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REGULAR PAPER

CRAS: cross-domain recommendation via aspect-level sentiment extraction

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Abstract

To address the problem of sparse data and cold-start when facing new users and items in the single-domain recommendation, cross-domain recommendation has gradually become a hot topic in the recommendation system. This method enhances target domain recommendation performance by incorporating relevant information from an auxiliary domain. A critical aspect of cross-domain recommendation is the effective transfer of user preferences from the source to the target domain. This paper proposes a novel cross-domain recommendation framework, namely the Cross-domain Recommendation based on Aspect-level Sentiment extraction (CRAS). CRAS leverages user and item review texts in cross-domain recommendations to extract detailed user preferences. Specifically, the Biterm Topic Model (BTM) is utilized for the precise extraction of 'aspects' from users and items, focusing on identifying characteristics that align with user interests and the positive attributes of items. These 'aspects' represent distinct, influential features of the items. For example, a good service attitude can be regarded as a good aspect of a restaurant. Furthermore, this study employs an improved Cycle-Consistent Generative Adversarial Networks (CycleGAN), efficiently mapping user preferences from one domain to another, thereby enhancing the accuracy and personalization of the recommendations. Lastly, this paper compares the CRAS model with a series of state-of-the-art baseline methods in the Amazon review dataset, and experiment results show that the proposed model outperforms the baseline methods.

Keywords Cross-domain recommendation · Aspect-level sentiment extraction · CycleGAN-mapping · BTM

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1 Introduction

With the rapid development of Internet technology, information resources are soaring rapidly and the problem of "information overload" is also coming. It is very difficult for users to obtain personalized information suitable for them from massive news, videos, pictures, commodities, and other resources. To solve this problem, recommendation systems have been proposed [1] to help users quickly find information of interest, improve user experience, and help users establish accurate connections with items. Among various recommendation systems, the collaborative filtering algorithm (CF) has been the most widely used, with numerous technologies developed around it. Collaborative filtering algorithms rely on historical user-item interaction data, such as ratings, purchase history and browsing history, to model user preferences and item characteristics. However, a major limitation of the collaborative filtering algorithm is its inability to provide reliable recommendations to users with few ratings or recommend items with limited ratings, i.e., the well-known cold-start problem in real-world recommendations systems. Moreover, they do not extract users' fine-grained preferences.

Recently, user reviews have been gradually being used in the recommendation system. Firstly, user reviews are easily accessible on many websites, such as *Amazon* and *Taobao*. Secondly, the review text often better represents the user's fine-grained preferences. User reviews often include the user's opinions on multiple aspects of the item. The rich semantic information of the review can help us understand which aspects of the item users like or dislike. For instance, a user gave a restaurant only two stars and wrote in the review: "The restaurant waits for a long time, but the food is delicious and the service is good." Obviously, the reason for the low rating of the restaurant is the long waiting time for meals. Therefore, a low score does not mean that the restaurant is not good, and users do not like it at all. On the contrary, the user is interested in some aspects of the restaurant, and some aspects of the restaurant are good. However, how to extract user concerns from user reviews is still a problem. At present, many studies apply reviews to recommendation systems [2–6], but these methods are either only applied to a single domain or do not advance users' fine-grained preferences well.

In recent years, aspect (topic) extraction models have seen extensive development. These models can identify aspects in documents, mine hidden information in the corpus, and have a wide range of applications in aspects aggregation, information extraction from unstructured text, feature selection, and other scenarios. The most popular aspect models are Latent Semantic Analysis (LSA) [7], Probabilistic Latent Semantic Analysis (PLSA) [8], Latent Dirichlet Allocation (LDA) [9], lda2vec [10] at present. However, they are all suitable for aspect extraction of long text, and their results are relatively weak on short texts similar to reviews. In 2014, some scholars proposed the Biterm Topic Model (BTM) [11] model to be used for the aspect extraction of the short text and achieved good results. This paper applies the BTM model to the field of recommender systems and uses the BTM model to extract the aspects concerned in user reviews. However, user reviews often contain both aspects that the user likes and aspects that the user dislikes, item reviews include both good aspects and bad aspects of the item. In the recommendation, we only need to focus on the aspects that the user likes or the good aspects of the item. Therefore, we first need to perform sentiment analysis on user reviews to remove the negative sentiment sentences in the reviews. Secondly, the reviews contain many words that have nothing to do with aspects, such as some conjunctions and adverbs. If the reviews are directly extracted using the BTM model, many invalid words will appear. Therefore, we first need to clean the review and only retain the nouns and verbs related to the aspect, then use the BTM model to extract the aspect.

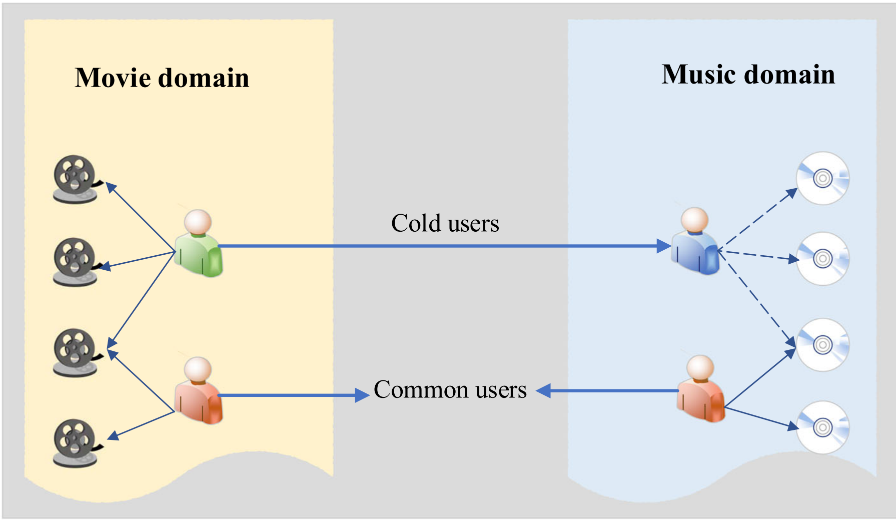

Fig. 1 Cross-domain structure diagram

In addition, a cross-domain recommendation system is proposed to cope with data sparsity and cold-start problems [12–19]. That is to give two unrelated domains (e.g., *Music* and *Movie*), users may have historical interactions in one domain (i.e., *Movie*), but not the other (i.e., *Music*), as shown in Fig. 1. Specifically, if a user has interacted with items in the movie domain but not in the music domain, the movie domain becomes the source domain and the music domain becomes the target domain for that user. It's important to note that this categorization is fluid and depends on the user's interaction history in each domain. In our experiments, we treat the domains as interchangeable, where each domain can be both a source and a target domain, to demonstrate the model's effectiveness in handling cold-start problems in different scenarios.

In cross-domain recommendation, the existing method mainly uses common users in two domains to perform the cross-domain mapping. The cross-domain structure diagram is shown in Fig. 1. The connection between two domains is established by the common users of both domains, and then the cold-start users of the source domain are mapped to the target domain through the connections obtained by the common users to predict the users' behavior in the target domain. In the cross-domain recommendation, the most important step is cross-domain mapping. Existing methods, such as Embedding and Mapping framework for Cross-Domain Recommendation (EMCDR) [20], Review and Content based Deep Fusion Model (RC-DFM) [15], all use user rating information to learn cross-domain mapping, but this mapping method cannot capture the fine-grained preferences of users. The highlight of this paper is that this paper fully uses the user historical information to learn the user preference representation of the cold-start users in the target domain by mapping the user preference of the source domain. Firstly, this paper captures user fine-grained preferences in the source domain by extracting the user-concerned aspects from the user reviews. Secondly, this paper uses the improved Cycle-Consistent Generative Adversarial Networks (CycleGAN) [21] to map the user representation from the source domain to the target domain effectively.

The main contributions of this paper are as follows:

- This paper proposes a novel cross-domain recommendation framework. This framework uses review text to extract user fine-grained preferences, try to learn an aspect-based cross-domain recommendation method, at the same time uses the CycleGAN-mapping to learn the mapping from the source domain to the target domain.
- In this paper, the topic model BTM is applied for the first time to the extraction of the user and item aspects in cross-domain recommendation, looking for the aspects that users are interested in and the good aspects of items.
- We demonstrate strong experimental results in three different domain datasets (Amazon review dataset), and the experimental results show that the proposed model has splendid performance.

The rest of the paper is organized as follows. We first introduce related work in aspect extraction models and cross-domain recommendations in Sect. 2. Then, we present the model structure of the cross-domain recommendation via aspect-level sentiment extraction system in detail in Sect. 3. Section 4 describes the model experiment settings, related baseline comparisons and experimental results, and analyzes the results. Next, we analyze the model and summarize our work.

2 Related work

Related work in this paper mainly involves the following areas: aspect extraction model [22, 23] and cross-domain recommendation [24–26].

2.1 Aspect extraction model

Aspect extraction models are widely used in machine learning and natural language processing to discover abstract aspects (topics) from a series of documents. LSA is one of the basic techniques of aspect extraction modeling. The core idea is to decompose the document-term matrix into an independent document-aspect matrix and aspect-term matrix. This method primarily employs singular value decomposition to project documents into a lower-dimensional space, thereby creating a latent semantic space. The LSA method is fast and efficient but requires a large number of documents and vocabulary to obtain accurate results, and the characterization efficiency is low. PLSA adopts probabilistic methods instead of Singular Value Decomposition (SVD) to solve the problem. The core idea is to find a probability model of a potential aspect. In PLSA, the document is a mixture of aspects, and the aspect is the probability distribution of words. PLSA is a more flexible model, but there are still some problems. The number of PLSA's parameters increases linearly with the document count, making it prone to overfitting. LDA, the Latent Dirichlet Distribution, which is the Bayesian version of PLSA, is extended based on PLSA. It uses Dirichlet priors to process document-aspect and word-aspect distributions, thus contributing to better generalization and extension. LDA has achieved great success in the field of text mining. Lda2vec [10] is an extension of word2vec and LDA. It is specifically modeled based on word2vec's skip-gram model to generate word vectors. The power of lda2vec is that it can learn not only word embedding (and context vector embedding) of words, but also aspect representation and document representation at the same time. However, the above models only deal with normal text, without considering the particularity of short texts (such as reviews, Weibo texts, and barrage in the live broadcast room).

In 2014, the BTM [11] was proposed to provide a reliable solution for aspect extraction of short texts. BTM learns the aspects in short texts by directly modeling the generation of word co-occurrence patterns (biterms) in the corpus. A Biterm is an unordered word pair. Any two different words in a short document form a biterm. For example, a document containing three different words will generate three biterms. $(w_1, w_2, w_3) = \{(w_1, w_2), (w_2, w_3), (w_1, w_3)\}$, where(.,.) is disordered. After extracting biterms from each document, the entire corpus becomes a collection of biterms. BTM assumes that two words in a biterm get the same aspect from the aspect mix of the entire corpus. BTM and LDA modeling methods are similar, both use Dir-Multi conjugate modeling and Gibbs solving, the difference is that LDA uses a single word modeling, BTM uses biterms modeling. However, it is not ideal to directly use the aspect extraction model to extract aspects from the review text, and there will be many invalid words. Therefore, it is necessary to clean the review text before using BTM to extract aspects of the review text.

2.2 Cross-domain recommendation

In recent years, a series of solutions have been proposed to solve the data sparsity and cold-start problem of the target domain by using source domain information as auxiliary information [1, 27]. First of all, Collective Matrix Factorization (CMF) [28] proposed to realize cross-domain knowledge integration by concatenating multiple matrices and sharing user factors across domains. Then the time domain CF [29] shares the static group-level scoring matrix in the time domain. On this basis, Coupled Matrix and Tensor Factorization (CDTF) [30] proposed the use of tensor factor decomposition to obtain the ternary relationship of the user-item domain. These works based on collaborative filtering have serious data sparsity problems when considering different fields as a whole.

Currently, with the renaissance of deep learning, many models based on a deep level have been proposed for cross-domain knowledge transfer. EMCDR [20] proposed a cross-domain recommendation framework for embedding and mapping, using user-item rating matrix and other information, using a latent variable to find the expression of the user or item in the hidden space, and then capturing a potential nonlinear mapping relationship between users or items in the source domain and the target domain through a multi-layer perceptron. The DCDCSR [13] integrates matrix factorization models and fully connected deep neural networks to implement cross-domain and cross-system recommendations, further extending EMCDR. Parallel Information-sharing Network (π-Net) [31] is oriented to a cross-domain sequential recommendation scenario for shared accounts. RC-DFM [32] uses Stacked Denoising AutoEncoder (SDAE) to train users or project factors and uses Multi-Layer Perceptron (MLP) to transfer potential factors of users between different domains to solve the cold-start problem. Cross-domain recommendation framework via Aspect Transfer Network (CATN) [26] learns aspect features from user and item review information as well as utilizes similar users' reviews as auxiliary reviews, and learns inter-aspect correlations across domains through an attention mechanism. Personalized Transfer of User Preferences for Cross-domain Recommendation (PTUPCDR) [33] learns meta-networks through user feature embedding to generate personalized bridge functions to achieve personalized preference transfer for each user.

The existing cross-domain recommendation methods have achieved good results, but they also have some shortcomings. They do not make full use of the review information and cannot map users' fine-grained preferences. Therefore, the paper proposes a cross-domain recommendation via an aspect-level sentiment extraction system to extract user fine-grained

Table 1 Notations and their definitions

Notation	Definition
$\mathcal{D}_S$	All users in the source domain, item ratings and reviews collection
$\mathcal{D}_T$	All users in the target domain, item ratings and reviews collection
S_u	User u in the source domain
S_i	User i in the source domain
$d^S_{u,i}$	User S_u review on item S_i in the source domain
$r^S_{u,i}$	User S_u rating on item S_i in the source domain
T_u	User u in the target domain
T_i	Items in the target domain i
$d^T_{u,i}$	User T_u reviews on item T_i in the target domain
$r^T_{u,i}$	User T_u rating of item T_i in the target domain
$D_{S,u}$	User u review document in the source domain
C_U	Common user collection of source and target domains
D_{S,c_u}	Review documents of common user c_u in the source domain
D_{T,c_u}	Review documents of common user c_u in the target domain
$D_{T,iS}$	Review document for item i in the target domain
$D'_{S,u}$	New source domain user review document after processing
D'_{S,c_u}	The processed new source domain common user review document
D'_{T,c_u}	The processed new target domain common user review document
$D'_{T,i}$	The processed new target domain item review document
$A_{S,u}$	Aspect representation of user u in the source domain
$A_{T,i}$	Aspect representation of item i in the target domain
A_{S,c_u}	Aspect representation of common user c_u in the source domain
A_{T,c_u}	Aspect representation of common user c_u in the target domain
$M_{S,u}$	Aspect embedding representation of user u in the source domain
$M_{T,i}$	Aspect embedding representation of item i in the target domain
M_{S,c_u}	Aspect embedding representation of common user c_u in the source domain
M_{T,c_u}	Aspect embedding representation of common user c_u in the target domain
$M'_{S,u}$	Embedded representation of the new source domain user u after cross-domain mapping
$r_{u,i}$	The final predicted rating of the source domain user u on the target domain item i

preferences from user review text and introduce them into cross-domain recommendations to improve the accuracy of cross-domain recommendations.

3 CRAS framework

In this part, this paper presents the proposed cross-domain recommendation via aspect-Level sentiment extraction (CRAS). First, this paper specifies the problem statement and the key notation used and then presents the overall framework of the model. Finally, each component of the model is described in detail.

3.1 Notation and problem definition

This paper uses $\mathcal{D}_S$ and $\mathcal{D}_T$ to represent all users, items, ratings, and review sets in the source domain and the target domain, respectively. The interaction between each user and the item in the source domain can be expressed as a tuple $(S_u, S_i, d^S_{u,i}, r^S_{u,i})$, where $d^S_{u,i}$ is user S_u reviews on the item S_i in the source domain, $r^S_{u,i}$ is the rating of the user S_u on the item S_i in the source domain. Each user interacting with the item in the target domain can also be expressed as a tuple $(T_u, T_i, d^T_{u,i}, r^T_{u,i})$, where $d^T_{u,i}$ is user T_u reviews on the item T_i in the target domain, $r^T_{u,i}$ is the rating of the user T_u on the item T_i in the target domain. Table 1 summarizes the main notations used in the rest of this paper.

Problem. The main purpose of the paper is to estimate the rating $\hat{r}_{u,i}$ of T_i for items in the target domain by user S_u in the source domains, where user S_u and item T_i have never interacted before.

3.2 Overview of CRAS

The entire framework of CRAS is shown in Fig. 2. Its structure consists of five parts: sentiment and part-of-speech analysis, aspect extraction, embedding layer, cross-domain mapping, and user-item rating prediction.

Firstly, the model differs from single-domain recommendation systems in that it takes the review document $D_{S,u}$ of user u in the source domain, and the review document $D_{T,i}$ of item i in the target domain as the input of the model. The review documents D_{S,c_u}, D_{T,c_u} of the common user C_U in the source domain and the target domain are also used for model training.

The second step is to use the sentiment and part-of-speech analysis layer to perform sentiment and part-of-speech analysis on documents $D_{S,u}$, document $D_{T,i}$ and documents D_{S,c_u}, D_{T,c_u} to remove negative emotions for review sentences, only non-negative sentiment reviews are retained. Then part-of-speech analysis is performed on the words in non-negative sentiment review sentences, and only nouns and verbs related to aspect expression are retained, and finally get a new user review document $D'_{S,u}$, item review document $D'_{T,i}$, a common user in the source domain, review document in the target domain D'_{S,c_u}, D'_{T,c_u}.

The third step is to use the aspect extraction layer to extract aspects of the new user review document $D'_{S,u}$, the paper review document $D'_{T,i}$, and the common user review document D'_{S,c_u}, D'_{T,c_u}, and obtain the user aspect representation $A_{S,u}$ and the item aspect representation $A_{T,i}$, the common user's aspect representation A_{S,c_u}, A_{T,c_u} in the source domain and the target domain.

The fourth step is to use the embedding layer to embed the user aspect representation $A_{S,u}$, the item aspect representation $A_{T,i}$, the common user aspect representation A_{S,c_u}, A_{T,c_u} words in the source domain and target domain, to obtain the embedded user aspect representation $M_{S,u}$, embedded item aspect representation $M_{T,i}$, and embedded common user aspect representation M_{S,c_u}, M_{T,c_u}.

The fifth step is to train the cross-domain mapping layer by using the embedded common user aspect representation M_{S,c_u}, M_{T,c_u}, and then carry out cross-domain mapping for the embedded user aspect representation $M_{S,u}$ in the source domain to get the new embedded user aspect representation $M'_{S,u}$.

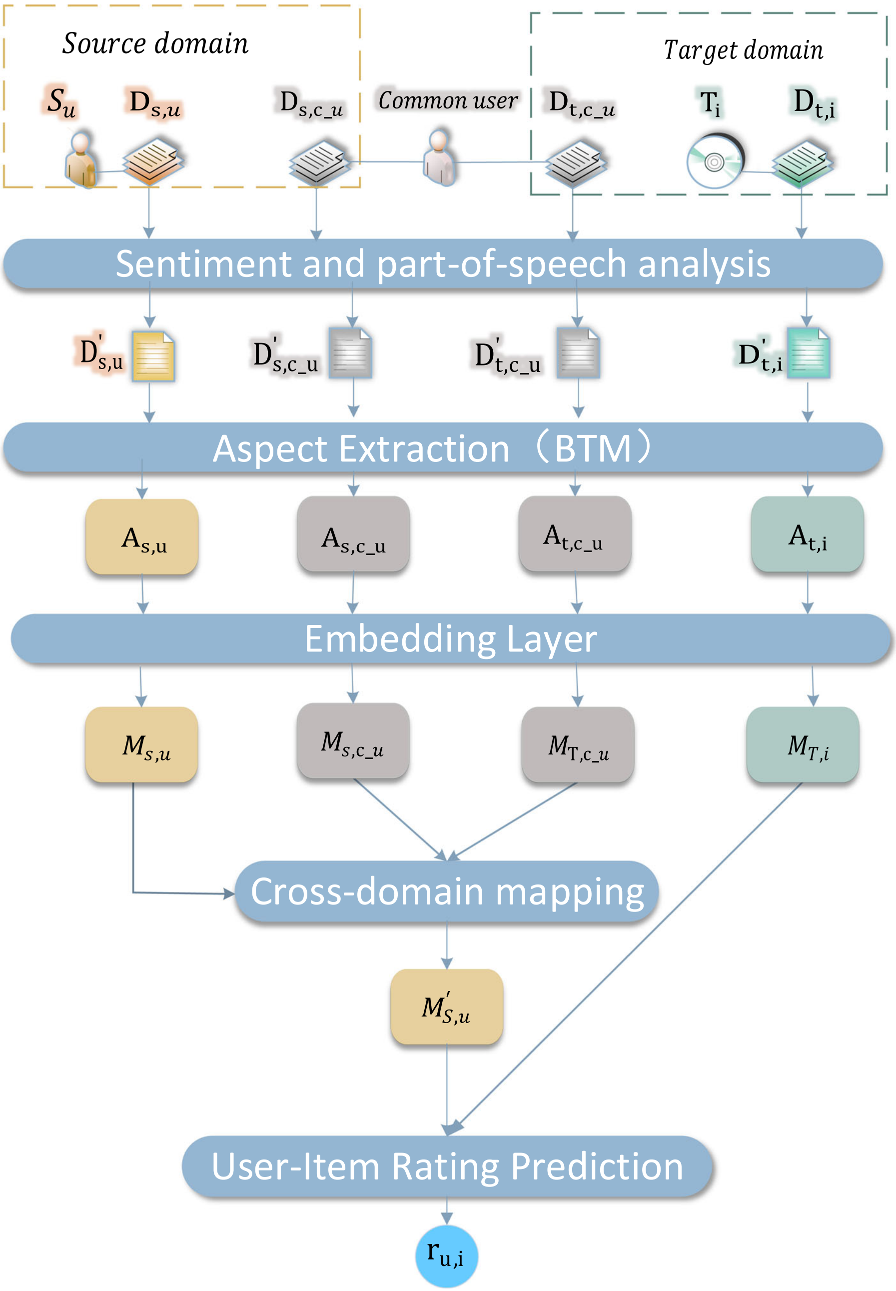

Fig. 2 Overall architecture of the proposed model

In the last step, the new embedded user aspect representation $M'_{S,u}$, and the embedded item aspect representation $M_{T,i}$ are used as the input of the user's item rating prediction layer to perform rating prediction to get the user $u's$ rating of item i in the target domain $r_{u,i}$.

Algorithm 1 Review Text Processing

Input: User $u^{'}s$ review document in the source domain $D_{S,u}$
Output: New User $u^{'}s$ review document after processing $D^{'}_{S,u}$
1: $sentence \leftarrow$ nltk.sent_tokenize($D_{S,u}$)
2: $text \leftarrow null$
3: /*Judge sentence sentiment*/
4: **for** $sent$ in $sentence$ **do**
5:     sia$\leftarrow$ nltk.sentiment.vader.SentimentIntensityAnalyzer()
6:     $ps \leftarrow$ sia.polarity_scores($sent$)
7:     **if** $ps >= 0$ **then**
8:         $text+ = sent$
9:     **end if**
10: **end for**
11: words$\leftarrow$ nltk.word_tokenize($text$)
12: /*Stemming words*/
13: words$\leftarrow$ Stemming($words$)
14: /*Remove stop words*/
15: $words \leftarrow$ Stop_Word_Removal($words$)
16: /*Determine the part of speech*/
17: $pos\_tags \leftarrow$ nltk.pos_tag($words$)
18: $D^{'}_{s,u} \leftarrow null$
19: /* Take only nouns and verbs*/
20: **for** $word, pos$ in pos_tags **do**
21:     **if** pos=='N' or pos=='V' **then**
22:         $D^{'}_{s,u}$+=$word$
23:     **end if**
24: **end for**

3.3 Sentiment and part-of-speech analysis

The pseudo-code of sentiment and speech analysis is shown in Algorithm 1. The algorithm mainly uses the Natural Language Toolkit (NLTK), which is the most commonly used Python library in the NLP field. The input of the algorithm is the review document $D_{S,u}$ of user u in the source domain, and the output is the new review document $D'_{S,u}$ of user u in the source domain. The first line uses nltk.sent_tokenize() to segment the review text. The fourth to tenth lines use SentimentIntensityAnalyzer() to perform sentiment analysis on the sentences obtained from the previous step to remove negative sentiment sentences and only keep non-negative sentiment sentences. The eleventh line uses nltk.word_tokenize() to segment non-negative sentiment review sentences and convert the sentences into words. The thirteenth line processes the words for stemming. The fifteenth line removes stop words unrelated to the aspect. The seventeen to twenty-four lines use nltk.pos_tags() to perform part-of-speech analysis of the words, and only keep nouns and verbs as a component of the new review document $D'_{S,u}$. The review document $D_{T,i}$ of item i in the target domain and the review documents D_{S,c_u}, D_{T,c_u} of the common users in the two domains adopt the same processing method and finally get a new item i review document $D'_{T,i}$, common user review document D'_{S,c_u}, D'_{T,c_u}.

3.4 Aspect extraction

The extraction layer uses the BTM model, which can handle short texts such as user reviews very well. The generation process of the BTM algorithm is shown in Algorithm 2.

Algorithm 2 BTM

1: Draw $\theta \sim$ Dirichlet (α)
2: **for** each topic $k \in [1, K]$ **do**
3: draw Φ_k ~Dirichlet(β)
4: **end for**
5: **for** each biterm $b_i \in B$ **do**
6: draw $z_i \sim$ Multinomial (θ),and
7: draw $w_{i,1}, w_{i,2} \sim$ Multinomial (Φ_{z_i})
8: **end for**

Among them, $z \in [1, K]$ is the subject indicator variable, and $B = \{b_i\}_{i=1}^{N_B}$ represents the set of N_B biterms $b_i = (w_{i,1}, w_{i,2})$.

User u's review document $D'_{S,u}$, item i's review document $D'_{T,i}$, common user's review document D'_{S,c_u}, D'_{T,c_u} through BTM model can get the user $u's$ aspect expression $A_{S,u} \in Z^{k\times n}$ model, and the item i aspect expression $A_{T,i} \in Z^{k\times n}$, the common user's aspect expression in the source domain and target domain $A_{S,c\_u} \in Z^{k\times n}$, $A_{T,c\_u} \in Z^{k\times n}$, where k is the number of aspects, n is the number of words in each aspect.

3.5 Embedding layer

The aspect representation of user u that $A_{S,u}$ is represented as a matrix $M_{S,u} \in R^{k\times n\times d}$ through the embedding layer, where d is the dimension of each word embedding vector. After the common one-hot encoding transformation, the vector dimension is too large and too sparse, and the mappings are completely independent, which cannot represent the relationship between different words. Embedding can not only reduce the data dimension but also explore the internal connections between words, which is helpful to find the similarity between the user's favorite aspects and the good aspects of the item. The embedding layer performs a search operation in the shared embedding matrix $f : V \rightarrow R^d$, which maps each word in the vocabulary V to a corresponding d-dimensional vector. The paper uses pre-trained word vectors on a large corpus to initialize the embedding matrix, such as word2vec2 [29] or GloVe3 [30], which is conducive to a better semantic representation of users(and items) aspects. The aspect representation $A_{T,i}$ of item i, the aspect representation A_{S,c_u}, A_{T,c_u} of the common user in the source domain and the target domain through the embedding layer gets the embedding matrix $M_{T,i} \in R^{k\times n\times d}$, $M_{S,c\_u} \in R^{k\times n\times d}$, $M_{T,c\_u} \in R^{k\times n\times d}$.

3.6 Cross-domain mapping

Based on the CycleGAN algorithm, this part improves the generator part of the algorithm. The new algorithm is named CycleGAN-mapping, and then the CycleGAN-mapping algorithm is used to learn the aspect mapping between the source domain and the target domain. As shown in Fig. 3, this part of the model mainly contains two mapping functions $G : M_{S,C\_U} \rightarrow M_{T,C\_U}$ and $F : M_{T,C\_U} \rightarrow M_{S,C\_U}$, and two related adversarial discriminators J_T and

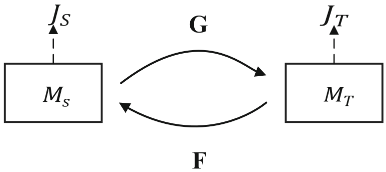

Fig. 3 Cross-domain mapping

J_S. J_T encourages G to transform the common user c_u aspect embedding matrix M_{S,c_u} in the source domain to the aspect embedding matrix M_{T,c_u} in the target domain, where $c\_u \in C\_U's$. For J_S, F and vice versa.

3.6.1 Generator and discriminator

This paper draws on the structure of the MLP model and uses the fully connected layer as the model generator and discriminator. The model contains two generators: G and F. For generator G, the aspect embedded representation M_{S,c_u} of the common user $c\_u(c\_u \in C\_U)$ in the source domain is used as input, and then the output is the aspect embedding representation $\widetilde{M_{T,c\_u}}$ of common user c_u in the target domain. The formula is as follows:

$$h = f_1\left(W_1 * M_{S,c\_u} + b_1\right) \tag{1}$$

$$h' = \text{dropout}(h) \tag{2}$$

$$\widetilde{M_{T,c\_u}} = f_2(W_2 * h' + b_2) \tag{3}$$

where f_1 is the ReLu function, f_2 is the sigmoid function, W_1, W_2 are the weights, b_1, b_2 are the biases, h is the hidden layer output, $dropout$ is the dropout function, and h' is the output after the dropout layer.

For generator F, the aspect embedded representation $\widetilde{M_{T,c\_u}}$ of the common user c_u generated by generator G in the target domain as input. The output is the embedded representation $\widetilde{M_{S,c\_u}}$ of the common user c_u in the source domain. The discriminator uses the same structure as the generator. The model mainly includes two discriminators J_T and J_S. J_T distinguishes between M_{T,c_u} and $G(M_{S,c\_u})$, namely $\widetilde{M_{T,c\_u}}$. Similarly, J_S distinguishes between M_{S,c_u} and $F(\widetilde{M_{T,c\_u}})$, namely $\widetilde{M_{S,c\_u}}$.

3.6.2 CycleGAN-mapping loss function

Similar to CycleGAN, the CycleGAN-mapping loss function in this paper is as follows:

$$\begin{aligned}\mathcal{L}(G, F, J_S, J_T) = \mathcal{L}_{\text{GAN}}(G, J_T, M_{S,C\_U}, M_{T,C\_U}) +\\ \mathcal{L}_{\text{GAN}}(F, J_S, M_{T,C\_U}, M_{S,C\_U}) +\\ \lambda\mathcal{L}_{\text{cyc}}(G, F)\end{aligned} \tag{4}$$

The loss function mainly includes two parts: the adversarial loss

$\mathcal{L}_{\text{GAN}}\left(G, J_T, M_{S,C\_U}, M_{T,C\_U}\right)$, $\mathcal{L}_{\text{GAN}}\left(F, J_S, M_{T,C\_U}, M_{S,C\_U}\right)$ and cycle consistency loss $\mathcal{L}_{\text{cyc}}(G, F)$, where λ controls the relative importance of these two losses.

Adversarial loss

$$\begin{aligned} \mathcal{L}_{\text{GAN}}\left(G, J_T, M_{S,C\_U}, M_{T,C\_U}\right) = \\ E_{M_{T,c\_u} \sim p_{\text{data}}(M_{T,c\_u})}[log J_T(M_{T,c\_u})] + \\ E_{M_{S,c\_u} \sim p_{\text{data}}(M_{S,c\_u})}[log(1 - J_T(G(M_{S,c\_u}))] \end{aligned} \tag{5}$$

where G tries to generate the aspect embedding mapping $G(M_{S,c\_u})$ similar to the aspect embedding mapping of the user c_u in the target domain, and the goal of J_T is to distinguish the generated sample $G(M_{S,c\_u})$ from the real sample M_{T,c_u}. The goal of G is to minimize this goal, while J is to maximize this goal, namely
$min_G max_{J_T} \mathcal{L}_{\text{GAN}}\left(G, J_T, M_{S,C\_U}, M_{T,C\_U}\right)$. $\mathcal{L}_{\text{GAN}}\left(F, J_S, M_{T,C\_U}, M_{S,C\_U}\right)$ is similar.

Cycle consistency loss

Referring to CycleGAN, this paper believes that the aspect mapping M_{S,c_u} for the user c_u in the source domain, G, F meets the forward cycle consistency: $M_{S,c\_u} \to G(M_{S,c\_u}) \to F(G(M_{S,c\_u})) \approx M_{S,c\_u}$, the aspect mapping M_{T,c_u} for the user c_u in the target domain, F, G meet the reverse cycle consistency:$M_{T,c\_u} \to F(M_{T,c\_u}) \to G(F(M_{T,c\_u})) \approx M_{T,c\_u}$. Then this paper uses the cycle consistency loss to express this behavior.

$$\begin{aligned} \mathcal{L}_{\text{cyc}}(G, F) = E_{M_{S,c\_u} \sim p_{\text{data}}(M_{S,c\_u})}[||F(G(M_{S,c\_u})) - M_{S,c\_u}||_1] + \\ E_{M_{T,c\_u} \sim p_{\text{data}}(M_{T,c\_u})}[||G(F(M_{T,c\_u})) - M_{T,c\_u}||_1] \end{aligned} \tag{6}$$

The ultimate goal of this paper is to solve:

$$G^*, F^* = \text{argmin}_{G,F} \text{max}_{J_S J_T} \mathcal{L}(G, F, J_S, J_T) \tag{7}$$

Finally, for the cold-start user u in the source domain, there is $G(M_{S,u}) \to M'_{S,u}$.

3.7 Cross-domain rating prediction

The new aspect embedding representation $M'_{S,u}$ of the user u in the source domain and the aspect embedding representation $M_{T,i}$ of the target domain item i have been obtained. it is necessary to predict the rating of user $u's$ in the source domain on item i in the target domain according to the aspect representation.

First, this paper uses cosine similarity to calculate the similarity between the user and the item. The formula is as follows:

$$C = \text{Cosine}\left(M'_{S,u}, M_{T,i}\right) \tag{8}$$

Finally, the prediction formula of user $u's$ rating $r_{u,i}$ for item i is as follows.

$$r_{u,i} = \text{softmax}(W * C + b) \tag{9}$$

where $r_{u,i}$ is $u's$ rating $r_{u,i}$ for item i, W is weight, and b is bias. The optimization process of the model can be regarded as a linear regression problem. The parameters W and b of the model can be learned by using the Mean Square Error (MSE) as the backpropagation technology of the loss function.

Table 2 Statistics of the datasets

	Movie	Music	Movie	Book	Book	Music
#(Users)	1077		1322		1776	
#(Items)	1568	1002	2108	1050	859	1199
#(Ratings)	54,581	31,798	80,460	35,508	19,960	28,696

4 Experiment

4.1 Datasets

This paper uses the Amazon review dataset[1] to compare several state-of-the-art baseline methods to evaluate our proposed model. The Amazon review dataset has been divided into 24 separate product categories. This paper selects select three pairs of categories for experiments, namely movie-music, movie-book, and book-music. Further, we filter out users with less than 10 interactions and items with less than 20 interactions. Given that deleting other users changes the amount of comments on the selected items, we performed the procedure again to ensure accuracy. For each experiment, we first keep only the common users of both domains, and then randomly select half of the users and remove their information in the target domain, designating them as cold-start users. The details of each category are shown in Table 2.

4.2 Baseline methods

This paper compares the proposed method with the four state-of-the-art baseline methods to improve the overall recommendation performance.

- EMCDR [20]: Firstly, matrix factorization is used to learn the latent factors, and then the MLP network is used to learn the mapping from the source domain to the target domain to map the user potential factors from the source domain to the target domain.
- R-DFM [15]: It is a simple version of the RC-DFM model. It combines rating information and review information through the extended aSDAE to enhance the presentation of users and items. At the same time, the model also uses the MLP network to learn the mapping from the source domain to the target domain.
- CATN [26]: The model aims to extract multiple aspects from user-item reviews as well as auxiliary reviews of similar users, and learn correlations between aspects across domains through an attention mechanism.
- PTUPCDR [33]: The model generates personalized bridge functions by embedding user features into the learning meta-network to achieve personalized preference transfer for each user.

4.3 Evaluation metric

In the experiment of this paper, Mean Square Error (MSE) is used as evaluation metrics, formulated as:

1 http://jmcauley.ucsd.edu/data/amazon/.

Table 3 Comparison result with state-of-the-art baseline methods in terms of Mean Square Error

	EMCDR	R-DFM	CATN	PTUPCDR	CRAS
Movie to Music	2.2326	1.7465	1.1219	<u>1.0175</u>	**0.9598**
Music to Movie	2.3850	1.8537	1.1629	<u>1.1179</u>	**1.0296**
Movie to Book	2.3103	1.5043	0.9742	<u>0.9624</u>	**0.8001**
Book to Movie	1.8665	1.6106	0.9755	<u>0.9657</u>	**0.9655**
Book to Music	2.5864	1.2931	<u>1.0071</u>	1.1361	**0.7176**
Music to Book	2.8048	1.4835	<u>1.0968</u>	1.1558	**0.8505**

The best and second-best results are highlighted in boldface and underlined respectively

$$\mathrm{MSE} = \frac{1}{m}\sum_{i=1}^{m}\left(r_i - \hat{r}_i\right)^2 \tag{10}$$

where m is the cold-start user test set for performance comparison, $\hat{r}_i$ represents the i-th predicted rating, and r_i represents the actual i-th rating.

4.4 Experimental setup

The setting of hyperparameters is very important for the training of the model. In the sentiment and part-of-speech analysis of the review text of the model, the paper uses the NLTK library[2] to process all review texts. For the aspect extraction part, the BTM model, this paper set α = 10 and β = 0.01. Gibbs Sampling runs 10 iterations, and the aspect number K is optimized from 2, 4, 6, 8, 10. For the embedding layer, this paper uses the existing word embedding glove.6B.100d that has been trained according to Wikipedia 2014[3] and Gigaword 5 to[4] obtain the initial embedding vector of each word, and each word is converted into a 100-dimensional word vector. For the cross-domain mapping and score prediction part, this paper uses Adam as the optimizer and employs Bayesian optimization to determine the optimal parameters for each experimental group.

4.5 Experimental results and analysis

The overall results of all methods over the six cross-domain recommendation scenarios are reported in Table 3. This paper made the following observations from the results.

First of all, CRAS achieves statistically significant improvement overall state-of-the-art baseline methods on all cross-domain recommendations. This result demonstrates the superiority of the cross-domain method proposed in this paper. From the results, the EMCDR model yields the worst performance on all evaluations. The main reason may be that the model only considers the user's rating information on the item, and does not consider the user's review information on the item. Although R-DFM uses review information, the model incorporates review information as incidental content into the rating information, and the utilization rate of reviews is not high. The CATN model extracts multiple aspects of users from reviews for cross-domain aspect transfer, making full use of the review data, so the performance is better

2 https://www.nltk.org/.

3 https://dumps.wikimedia.org/enwiki/20140102/.

4 https://catalog.ldc.upenn.edu/LDC2011T07.

Table 4 Comparison results with the model variants in terms of Mean Square Error

	CRAS-LDA	CRAS-NS	CRAS-MLP	CRAS
Movie to music	0.9742	0.9712	0.9647	0.9598
Music to movie	1.0329	1.0355	1.0304	1.0296
Movie to book	0.8003	0.8005	0.8002	0.8001
Book to movie	0.9661	0.9661	0.9659	0.9655
Book to music	0.7208	0.7213	0.7201	0.7176
Music to book	0.8534	0.8538	0.8530	0.8505

than R-DFM. The PTUPCDR model uses personalized preference transfer for each cold-start user individually for cross-domain transfer and has improved performance over the above models.

5 Model analysis

Now the proposed CRAS model is analyzed in detail. First, three ablation studies are used to analyze the contribution of different components in the proposed model to the overall results. Then, this paper analyzes the influence of aspect number K on the performance of the CRAS model.

5.1 Ablation study

To verify the ablation of CRAS and analyze the influence of different aspects extraction methods and cross-domain mapping methods on the model results, this paper proposes three variants of CRAS as follows.

- CRAS-LDA: In order to verify the impact of different aspect extraction methods on the model, and compare the effects of the aspect extraction of the two topic models, LDA and BTM, the CRAS-LDA model replaces the aspect extraction model BTM of the CRAS model proposed in this paper with LDA, while the other parts of the model remain unchanged.
- CRAS-MLP: In order to verify the contribution of CycleGAN-mapping to the cross-domain recommendation and analyze the influence of different cross-domain mapping methods on the performance of the model, the CRAS-MLP model modifies the cross-domain mapping part of the CRAS model proposed in this paper from the original CycleGAN-mapping to MLP, while the other parts of the model remained unchanged.
- CRAS-NS: In order to verify whether the addition of negative reviews has an impact on the model, the CRAS-NS model removes the sentiment analysis of reviews and carries out aspect extraction for all reviews.

Table 4 shows the results of the ablation study for all evaluation settings. It is found by observation that: (1) CRAS outperforms most baselines in all recommendation scenarios, demonstrating the effectiveness of CRAS; (2) CRAS-LDA is less effective than CRAS, indicating that LDA underperforms BTM on short text extraction, thus demonstrating the superiority of BTM in the extraction of short texts; (3) Compared with CRAS, CRAS-MLP model has an inferior result, indicating that CycleGAN-mapping performs better than MLP

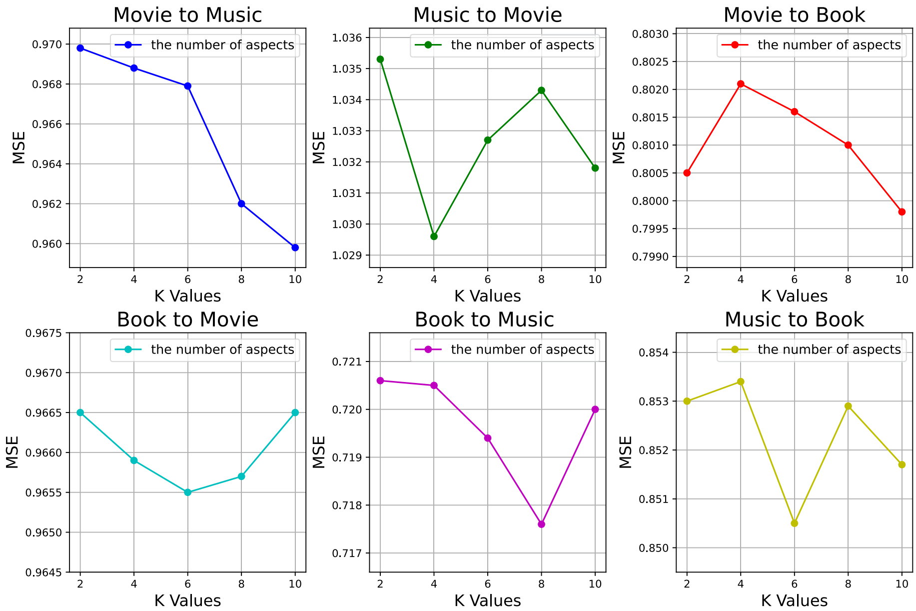

Fig. 4 The influence of number of aspects

in cross-domain mapping. (4)CRAS-NS is less effective than CRAS, showing that removing negative reviews can make the model perform better. (5)It should be pointed out that in the context of Experiments A and B, the performance of CRAS-LDA is close to that of CRAS. This phenomenon can be attributed to the higher volume of user comments in these scenarios, as indicated in Table 2, which diminishes the distinct benefits of BTM in processing short texts.

5.2 Aspect number K

Figure 4 shows the influence of changes in the number of aspects k between 2 and 10 on the CRAS model for different data sets. Through observation, it can be found that the optimal number of aspects for different data sets is different, which is likely to depend on the characteristics of the review content of a given data set. In general, reasonably good performance can be observed from 4 to 10 aspects. In addition, this paper assumes that changing the total number of aspects will only affect the granularity of each aspect, that is, a large number of fine-grained aspects and a few broader aspects. Therefore, the number of changes (within a range) has little effect on the overall model's performance.

6 Conclusions

This paper proposes a novel cross-domain recommendation via an aspect-level sentiment extraction model. This model extracts non-negative reviews in the review, as well as nouns and verbs related to aspects from the user (item) reviews to represent user preference (item advantage), this approach can better capture users' fine-grained preferences. Then, we use the improved CycleGAN learning cross-domain mapping from the source domain to the target domain to improve the problem of cold-start and data sparsity. In addition, we show that our model performs better than existing models.

In future, we will further study the following three aspects. First of all, we will consider cross-domain recommendations based on multiple auxiliary domains to further improve the richness of information content and improve cold-start and data sparse problems. Second, we will further consider applying multi-source information to cross-domain recommendations. Currently, only user ratings and reviews are considered. Next, we will increase the diversity of information and add more user-item interaction information to recommendations. Finally, the most important part of the cross-domain recommendation is cross-domain mapping. This paper applies CycleGAN-mapping to cross-domain mapping. Although it has achieved good results, the performance still needs to be improved. In the next step, we will continue to study the information conversion between different domains to further improve the performance of cross-domain mapping and improve the accuracy of cross-domain recommendations.

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Declarations

Conflict of interest The authors have no Conflict of interest.

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