	
Domain	D_s	D_t	D_s	D_t	D_s	D_t
data set	Books	Movies	Movies	Music	Books	Music
Overlap users	6074		2782		1705	
Overlap ratio	4.80%	21.83%	10.00%	25.17%	1.35%	15.43%

- Preference propagation graphnet (PPGN) (Zang et al., 2021). This method constructs an interaction graph between users and products, mining structured information, and converting CDR tasks into link prediction tasks. Based on graph convolutional neural networks, graph information is fully utilized, but text information is not used.
- Dual cross-domain with multi-channel interaction (DCMI) (Zhang, Hua, et al., 2023). This method is aimed at addressing the issue of session modeling difficulties caused by complex situations during the CDR process. It utilizes dual cross-domain session information to propose an interactive model for cross-domain personalized recommendation.
- Hierarchical user and item representation model with three-tier attention (HUITA) (Zhang, Chen, et al., 2023). This model utilizes attention mechanism to assign different importance to different comments, and it conducts user profile mining by selecting representative relevant comments. Based on this, a user preference recommendation model is proposed.

Comparison With Other Advanced Models

In order to verify the accuracy of model recommendations, the C-KE-AUT model proposed in this article was experimentally evaluated and compared with existing models PTUPCDR, CATN, PPGN, ANR, DCMI, and HUITA on the Amazon 2018 review dataset. The errors of different models are as follows.

Tables 6 and 7 and Figures 5 and 6 analyze the MAE and MSE on different data pairs. The proposed C-KE-AUT model is significantly superior to other comparative models in experiments with different data pairs. In the three scenarios, the MAE of C-KE-AUT is 0.821, 0.784, and 0.735, respectively, and the MSE is 1.052, 1.033, and 0.852, respectively. This is because the user aspect-level preference cross-domain migration architecture based on two-stage generative adversarial networks in the C-KE-AUT model can utilize data and user feedback between different domains for cross-domain analysis and recommendation, providing more diverse and rich recommendation results with much better performance than single-domain recommendation methods. In addition, the C-KE-AUT model uses a RoBERTa pre-trained language model to convert text into word vectors and perform preliminary feature extraction. Knowledge enhancement through a representation dictionary can better solve the problem of polysemy. Based on this, utilizing comment text and partitioning aspect-level features can more effectively improve the accuracy of rating prediction.

Performance Verification of Word Embedding Model

In the proposed CDR method, RoBERTa, BERT, Glove, and Word2Vec were used as word embedding models, and the MAE and MSE obtained in different cross-domain scenarios are shown in Table 8.

In Table 8, in the three scenarios, the MAE of using +RoBERTa as the word embedding model is 0.821, 0.784, and 0.735, respectively, and the MSE is 1.052, 1.033, and 0.852, respectively. This shows that the +RoBERTa model is optimal compared to the other three word embedding models.

Analysis of Complexity

When analyzing the computational complexity of an algorithm like the C-KE-AUT model, we consider the individual operations and their complexities during each stage of the algorithm.

1. Feature extraction: Extracting features with RoBERTa and transformer architectures involves matrix multiplications which are typically $O(n \cdot d^2)$, where n is the sequence length and d is the dimensionality of the representations. Assuming U users, I items, and an average comment length of C, this step has a complexity of $O((U + I) \cdot C \cdot d^2)$.
2. Aspect-level attention learning: Attention mechanisms compute weights across the length of the input sequences, leading to a complexity of $O(C^2 \cdot d)$ per user or item. The total complexity across all users and items for attention can be $O((U + I) \cdot C^2 \cdot d)$.
3. Aspect-level knowledge transfer: The transfer of aspect-level features across domains might involve operations like matrix factorization or neural network predictions, which can vary from $O(k \cdot d)$ to $O(d^2)$, where k is the number of aspects.
4. Optimization: The complexity of optimization depends on the loss function calculation, typically for $O(U \cdot I)$ the entire rating matrix, and the optimization algorithm used (e.g., gradient descent, which is $O(iter \cdot param)$, where $iter$ is the number of iterations and $param$ is the number of parameters).
5. Cold-start prediction: Making predictions for cold-start users involves a matrix-vector multiplication, which is $O(d^2)$ for each user.

The overall complexity of the algorithm is the sum of the complexities of its parts. However, in practice, the most computationally expensive steps tend to dominate the overall complexity. For recommendation systems like C-KE-AUT, feature extraction and attention mechanisms are often the most intensive, especially for large datasets with many users and items or when dealing with long sequences of text in comments. Additionally, the optimization step can be particularly costly due to the need for multiple iterations over large parameter spaces. It is also important to note that optimizations such as batching operations and parallel processing can significantly reduce wall-clock time, though the theoretical complexity remains the same.

Table 6. MAE of Different models

Model	Books-Movies	Music-Movies	Music-Books
PTUPCDR	0.889	0.849	0.796
CATN	0.935	0.893	0.837
PPGN	1.170	1.117	1.047
ANR	1.269	1.212	1.136
DCMI	0.850	0.811	0.761
HUITA	0.897	0.857	0.803
C-KE-AUT	0.821	0.784	0.735

Analysis of the Number of Aspects

The number of aspects will affect the granularity of user aspect-level interest preference features. A total of eight different aspects, ranging from 3 to 10, were selected from multiple domains to conduct experimental investigations on the impact of aspect numbers on user preference mining. The MAE and MSE results obtained in different cross-domain scenarios are shown in Figures 7 and 8.

In Figures 7 and 8, the number of aspects corresponding to achieving optimal results is not entirely consistent for different data sets. This is because the content of comments in each domain dataset is different, resulting in differences in the aspect-level features it contains. At the same time, it can be observed that the optimal number of aspects for Books Movies, Music Movies, and Music Books is 5, 6, and 7, respectively. As the number of aspects increases, MAE and MSE show a significant growth trend in the later stage, which means that the recommendation effect decreases. This is because the number of aspects can affect recommendation effectiveness by changing the granularity of knowledge in each aspect of the domain. A small number of aspects can lead to a larger granularity of aspect-level features and a less specific expression. However, an excessive number of aspects can lead to fine-grained aspect-level features, making it difficult to express common features in the domain. In addition, although the number of different aspects has an impact on the effectiveness of personalized recommendations, the overall fluctuation is not significant, which further indicates that the proposed C-KE-AUT model has robustness.

Relieve Data Sparsity Issues

In order to verify that the proposed C-KE-AUT model can alleviate the data sparsity in the D_t, a comparative experiment was set up to compare and analyze it with other recommendation models. The experiment was conducted by different user comments. Assuming that *a* can be used to reflect the sparsity of data. In the Books Movies scenario, several models were tested using different a values, and the MAE and MSE obtained are shown in Figures 9 and 10.

In Figures 9 and 10, regardless of the value of *a*, the C-KE-AUT model can achieve low and stable MAE and MSE values in the movie book scenario, indicating that the proposed C-KE-AUT model can alleviate the adverse impact of data sparsity on recommendation results. In addition, the proposed C-KE-AUT model can obtain lower MAE and MSE values than other comparative models, indicating that it can better alleviate data sparsity and effectively improve recommendation performance in cross-domain scenarios.

Alleviate User Cold Start Issues

User cold start is an issue that cannot be ignored in recommendation systems. When there are few new user behavior messages, the system cannot grasp their preferences, and recommendation performance will decrease. CDR has better effectiveness in this regard. To verify the performance

Figure 5. MAE of Different Models

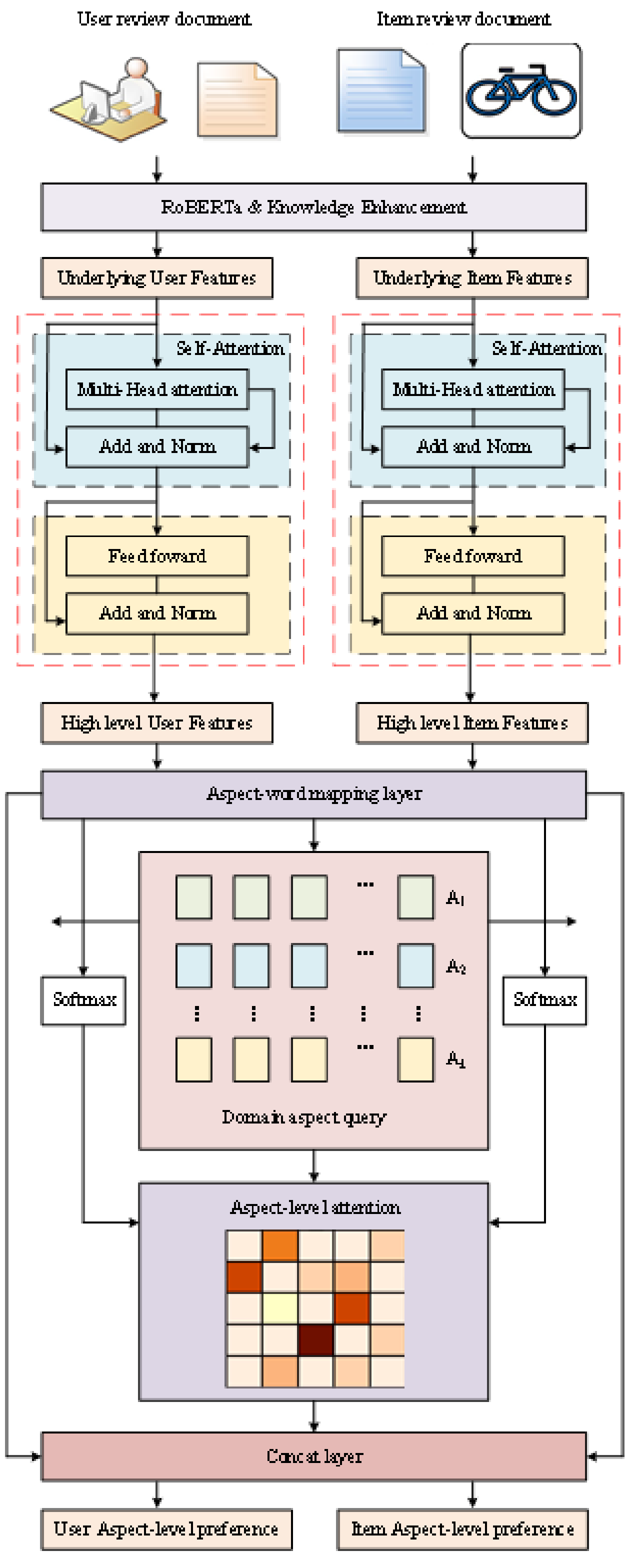


Table 7. MSE of Different Models

Model	Books-Movies	Music-Movies	Music-Books
PTUPCDR	1.139	1.119	0.923
CATN	1.198	1.177	0.970
PPGN	1.499	1.472	1.214
ANR	1.626	1.597	1.317
DCMI	1.089	1.069	0.882
HUITA	1.150	1.129	0.931
C-KE-AUT	1.052	1.033	0.852

Table 8. Experimental Results of Word Embedding Model

Model	Books-Movies		Music-Movies		Music-Books	
	MAE	MSE	MAE	MSE	MAE	MSE
+Word2vec	1.154	1.478	1.102	1.451	1.033	1.197
+Glove	0.922	1.181	0.880	1.160	0.825	0.957
+BERT	0.865	1.108	0.826	1.088	0.774	0.897
+RoBERTa (ours)	0.821	1.052	0.784	1.033	0.735	0.852

of C-KE-AUT in addressing the cold start problem of users in D_t, a comparative experiment was conducted to compare and analyze the C-KE-AUT model with other recommended models in the Book Movies scenario. We selected 800 new users from the Books and Movies datasets that do not

Figure 6. MSE of Different Models

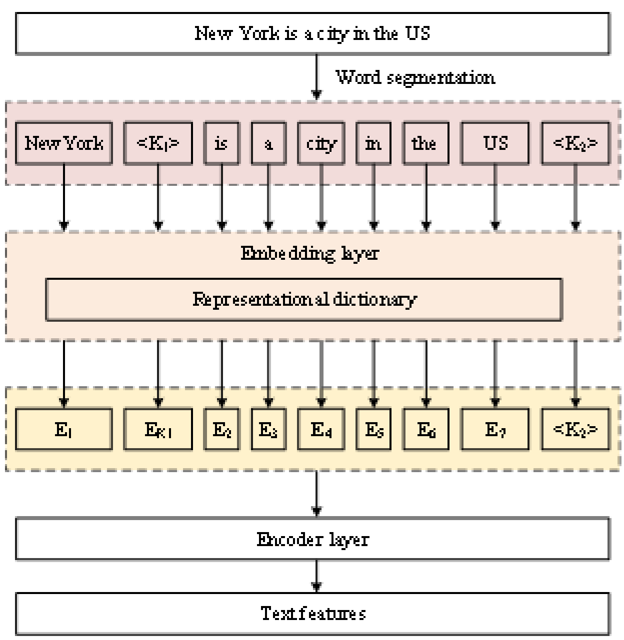
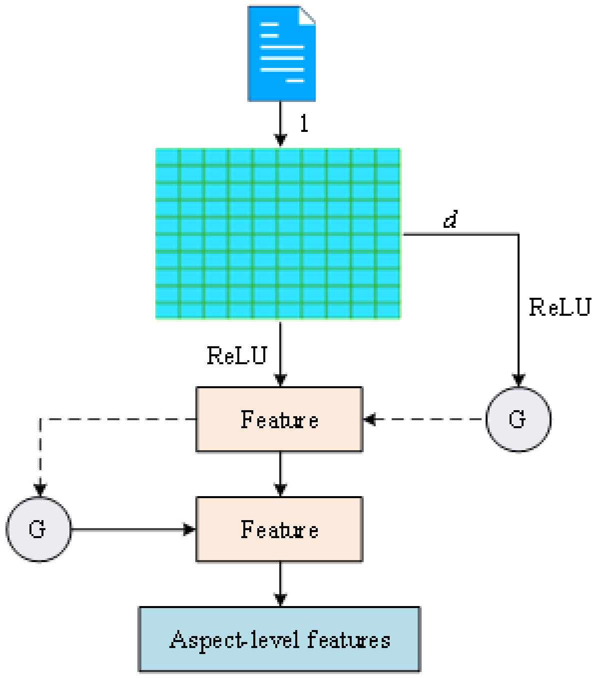


Figure 7. The Impact of The Quantity of Aspects on MAE



overlap with the training set users, and controlled new user comments to 1, 3, and 5 for testing. The obtained MAE and MSE are shown in Figures 11 and 12, respectively.

In Figures 11 and 12, in the Books Movies scenario, the results of different recommendation models being affected by user cold start issues under different evaluation indicators are shown. It can be observed that as the number of comments increases, the C-KE-AUT model has achieved better results compared to other models, especially for least comments and cold start, the advantages of C-KE-AUT are more obvious. This result verifies the advantages of the proposed C-KE-AUT model in alleviating user cold start problems.

Ablation Experiment

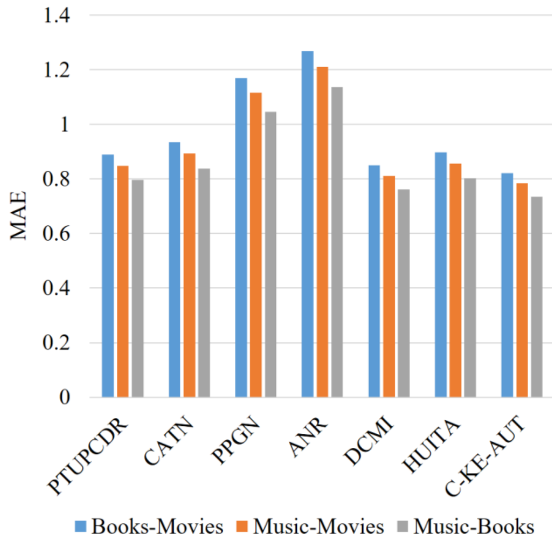
In order to further validate the effectiveness of each module in the model, a model ablation experiment was designed to compare the impact of different modules on the overall performance of the model. The design is as follows:

- Model 1: w/o RoBERTa: Remove the pre-trained language module RoBERTa and directly input the word vector into the transformer module.
- Model 2: w/o transformer: Remove the transformer module and directly represent low-level features at the aspect level and interact with aspect-level attention.
- Model 3: w/o aspect attention: Remove attention interaction and directly concatenate user aspect-level features with project aspect-level features.

The results of the model ablation experiment are shown in Table 9.

In Table 9, regardless of which module is removed from the model, it will cause an increase in the MAE and MSE of the model's CDR results—that is, removing any module from the model will lead to a decrease in the model's recommendation performance. At the same time, it can be seen

Figure 8. The Impact of the Quantity of Aspects on MSE



that the experimental results of Model 3 are the worst, indicating that aspect attention has a greater impact on the results and that this module is the most important. When integrating three features simultaneously, the model can learn more feature information, which is more conducive to accurate CDR. This result fully verifies the necessity of each module for the proposed C-KE-AUT model to achieve the best experimental results.

CONCLUSION

A CDR model that integrates knowledge augmentation and comment aspect-level user preference transfer is proposed to address the current difficulties in deeply mining user preferences from comment information, as well as the issues of polysemy in comment text, sparse comment data, and user cold start. Through recommendation experiments in three different cross-domain scenarios, it has been shown that during the transfer learning process, strategies such as fixing the D_s encoder parameters and introducing domain discriminators can solve the problem of data distribution differences between the D_s and D_t, effectively utilizing the rich data in the D_s to alleviate the user cold start problem caused by sparse data in the D_t. The RoBERTa pre-trained language model is used to convert text into word vectors and perform preliminary feature extraction, which can enhance knowledge through representation dictionaries and effectively solve the problem of polysemy. Using a transformer can capture richer contextual high-level features, thereby capturing fine-grained aspect-level knowledge features of users, greatly improving the accuracy of CDR.

The C-KE-AUT model carries managerial significance by offering insights into customer preferences, which are critical for personalizing product recommendations, enhancing user engagement, and guiding data-driven decision-making. Its nuanced preference analysis is particularly valuable for new product introductions and market expansions, where initial user data is limited, enabling businesses to effectively tailor their strategies and gain a competitive advantage.

However, the proposed CDR model did not fully consider the importance of each aspect, and future work will focus on taking cold-start rate into consideration and exploring the effectiveness of aspect-level knowledge in CDR to explore the role of different aspects in the knowledge transfer process. In addition, more effective methods for modeling user preference transfer in different fields

Figure 9. Test of the Impact of Data Sparsity on MAE

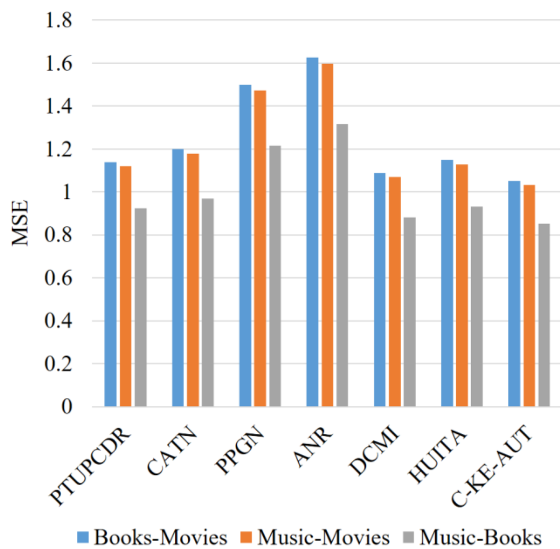
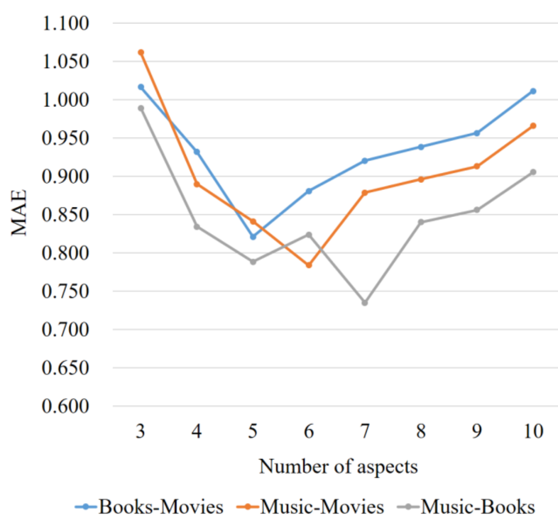


Figure 10. Test of the Impact of Data Sparsity on MSE



will be explored, and consideration will also be given to combining richer heterogeneous data to fully utilize relevant information.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

Figure 11. Test of the Impact of New User Comments Quantity on MAE

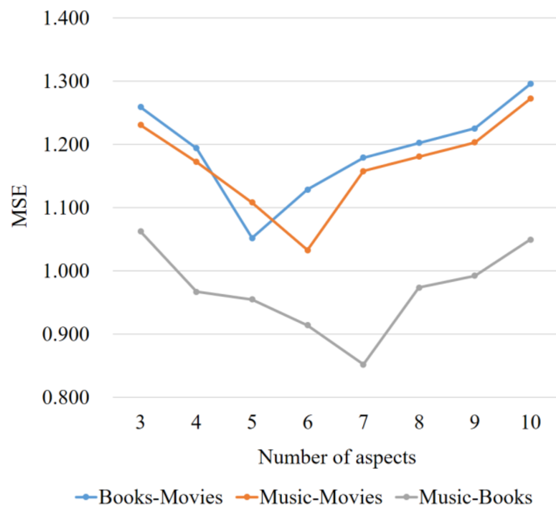
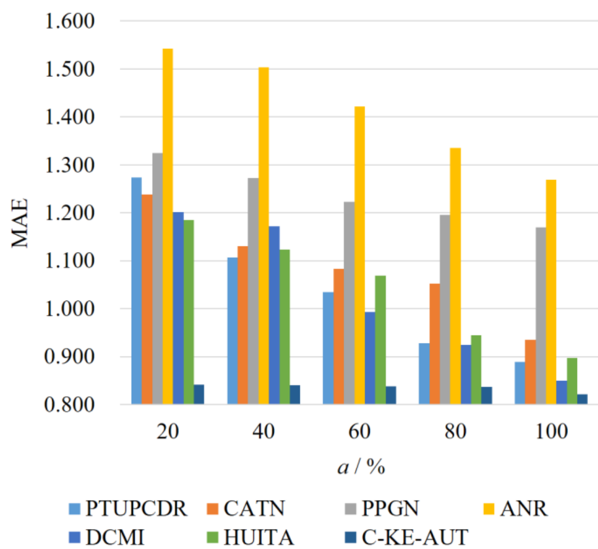


Figure 12. Test of the Impact of New User Comments Quantity on MSE



FUNDING STATEMENT

No funding was received for this work.

PROCESS DATES

Received: This manuscript was initially received for consideration for the journal on 02/23/2024, revisions were received for the manuscript following the double-anonymized peer review on

Table 9. Model Ablation Experimental Results

Model	Books-Movies		Music-Movies		Music-Books	
	MAE	MSE	MAE	MSE	MAE	MSE
Model 1	0.929	1.138	0.865	1.142	0.807	0.952
Model 2	0.935	1.182	0.884	1.136	0.825	0.927
Model 3	1.075	1.108	0.956	1.258	0.974	1.097
C-KE-AUT (ours)	0.821	1.052	0.784	1.033	0.735	0.852

Table 10. Algorithm 1: Comment Knowledge Enhancement and Aspect-Level User Preference Transfer for CDR (C-KE-AUT)

Input:
- Overlapping user set U_o between source and target domains.
- Item sets I_s (source) and I_t (target).
- Rating matrices R_s (source) and R_t (target).
- Direct and indirect side-information of users and items: D_ui_s, D_ui_t (direct user), D_ud_s, D_ud_t (direct item), D_idi_s, D_idi_t (indirect user), and D_idd_s, D_idd_t (indirect item).
- Global property set A.
Training Stage:
1. Extract source domain user and item aspect-level features to obtain A_us, A_is.
2. Extract target domain user and item aspect-level features to obtain A_ut, A_it.
3. Apply RoBERTa for word embedding on user comments to enhance feature representation.
4. Utilize Transformer architecture to capture high-level feature representations of users and items.
5. Apply aspect-level attention learning to weight the importance of various aspects.
6. Perform aspect-level knowledge transfer to adapt user preferences from source to target domain.
Optimization Stage:
1. Minimize MSE and MAE to align predicted ratings with actual ratings.
2. Tune the model using optimization strategies that refine aspect-level embeddings and cross-domain transfer effectiveness.
Cold-start Users Rating Prediction Stage:
1. For a new user u in target domain, predict ratings using transferred aspect-level preferences from source to target domain.

04/21/2024, the manuscript was formally accepted on 04/07/2024, and the manuscript was finalized for publication on 04/23/2024.

CORRESPONDING AUTHOR

Correspondence should be addressed to Wumei Zhang; Wumeizhang2023@163.com

REFERENCES

Abdi, M. H., Okeyo, G., & Mwangi, R. W. (2018). Matrix factorization techniques for context-aware collaborative filtering recommender systems: A survey. *Computer and Information Science*, *11*(2), 1. Advance online publication. 10.5539/cis.v11n2p1

Bernardis, C., & Cremonesi, P. (2021). NFC: A deep and hybrid item-based model for item cold-start recommendation. *User Modeling and User-Adapted Interaction*, *32*(4), 747–780. 10.1007/s11257-021-09303-w

Chin, J., Zhao, K., Joty, S. R., & Cong, G. (2018). ANR: Aspect-based neural recommender. In *CIKM '18: Proceedings of the 27th ACM international conference on information and knowledge management* (pp. 147–156). ACM. 10.1145/3269206.3271810

Da'u, A., & Salim, N. (2019). Recommendation system based on deep learning methods: A systematic review and new directions. *Artificial Intelligence Review*, *53*(4), 2709–2748. 10.1007/s10462-019-09744-1

Dong, S., Wang, P., & Abbas, K. (2021). A survey on deep learning and its applications. *Computer Science Review*, *40*, 100379. Advance online publication. 10.1016/j.cosrev.2021.100379

Du, Y., Wang, L., Peng, Z., & Guo, W. (2023). Review-based hierarchical attention cooperative neural networks for recommendation. *Neurocomputing*, *447*, 38–47. 10.1016/j.neucom.2021.03.098

Fernández-Tobías, I., Cantador, I., Tomeo, P., Anelli Vito, W., & Di Noia, T. (2019). Addressing the user cold start with cross-domain collaborative filtering: Exploiting item metadata in matrix factorization. *User Modeling and User-Adapted Interaction*, *29*(2), 443–486. 10.1007/s11257-018-9217-6

Hong, W., Zheng, N., Xiong, Z., & Hu, Z. (2020). A parallel deep neural network using reviews and item metadata for cross-domain recommendation. *IEEE Access : Practical Innovations, Open Solutions*, *8*(2), 41774–41783. 10.1109/ACCESS.2020.2977123

Huang, M., & Xiao, N. (2022). A recommendation model of deeply fusion rating matrix and review text. In *2022 IEEE International Conference on Electrical Engineering, Big Data and Algorithms (EEBDA)* (pp. 793–796). IEEE. 10.1109/EEBDA53927.2022.9745009

Huang, W., Hao, F., Shang, J., Yu, W., Zeng, S., Bisogni, C., & Loia, V. (2023). Dual-LightGCN: Dual light graph convolutional network for discriminative recommendation. *Computer Communications*, *204*, 89–100. 10.1016/j.comcom.2023.03.018

Javed, U., Shaukat, K., Hameed, I., Iqbal, F., Alam, T., & Luo, S. (2021). A review of content-based and context-based recommendation systems. *International Journal of Emerging Technologies in Learning*, *16*(3), 274–306. 10.3991/ijet.v16i03.18851

Jeong, C., Jang, S., Park, E., & Choi, S. (2020). A context-aware citation recommendation model with BERT and graph convolutional networks. *Scientometrics*, *124*(3), 1907–1922. 10.1007/s11192-020-03561-y

Lai, X., & Jie, Q. (2023). Deep semantic-level cross-domain recommendation model based on DSV-CDRM. *International Journal of Information Technology and Web Engineering*, *18*(1), 1–20. 10.4018/IJITWE.333639

Li, A., & Li, T. (2023). Fusion of XLNet and BiLSTM-TextCNN for Weibo sentiment analysis in Spark big data environment. *International Journal of Ambient Computing and Intelligence*, *14*(1), 1–18. 10.4018/IJACI.331744

Li, C., Zhao, M., Zhang, H., Yu, C., Cheng, L., Shu, G., Kong, B., & Niu, D. (2022). RecGURU: Adversarial learning of generalized user representations for cross-domain recommendation. In *Proceedings of the fifteenth ACM international conference on web search and data mining*, (pp. 571–581). ACM. 10.1145/3488560.3498388

Li, P., & Tuzhilin, A. (2020). DDTCDR: Deep dual transfer cross domain recommendation. In *Proceedings of the 13th international conference on web search and data mining* (pp. 331–339). ACM. 10.1145/3336191.3371793

Li, S., Zhang, Y., Li, Y., & Yu, Z. (2019). The user preference identification for product improvement based on online comment patch. *Electronic Commerce Research*, *21*(2), 423–444. 10.1007/s10660-019-09372-5

Liu, F., Cheng, Z., Zhu, L., Liu, C., & Nie, L. (2020). An attribute-aware attentive GCN model for attribute missing in recommendation. *IEEE Transactions on Knowledge and Data Engineering*, *34*(9), 4077–4088. 10.1109/TKDE.2020.3040772

S., & Pan, L. (2023). BTSAMA: A personalized music recommendation method combining TextCNN and attention. *International Journal of Ambient Computing and Intelligence*, *14*(1), 1–23. 10.4018/IJACI.327351

Ni, X., Nie, J., Zuo, Z., Xie, H., Liang, X., Jiang, M., Xu, J., Yu, S., & Liu, M. (2023). DITN: User's indirect side-information involved domain-invariant feature transfer network for cross-domain recommendation. *Information Processing & Management*, *60*(6), 103494. Advance online publication. 10.1016/j.ipm.2023.103494

Nie, J., Zhao, Z., Huang, L., Nie, W., & Wei, Z. (2021). Cross-domain recommendation via user-clustering and multidimensional information fusion. *IEEE Transactions on Multimedia*, *25*, 868–880. 10.1109/TMM.2021.3134161

Qian, F., Zhang, C., Feng, L., Lu, C., Zhang, G., & Hu, G. (2020). Tubal-sampling: Bridging tensor and matrix completion in 3-D seismic data reconstruction. *IEEE Transactions on Geoscience and Remote Sensing*, *59*(1), 854–870. 10.1109/TGRS.2020.2995573

Sang, S., Yuan, W., Li, W., Yang, Z., Zhang, Z., & Liu, N. (2023). Position-aware graph neural network for session-based recommendation. *Knowledge-Based Systems*, *262*, 110201. Advance online publication. 10.1016/j.knosys.2022.110201

Soydaner, D. (2022). Attention mechanism in neural networks: Where it comes and where it goes. *Neural Computing & Applications*, *34*(16), 13371–13385. 10.1007/s00521-022-07366-3

Wang, C., Liang, Y., Liu, Z., Zhang, T., & Yu, P. S. (2021). Pre-training graph neural network for cross domain recommendation. In *Proceedings of the 2021 IEEE Third International Conference on Cognitive Machine Intelligence (CogMI)*, 140–145. 10.1109/CogMI52975.2021.00026

Wei, W. (2021). Multi-channel relation modeling for session-based recommendation with self-supervised learning. In W. Cao, A. Ozcan, H. Xie, & B. Guan, B. (Eds.) *CONF-CDS 2021 Communications in computer and information science: Vol. 1513. Computing and data science* (pp. 158–170). Springer. 10.1007/978-981-16-8885-0_13

Wu, S., Zhang, Y., Gao, C., Bian, K., & Cui, B. (2020). GARG: Anonymous recommendation of point-of-interest in mobile networks by graph convolution network. *Data Science and Engineering*, *5*(4), 433–447. 10.1007/s41019-020-00135-z

Xie, R., Liu, Q., Wang, L., Liu, S., Zhang, B., & Lin, L. (2022). Contrastive cross-domain recommendation in matching. In *Proceedings of the 28th ACM SIGKDD conference on knowledge discovery and data mining* (pp. 4226–4236). ACM. 10.1145/3534678.3539125

Xu, Z., Lin, H., & Wu, M. (2023). A course recommendation algorithm for a personalized online learning platform for students from the perspective of deep learning. *International Journal of Information Technology and Web Engineering*, *18*(1), 1–17. 10.4018/IJITWE.333603

Yang, O., Guo, B., & Tang, X. (2021). Mobile app cross-domain recommendation with multi-graph neural network. *ACM Transactions on Knowledge Discovery from Data*, *15*(4), 55. Advance online publication. 10.1145/3442201

Zang, T., Zhu, Y., Liu, H., Zhang, R., & Yu, J. (2021). A survey on cross-domain recommendation: Taxonomies, methods, and future direction. *ACM Transactions on Information Systems*, *41*(2), 42. Advance online publication. 10.1145/3548455

Zhang, J. J., Hua, X., Zhao, P., & Kang, K. (2023). Dual cross-domain session-based recommendation with multi-channel integration. *AI Communications*, *36*(4), 341–359. 10.3233/AIC-230084

Zhang, Q., Hao, P., & Lu, J. (2019). Cross-domain recommendation with semantic correlation in tagging systems. In *2019 International joint conference on neural networks (IJCNN)* (pp. 1–8). *IEEE*. 10.1109/IJCNN.2019.8852049

Zhang, T., Chen, C., Wang, D., Guo, J., & Song, B. (2023). A VAE-based user preference learning and transfer framework for cross-domain recommendation. *IEEE Transactions on Knowledge and Data Engineering*, *35*(10), 10383–10396. 10.1109/TKDE.2023.3253168

Zhao, C., Li, C., Xiao, R., Deng, H., & Sun, A. (2020). CATN: Cross-domain recommendation for cold-start users via aspect transfer network. In *SIGIR '20: Proceedings of the 43rd international ACM SIGIR conference on research and development in information retrieval* (pp. 229–238). ACM. 10.1145/3397271.3401169

Lv,

Zhong, S. T., Huang, L., Wang, C. D., Lai, J.-H., & Yu, P. S. (2020). An autoencoder framework with attention mechanism for cross-domain recommendation. *IEEE Transactions on Cybernetics*, *52*(6), 5229–5241. 10.1109/TCYB.2020.302900233156800

Zhu, F., Wang, Y., Zhou, J., Chen, C., Li, L., & Liu, G. (2021). A unified framework for cross-domain and cross-system recommendations. *IEEE Transactions on Knowledge and Data Engineering*, *5*(8), 69–78. 10.1109/TKDE.2021.3104873

Zhu, Y., Tang, Z., Liu, Y., Zhuang, F., Xie, R., Zhang, X., Lin, L., & He, Q. (2021). Personalized transfer of user preferences for cross-domain recommendation. In *WSDM '22: Proceedings of the fifteenth ACM international conference on web search and data mining* (pp. 1507–1515). ACM. 10.1145/3488560.3498392

Zuo, Z., Nie, J., Zhao, Z., Xie, H., Ding, X., Yu, S., Yue, Y., Huang, L., & Wang, X. (2022, July). RPITN: Review based preference invariance transfer network for cross-domain recommendation. In *2022 IEEE international conference on multimedia and expo (ICME)* (pp. 1–6). IEEE. 10.1109/ICME52920.2022.9859771