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Multi-source heterogeneous data fusion of cross-border e-commerce platform based on the neural network model

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Abstract: *At present, the fusion representation for multi-source texts is relatively simple, the difference between long and short texts is not considered, and the representation accuracy needs to be improved; in addition, when performing heterogeneous data fusion, the deep learning proposed in recent years can map each structural data to the same shared space. However, few studies have focused on user-generated content in e-commerce platforms. Therefore, we did a study on multi-source heterogeneous data fusion and representation strategies for user-generated content on e-commerce platforms. The convolutional neural network model is used to realize the fusion representation of heterogeneous data so that the various modalities and information of user-generated data can be considered when the product feature representation is performed, especially when the product text data is small, the integrated heterogeneous data may be it plays a better role in feature expansion, and further improves the accuracy and robustness of product feature representation in e-commerce platforms. A user preference estimation algorithm based on RBM is constructed in combination with the category attributes of the product itself; based on the existing explicit preference combined with the user's implicit preference, joint learning is performed to complete the user personalized recommendation based on collaborative filtering; the proposed algorithm is applied to multiple Amazon sub-datasets to verify the superiority of the proposed algorithm and the feasibility and accuracy of user-generated multi-source heterogeneous data fusion. The results show that the fusion of user-generated multi-source heterogeneous data can effectively improve the overall performance of the recommendation algorithm.*

Keywords: *Neural Network Model; Multi-source Heterogeneous Data; Cross-border E-commerce Platform*

1. Introduction

The user-generated content analysis includes the representation and application of user-generated content. Among them, the fusion representation of user-generated content has a wide range of application requirements [1]. In recent years, it has attracted extensive attention and achieved fruitful research results, especially the fusion of user-generated multi-source heterogeneous data. However, the accuracy of data representation is still difficult to meet the needs of practical problems, and there are still many difficulties in practical applications [2]. How to effectively improve the representation accuracy is still a key problem that needs to be solved urgently for users to generate multi-source heterogeneous data fusion representation. User-generated content is mostly in the form of multi-source and heterogeneous in e-commerce platforms. By processing such data through fusion representation, valuable potential information and knowledge in the data can be mined, and users' interests and preferences can be based on the learned knowledge[3]. Making scientific estimates is conducive to improving the performance of applications such as personalized recommendation and search for users. Therefore, we study the fusion and representation of user-generated multi-source heterogeneous data in e-commerce platforms, consider the multi-source and heterogeneous aspects of user-generated content, and present two different implementation strategies, in order to further improve the user-generated content in e-commerce platforms [4]. Generate the fusion representation accuracy of multi-source heterogeneous data, and solve practical problems more effectively.

The concept of Web 2.0 was born out of a brainstorming forum between O'Reilly and Media Live International in 2004. The Web2.0 era grants users more initiative, and further highlights the display of users' subjective initiative, the user identity has completed the transformation from information consumers to information producers, and information presents a two-way transmission relationship

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between users and websites. User Generated Content (UGC) is a product that emerges as the times require under the Web2.0 environment whose main feature is to advocate personalization. The understanding of UGC can be viewed from two broad and narrow perspectives [5]. In a broad sense, UGC refers to any form of data uploaded to the Internet-by-Internet users. According to the report of the Organization for World Economic Cooperation and Development (OECD) in 2007, three characteristics of UGC in a narrow sense can be summarized: first, the content is innovative; second, the created content needs to be made public on the Internet; third, the original author must be right or wrong. Authority figures [6]. Therefore, UGC in a narrow sense pays more attention to originality and sharing. User-generated content has the meaning of participation of the whole people and has penetrated all aspects of current Internet behavior, affecting many areas of our lives. The UGC model has the characteristics of originating from Internet applications and will eventually serve network applications. The research content of UGC technology includes UGC retrieval and mining system, UGC calculation method and UGC design modeling, etc [7]. The characteristics of UGC that are not conducive to capture, and the large scale of data are a huge challenge for search and recommendation in the Web2.0 era. The quality assessment of UGC is considered in two aspects. One is to analyze user-generated content. The second is the quality assessment for the purpose of managing user-generated content. Most of the research by scholars is on user-generated content itself, while there are few related studies on the fusion and representation of user-generated multi-source heterogeneous data in e-commerce platforms.

In the context of the era of big data, science and technology are developing rapidly, the degree of social informatization is increasing day by day, the shared data of users or enterprises in various industries is increasing, and its manifestations are also more diverse. Based on the urgent need for data applications with various sources and different structures, the concept of multi-source heterogeneous data emerged as the times require [8]. It includes two characteristics: one is multi-source, that is, the description and Evaluation, etc. are given by different people from different perspectives; the second is the heterogeneity, that is, the types and forms of these data are different and complex, such as text, images, videos, etc. Multi-source heterogeneous data is generated by a variety of data sources, including different databases, the information given by different users from different angles, and data generated by different devices in practical applications. The data generated by different data sources are not only different in storage mode and information content, but also in the time of generation, the user's perspective, the place of generation, the code rules to follow, etc., which also causes the "multi-source" feature of data [9]. In addition, multi-source heterogeneous data can be divided into unstructured data, semi-structured data, and structured data according to their different data structures. With the development of intelligence and informatization, the gradual development of online shopping habits in people's daily life, and the increase in the proportion of online shopping in daily consumption, a large amount of multi-source heterogeneous data has been accumulated on some large e-commerce platforms. From the point of view of the source of the data, when displaying the products, the shops on the platform use a combination of text and images to describe the basic characteristics of the products more intuitively and in detail. From the user's point of view, the data generated is more varied [10].

A neural network simulates the structure and function of the biological nervous system. It is composed of many simple parallel working processing units. It stimulates the information processing mechanism of the brain to varying degrees and can perform complex logical operations and computing power[11]. At present, the neural network has been widely used in the medical field, information field, engineering field, economic field prediction, and other fields. The neural network has a high degree of parallel structure and computing power, so it has better error correction ability and fast processing efficiency. In addition, neural networks are capable of self-learning. When the external environment changes, a trained neural network can automatically adjust the parameters, solving problems that are difficult to deal with by mathematical models or rules[12]. The neural network is mainly composed of the following three neurons: input layer, hidden layer, and output layer. There are no connections between neurons in the same layer, only connections between neurons in adjacent layers but no feedback. The learning of the neural network consists of two parts: the first is the forward transmission of the signal. When the sample data is input from the input layer to the network, it reaches the output layer after being processed by the hidden layer, and the output result of the output layer will be compared with the expected output. If the error of the two is too large, the reverse transmission of the error signal is entered, which is the second step of the neural network [13]. The error propagates to the input layer through the hidden layer, returns through the original path, and is apportioned to the neurons of each layer to correct the weight of each output value. In this way, the forward propagation of the signal and the reverse transmission of the error continues until the error output by the network reaches the desired value. The learning algorithm of the entire Zongying network is divided into 7 steps: (1) parameter setting of the neural network, setting learning efficiency, training function, transfer function, expected error, number of hidden layer nodes,

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etc.; (2) randomly input a set of sample values and corresponding expected output values from the training samples; (3) through the neural network forward information transmission, the output of each neuron is calculated; (4) calculate the error between the actual output of the neural network and the expected output value; (5) determine whether the error reaches the expected error, and if it does, the learning of the neural network is ended; (6) if the error does not reach the expected error, continue the learning of the neural network, and use backpropagation to correct the connection weights of the network layer by layer; (7) go back to step 3 until the sample error of the training set reaches the expected value.

This paper studies the fusion and representation method of user-generated multi-source heterogeneous data in e-commerce platforms. First, the multi-source text is fused and represented. Then, the global feature representation of products with the aid of image information is further considered, that is, to achieve heterogeneous representation. Finally, the existing research content is applied to the user personalized recommendation problem of the actual e-commerce platform, to illustrate the accuracy and practicability of data fusion.

2. Methods

2.1. Evaluation of fusion and presentation

To better evaluate the data representation of each model, researchers have designed many error measurement methods. However, there is no literature to explain which evaluation criterion is universal in different practical problems. The problem side reflects the performance of the algorithm. Currently, the more popular evaluation methods of representation learning evaluate the accuracy of fusion and representation through the quality of downstream applications, such as converting the evaluation of the original problem into a classification problem or a recommendation problem[14]. For classification problems, Herlocker et al. gave accuracy measures, including prediction accuracy, classification accuracy, and ranking accuracy [15]. Classification accuracy includes precision, accuracy, recall, F1_score, confusion matrix, ROC curve Etc., this paper uses the accuracy rate and F1_score to evaluate the classification effect of each model. Each indicator is defined as follows:

Precision (P): In text classification problems, precision refers to the proportion of samples that are positive and predicted to be positive:

$$P = \frac{TP}{TP+FP} \tag{1}$$

Accuracy (ACC): refers to the proportion of correctly classified samples in the total sample:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

Due to the contradiction in the measurement of precision and recall, the F1 value is introduced for measurement. The F1 value is based on the harmonic mean of precision P and recall R:

$$F_1 = \frac{2PR}{P+R} \tag{3}$$

Where TP refers to the number of predicted positive classes as positive classes, TN refers to the number of predicted negative classes as negative classes, FP refers to the number of predicted negative classes as positive classes, FN refers to the predicted positive classes as negative classes number of classes.

The evaluation indicators of score prediction use the root mean square error (Root Mean Square Error, RMSE) and the mean absolute error (Mean Absolute Error, MAE), these two indicators have their different focuses. User u and item i defined in the test set T; the definition of root mean square error (Root Mean Square Error, RMSE) is shown in Eq. (4):

$$RMSE = \frac{\sqrt{\sum_{u,j \in T} r_{u,j} - \widehat{r_{u,j}}}}{|T|} \tag{4}$$

Where $r_{u,j}$ are the actual grades of users to item i, $r_{u,j}$ is predicted scores obtained through the RBM user preference estimation model. From Eq. (4), it can be seen more intuitively that the RMSE indicator gives the quantitative deviation between the predicted rating value and the actual rating value, while the MAE calculates the average value of the absolute error between the user's predicted rating value and the actual rating value, the definition of MAE is shown in Eq. (5):

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$$\mathrm{MAE} = \frac{\sum_{u,j \in T} |r_{u,j} - \widehat{r_{u,j}}|}{|T|} \tag{5}$$

Regarding root mean square error (RMSE) and mean absolute error (MAE), it can be seen from the above formula that they are the sum of errors, so the smaller the values of RMSE and MAE, the higher the accuracy. Precision evaluation refers to the proportion of the products selected by the user in the recommendation list given to the user by the recommendation system, as shown in Eq. (6):

$$P = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |R(u)|} \tag{6}$$

Coverage (Co), the proportion of recommended products to users in the total products, the formula is shown in Eq. (7):

$$Co = \frac{\bigcup_{u \in u} R(u)}{|C|} \tag{7}$$

Recall rate evaluation (R), the percentage of the user's actual selection of the product after the intersection of the product selected by the user and the product list recommended by the recommendation system, the formula is shown in Eq. (8):

$$R = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |T(u)|} \tag{8}$$

Where U is the user set, R(u) is the collection of products recommended for U, T(u) is the data set that user selected, and C is the total set.

2.2. Algorithm framework

Transfer learning is a large research branch in the field of machine learning at present. The so-called transfer learning is to improve the learning ability of a new field by transferring information in related fields. In the process of transfer learning, it is to apply the knowledge that has been learned to ensure that recent problems can be solved. The model-based transfer method refers to the fact that the target domain and the source domain share part of the network structure and parameters of the pre-trained network[16]. This method is based on a basic assumption that the network models of the source domain and the target domain share some network parameters or follow the same empirical distribution knowledge. Then, the focus of the model-based transfer method is to find this part of the shared information in the source domain network model and use this part of the data in the target domain network to complete the task of transfer learning. The model-based migration method can retain the generalization ability of the trained model, and further train based on the pre-trained model. Common methods include weight sharing, Finetuning, etc. Since the deep neural network has shown obvious advantages in various applied research fields of the ImageNet dataset, the deep neural network that came out later has developed in the direction of deepening the number of layers. It is believed that as the depth of the network increases, the model can extract more complex and informative features [17].However, experiments have shown that this is not the case. Some researchers have found that the model accuracy and network depth are not always positively correlated. Since test errors and training errors increase with the deepening of the network, the cause of this problem is not overfitting (overfitting). It can be shown that under ideal training methods, deeper networks will outperform shallower ones. The proof process is as follows: suppose several layers are added behind the network L to form a new network N, if the added layers are only the identity mapping of the output of L, the error rates of the networks L and N are equal, that is, the deepened network will not be worse than the network effect before deepening[18].

The residual module contains a branch directly connected to the output, which is arithmetically added to the output of the convolutional layer to obtain the result, as shown in Eq. (9):

$$H(x) = F(x) + x \tag{9}$$

where the input is x, the output of the convolution branch is F(x), and H(x) represents the output of the entire structure. It can be shown that if all parameters in the F(x) branch are 0, H(x) is an identity map. The residual module artificially constructs the identity map of the network, so that the structure of the entire network converges in the direction of the identity map, ensuring that the error rate will not increase with the increase of the number of network layers. In the user-generated image content representation learning task, an image feature extraction network is needed to complete the representation learning task of product image features. To highlight the generality of the heterogeneous data fusion method, this chapter adopts the more commonly used Res Net-50 network as the Feature extraction network for user-generated image content. ResNet-50 is a typical convolutional neural network with a

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local connection, weight sharing, and other characteristics, which is often used in image and video representation and classification tasks.

First, a residual network is pretrained using the ImageNet dataset, and then the network is transferred to the item image feature extraction in this chapter for fine-tuning. First, a residual network is pretrained using the ImageNet dataset, and then the network is transferred to the item image feature extraction in this chapter for fine-tuning. The vector obtained after synthesizing all the image information is shown in Eq. (10) as the image feature representation of the item.

$$V_p(y_j^k) = \frac{\sum_{i=1}^{P_j} V_p(P_{ij})}{p_j} \tag{10}$$

Where y_j^k is item, $V_p(P_{ij})$ is figure feature, $P_{ij}$is figures set.

The physical meaning of convolution is the weighted superposition of one function on another. In signaling, for a linear time-invariant system, if the unit response of the system is known, then the convolution operation on the input signal and the unit response means that the unit response at each time point of the input signal is weighted and superimposed, and it is directly obtained. For integrated feature of text of item y_j^k, $V_T(y_j^k) = \{v_{Tj}(i)|i = 1,2, \ldots, I_t\}^T$, and figure feature $V_P(y_j^k) = \{v_{pj}(i)|i = 1,2, \ldots, I_\tau\}^T$, then the fusion of the two types of features based on convolution is shown in Eq. (11):

$$V(y_j^k) = (V_T * V_P)[n] = \sum_{\tau=1}^{I_\tau} V_T(\tau)V_T(\tau)\, V_P(n-\tau) \tag{11}$$

This operation does not need to consider the dimension of the feature to be fused, and the dimension of the fused feature is much lower than the dimension of tensor fusion. Compared with splicing and fusion, this method can not only fully consider the interaction of heterogeneous data features in various dimensions, but can also enhance key features in the data, and play the role of filtering noise features.

3. Results and discussion

3.1. Feature Fusion Strategy of Heterogeneous Data

To verify the effectiveness of the proposed heterogeneous data fusion algorithm, this section applies the proposed algorithm to the Amazon public dataset. The purpose of the experiment is to determine whether the image features of the product can be enhanced by using the convolution fusion strategy proposed in this chapter after obtaining the product text feature representation. To test the performance of the proposed heterogeneous data fusion algorithm, this chapter crawls out the image data corresponding to the product according to the product image link in the Amazon metadata and then merges it according to the product number to form the used augmented data set. Due to the consideration of the feature representation of less popular products, an example of a merged dataset is shown in Table 1.

Table 1: Data example No. B002M7XXAI.

description	Review text
The flexible organization tool that combines the best of notes, tabs, and flags in one. Made of durable film material with a paper tab overlay. Writable on both tab and body surfaces. See-through and repositionable. Turns pages like a divider. For easy reference. Unprinted or preprinted. styles are available.	User 1: Key question to bear in mind: do you want paper or plastic? An alternative is to use. ordinary Post-it notes.
	User 2: Although I love the Pastel colors, this item is. wasteful. Unfortunately, I will never use the note tabs.
	Ser n: These tabs I used for organizing my paperwork. The two colors help code them. They are especially useful.

Considering that user-generated image data is added to represent product features, this study uses the application library in Kera's to call the ResNet-50 model, and its parameter weights select "ImageNet", that is, the network weight parameters pre-trained using the ImageNet dataset are automatically downloaded to participate in the image. Feature extraction: since this part of the experiment is intended to extract image features, include top is set to False, that is, the involved network does not include the

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last three fully connected layers, to facilitate subsequent network fine-tuning and adapt the network parameters to the data used in this study. The hardware and software environment of the experiment is as follows: a PC with Intel Core i7-7700HQ processor, main frequency 2.8GHz, 16GB memory, and 1TB hard disk. The operating system is Windows 10 Enterprise Edition operating system, the software used in the experiment includes Python3.7, Keras2.2, and TensorFlow1.8, and the compilation environment is JetBrains PyCharm 2017. Basic information of the Amazon dataset, including the number of product text and image descriptions, the number of product reviews, and the number of users who purchased the product, see Table 2.

Table 2: Description of datasets used in multi-source heterogeneous data fusion experiments.

Amazon Product Dataset	Number of figures	Number of text descriptions	Number of comments	Number of users
Office_Products (Office)	2400	2400	53025	5003
Pet_Supplies(Pet)	8400	8400	166102	20056
Software(Software)	17610	17610	286900	25189
Toys_and_Games(Toy)	11856	11856	175423	18530

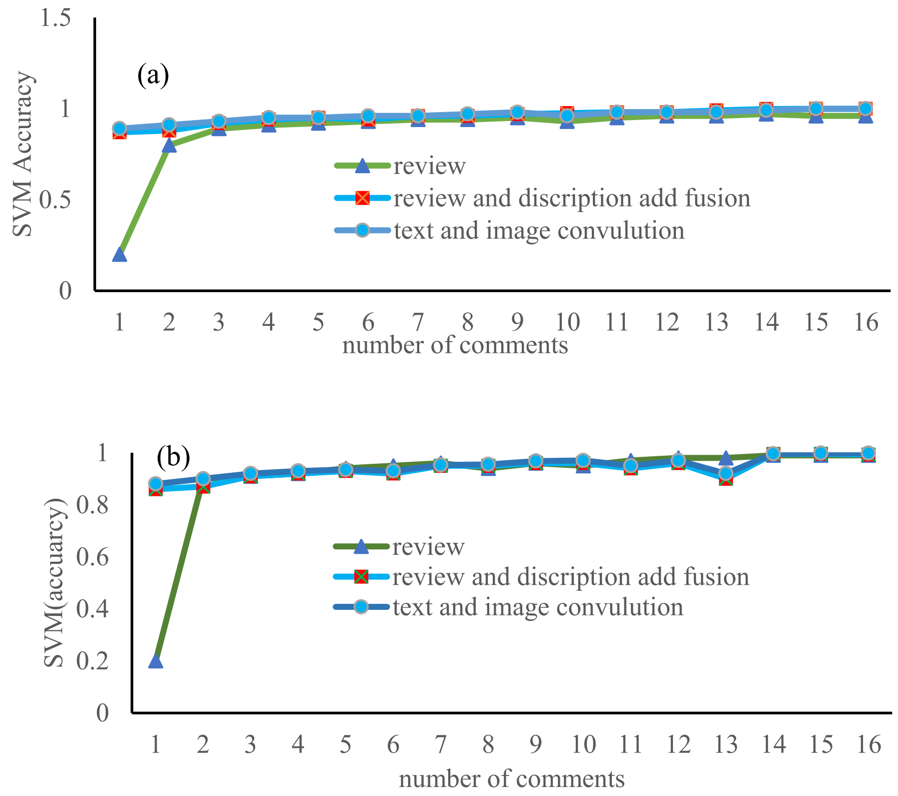

Figure 1: Classification performance after image-text convolution fusion. After the text is added, it is combined with the image convolution and fusion effect diagram (a); Effect diagram of convolution fusion of text and image after splicing(b).

According to the text description link of the product in the Amazon data set, the corresponding product image data is crawled out according to the product number, and the image data crawled out is trained with the ResNet model to obtain the corresponding image features, and the convolution fusion strategy is used to add the image features of the product. Classification accuracy is used to measure whether the global information of the product can be more accurately represented by adding image features. The experimental results are shown in Figure 1, where the blue o is the classification result of image and text convolution fusion. To illustrate the superiority of the text and image convolution fusion strategy proposed in this chapter, the multi-source text fusion method is compared with the heterogeneous data fusion method in this section. Since the image data contains more abundant information, the feature dimension obtained by the residual network on the high side, if the tensor fusion method is used at this time, it will cause a dimensional disaster and make the application inefficient; The additive fusion has consistent requirements on the dimension of the features to be fused. The product features after splicing

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fusion and convolution fusion are classified and compared to illustrate the superiority of the heterogeneous data fusion strategy. The experimental results are shown in Figure 2. When merging text and images, while considering the space complexity (i.e. feature dimension) after fusion, the time complexity (i.e. fusion efficiency) of the fusion method is also an important evaluation index for the fusion method. Table 3 shows the time consumed for different quantities of commodity features.

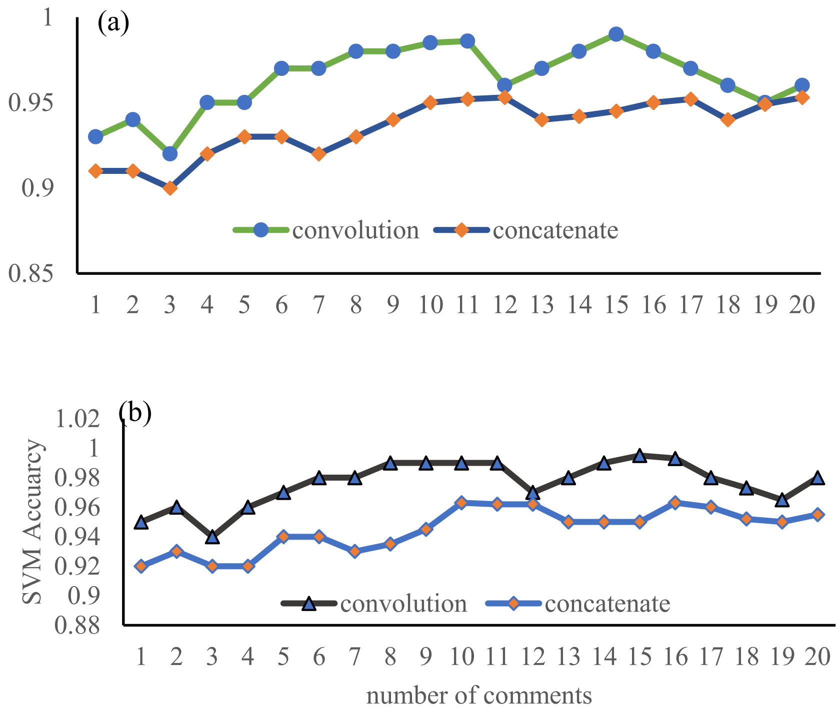

Figure 2: Comparison of image and text stitching and convolution fusion classification. Fusion effect diagram of text addition and image stitching (a); Fusion effect diagram of text stitching and image stitching (b).

Table 3: Comparison of fusion time of different fusion methods.

	1	**2**	**4**	**6**	**8**	**10**	**20**	**40**
Evaluation indicator	TC	TC	TC	TC	TC	TC	TC	TC
Convolution fusion	0.09	0.222	0.446	0.592	0.892	1.18	2.30	5.9
splice fusion	0.01	0.019	0.193	0.269	0.517	0.878	1.00	4.32
Tensor Fusion	3.166	3.747	4.321	24.36	58.69	90.263	96.265	110.25

We can conclude that (1) the convolution fusion operation of the text features and image features of the products can effectively improve the accuracy of the product representation regardless of the number of comments selected during the text feature representation of the products. Especially when the number of text comments is small, the improvement in accuracy is more obvious, from about 85% to about 97%. When representing products with very few comments, an appropriate fusion method is used to integrate the image data of the products. It can more effectively play the role of feature expansion and supplementation, and can effectively improve the global information representation of products; (2) when selecting and designing fusion methods for text and image data generated by users of e-commerce platforms that are both different and complementary at the same time, the interaction between each structural data and the accuracy of fusion results should be considered at the same time. Compared with the classification results based on convolution fusion, no matter what method is used in multi-source text fusion, no matter how many texts are involved in fusion, its performance is excellent in fusion. The classification accuracy is significantly lower than that after convolution fusion, which also shows that convolution fusion has better classification performance than other fusion methods in text and image

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fusion scenarios, and the fusion results are more accurate; (3) since the fusion accuracy is simply considered and the time cost of the fusion method is ignored, it will lead to low efficiency in a later application. According to Table 3, the time consumed by each fusion method when merging the features of different quantities of goods is due to splicing. Fusion is simple, and only considers the vertical stacking of features, so its time cost is the lowest. Although convolution fusion considers the interaction between the dimensions of features, its time complexity is always on the same order of magnitude as splicing fusion. The time cost of this method is much less than the time consumed by tensor fusion. In summary, the experimental results further demonstrate the effectiveness of the multi-source heterogeneous UGCs vectorized fusion representation learning proposed in this chapter.

3.2. Personalized recommendation based on User-Generated multi-source heterogeneous data fusion representation.

In order to further verify the superiority of the multi-source heterogeneous fusion method mentioned above and apply the research results to improve the recommendation performance of the recommender system, this chapter studies a personalized recommendation algorithm based on the fusion representation of multi-source heterogeneous data generated by users (Personalized Recommendation based on User-generated Multi-source Heterogeneous Data Fusion Representation, PR-UGMHDFR) to improve the recommendation performance of collaborative filtering recommendation algorithm by alleviating the problem of the sparse scoring matrix[19]. First, use the existing multi-source heterogeneous fusion features and assist to build an RBM network with the category features of the products to quantify the user's preference for unpurchased products; then, based on the realized user preference estimation data, fill in the collaborative filtering. The scoring matrix is used to alleviate the matrix sparsity problem, that is, the user's explicit preference and implicit preference are used for collaborative joint learning to complete the user's personalized recommendation.

The prediction and recommendation performance of the related algorithms is evaluated using the Amazon multi-category product dataset. The dataset contains 4 sub-datasets with different degrees of sparsity in different domains. The statistical information description of the dataset is shown in Table 4, including the number of users, items, and ratings. The user rating values in the four subclass datasets are in the range of 1-5 points, and the rating values are integer values. When the rating value is 3 points and above, it means that the user likes the purchased product, and when the rating value is below 3 points, it means that the user does not like it. The experiment randomly selects 70% of the data in the data set for training and 30% for the test set. When estimating user preferences, the root means square error (RMSE) and the mean absolute error (MAE) are used as evaluation indicators, and the precision rate (Precision) is used as evaluation indicators in the personalized recommendation experiment for users. In the user preference estimation algorithm experiment, based on the experience of existing research, the learning rate is set to 0.1, and the initial momentum and final momentum are set to 0.5 and 0.9, respectively. In the collaborative filtering recommendation algorithm, the number of reference items is selected as 50, the recommendation is made for 10 users in each sub-data set, and the number of items recommended for each user is 10. All experiments were repeated 5 times to take the mean value. The hardware and software environment of the experiments were: Intel Core i7-7700HQ processor, a PC with a main frequency of 2.8GHz, a memory of 16GB, and a hard disk of 1TB. The operating system is Windows 10 Enterprise Edition operating system, the programming language is Python, and the compilation environment is Jet Brains PyCharm 2017.

To illustrate the accuracy and practicability of multi-source heterogeneous data fusion generated by users of e-commerce platforms, this section uses the user preference estimation algorithm proposed in 5 to compare the results of only commodity categories, fusion user-generated multi-source text, and fusion user-generated multi-source data. For the accuracy of user preference prediction in heterogeneous data, the experimental evaluation indicators choose RMSE and MAE, two error measurement methods to illustrate the accuracy and reliability of the prediction results. At the same time, to solve the problem of the matrix sparseness of the traditional collaborative filtering recommendation algorithm, the user preferences predicted by the above three methods are used to fill the user-product rating matrix to complete the user's personalized recommendation, and the performance of the recommendation algorithm using three different data is compared. Influence, the experimental evaluation index selects the precision (Precision) to evaluate the accuracy of the recommendation algorithm. In Table 5, the prediction results obtained by using different data to train the user preference estimation model and the user recommendation results obtained by joint learning of user implicit preference and explicit preference are given, among which the best results are shown in bold.

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Table 4: Statistical information for the data set.

Data set	item	point	user
Office_Products(Office	2380	52366	5021
Pet_Supplies(Pet)	8520	159201	19856
Software(Software)	16620	295900	25149
Toys_and_Games(Toy)	11746	157820	19523

We can conclude that (1) in the four datasets used in the experiment, using the user-generated data to assist the product category attribute to construct the RBM preference estimation model has a smaller error than simply using the product category attribute to complete the prediction. For example, in the Toy dataset, using the product feature fusion representation results, the average RMSE value of the auxiliary product category attribute is reduced by 0.233, and the average MAE value is reduced by 0.2 compared with the simple use of the product category to predict the user preference. However, using the product feature fusion representation result combined with the product category to complete the user preference prediction is better than using the fusion in Chapter 3. As a result, the average RMSE value combined with the commodity category decreased by 0.184, and the average MAE decreased by 0.182. The other three datasets also show the same trend in predicting user preference estimation experiments. (2) in the experiment of using three kinds of data to complete the quantitative representation of user preference combined with user explicit preference to complete user personalized recommendations, the experimental results show that the accuracy rate of using user-generated content data in the four data sets is higher than that of simply using product category attributes. There are various degrees of improvement, for example: in the Office dataset, using the fusion result combined with the product category to complete the recommendation for users is 24.8%, which is higher (4%) than the recommendation accuracy using the product category alone, and the recommendation accuracy using the fusion representation result is higher than that using the fusion representation result. In the Software dataset, although the recommendation accuracy rate using user-generated multi-source text is 1.2% higher than that of using user-generated multi-source heterogeneous data, the difference is almost the same. The two are 17.5% and 16.3% higher than the recommendation results of purely using commodity categories, respectively. (3) The user-generated content is integrated into the collaborative filtering recommendation algorithm, regardless of the deviation of the user rating estimation experiment or the recommendation accuracy of the user-recommended system, compared with the four sub-datasets without user-generated content.

Table 5: Comparison of recommendation algorithms that integrate user preferences using three different data.

Data set	Data used.	RMSE	MAE	Precision
Toys_and_Games(Toy)	Item type+ muti-source text data Item type+muti-source heterogeneous data	1312 1.079 0.895	1.205 1.005 0.823	0.315 0.590 0.642
Software(Software)	Item type+multi-source text data Item type+muti-source heterogenous	1.286 1.062 0.996	1.1625 1.106 0.981	0.346 0.521 0.514
Office_Products(Office)	Item type+muti-source text data Item+muti-source heterogeneous data	1.209 0.966 0.786	1.115 1.062 0.851	0.236 0.458 0.521
Pet_Supplies(Pet)	Item type+muti-source text data Item+muti-source heterogeneous data	1.369 1.113 0.926	1.235 0.965 0.811	0.456 0.532 0.586

4. Conclusion

The fusion and representation of multi-source heterogeneous data have extremely important value and significance in many fields. In the research of multi-source heterogeneous fusion representation, improving representation accuracy and fusion efficiency has always been the main purpose of developing various models. However, the existing multi-source heterogeneous data fusion algorithms still have some limitations, mainly in in the process of fusing user-generated multi-source text, the difference between long and short texts is not considered; in the process of text and image data fusion, The interaction and complementation of data and features between dimensions are not considered. At present, the scale of multi-source heterogeneous data generated by users in e-commerce websites is constantly expanding, the data representation forms are various, and the value density of user comment data is low, which makes it difficult to improve the accuracy of multi-source heterogeneous data fusion representation. Therefore,

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designing a fusion and representation strategy for multi-source heterogeneous data generated by users in e-commerce platforms is of great significance for improving the performance of recommendations or searches based on e-commerce platform data. Given this, this paper conducts related research on the fusion and representation of user-generated multi-source heterogeneous data in e-commerce platforms to improve the accuracy and robustness of some downstream applications.

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