Hindawi
Security and Communication Networks
Volume 2023, Article ID 9812593, 1 page
https://doi.org/10.1155/2023/9812593

Retraction

Retracted: Optimization of Rural Smart Tourism Service Model with Internet of Things

Security and Communication Networks

Received 8 August 2023; Accepted 8 August 2023; Published 9 August 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] X. Hu, "Optimization of Rural Smart Tourism Service Model with Internet of Things," *Security and Communication Networks*, vol. 2022, Article ID 6004728, 10 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 6004728, 10 pages
https://doi.org/10.1155/2022/6004728

Research Article

Optimization of Rural Smart Tourism Service Model with Internet of Things

Xiaoqing Hu

Hunan International Business Vocational College, Hunan Agricultural University, Changsha 410000, Hunan, China

Correspondence should be addressed to Xiaoqing Hu; huxiaoqing@stu.sqxy.edu.cn

Received 9 March 2022; Revised 29 March 2022; Accepted 2 April 2022; Published 16 June 2022

Academic Editor: Muhammad Arif

Rural smart tourism is a new tourism form supported by information technology, especially the Internet of Things technology. Smart tourism not only makes it easier for tourists to get diverse tourism information, but it also helps attractive sites improve their service capabilities. The optimization of the rural smart tourist service model, which is explored in this work, includes personalized recommendations of scenic sites. The main research contents of the paper are as follows: (1) A new algorithm for recommending tourism destinations with domain adaptability has been suggested. In the field of personalized recommendation of tourist attractions, most of the target domain data are unlabeled, and the model cannot be trained. When it comes to training, however, there exist source domain data sets that are completely labeled and can be used as a supplement to the target domain training data sets. (2) A personalized recommendation algorithm for tourist attractions with deep migration has been studied. Owing to the distribution difference between target data and source data, an adaptive layer is added to the convolutional neural network. The domain loss is then minimized to achieve deep feature transfer, and the model can then be trained to find scenic areas of interest to the user. Finally, the recommendation for tourist destinations with deep migration is done by examining the relationship between the target user and other users.

1. Introduction

People pay more attention to the construction of spiritual civilization, and tourism has developed into one of the largest industries. Not only that, the globalization trend of tourism is becoming more and more obvious. Tourism is gradually integrating multiple industries, so tourism has also become a highly comprehensive industry. However, the rapid development also exposes the current situation of tourism. The single mode of tourism, incomplete infrastructure, lack of comprehensive management, and disorderly competition in the market all restrict the development of the tourism industry. How overcoming these problems and forming a complete tourism system has been perplexing for many tourism practitioners. Tourism resources not only refer to tourism facilities and existing material resources but also tourism services, including transportation, publicity, tour guides, and other services. Tourism's long-term success hinges on making efficient use of all available resources. In light of this, the idea of a rural smart tourist system is advanced. Information technology has advanced so far that sophisticated information processing technology has been incorporated into the tourism sector. The Internet media, the formation of tourism resources informatization, and digitization, are crucial to the next development of the tourism industry [1–5].

Rural smart tourism actually refers to the use of information processing technologies such as the Internet of Things (IoT) and cloud computing in the tourism business. A new form of tourism is created by combining existing tourism resources with information technology. The use of IoT technology can meet the enormous characteristics and real-time collection needs of tourism information as an important direction of the IoT application. At the same time, with the increase in the proportion of self-guided tours, the coverage of tourism areas, the improvement of tour depth, and the uncertainty of tourism directly lead to the difficulty of tourism services and effective management. The emergence of the IoT connects tourists with tourism service providers and tourism public administration departments to

the greatest extent possible. With the help of the strengths of both parties, it is necessary to advocate and promote the construction of the IoT [6–10].

Through the effective integration of informatization construction and the construction of tourist attractions, the realization of smart tourism in scenic spots can promote the development of domestic tourism. Smart tourism is the fusion product of scientific management practice of scenic spots and modern information and communication technology. It is the main direction of the strategic development of domestic tourism and the basic policy of modern tourism. In fact, smart tourism is based on rapidly developing technologies. Through the Internet, smartphones, tablets, and computers are used as information terminal modules to realize the effective perception of tourists, tourism activities, economy, and resources. And the information can be released in a timely manner for the reference of tourists so that they can change and adjust their travel plans in time. This can greatly enhance the recognition experience of tourists and also promote upgrading and development. In the process of operation, different from the traditional fixed tourism mode, tourists are regarded as the core of the entire tourism development, and the user actively integrates entertainment, shopping, play, travel, accommodation and meals, and other aspects for users. It fully integrates informatization and tourism to achieve the goal of personalized service [11–15].

In the optimization of rural smart tourism service model with IoT technology, personalized recommendation of scenic spots is an important topic. This work takes this as the starting point and takes the personalized recommendation of tourist attractions with transfer learning as the research object. The transfer learning, as well as deep learning, are applied to the tourist attraction recommendation system, and then the personalized recommendation of tourist attractions is realized, which effectively solves the problems existing in the traditional recommendation system.

The paper's divisional layout is as follows: The related work is presented in Section 2. Section 3 analyzes the personalized recommendation of tourist attractions with domain adaptation. Section 4 discusses the personalized recommendation of attractions with deep migration. Section 5 discusses the experimentation and evaluation. Finally, in Section 6, the research work is concluded.

2. Related Work

Li et al. [16] pointed out that tourism intelligence is another huge breakthrough after tourism informatization, and it will become a catalyst to promote the innovative development of the tourism industry and transform and upgrade from traditional tourism to the modern service industry. Using a long-term, holistic, and sustainable strategy for creating, developing, and marketing tourism products and enterprises is what the literature refers to as smart tourism according to Dodds and Graci [17]. Despite the fact that Morales et al. categorize smart tourism into four distinct categories—clean, green, ethical, and high-quality services—it fails to recognize the profound impact that technological elements have had on the travel industry and the resulting shifts in consumer demand. As a result, Gretzel et al. [18] refer to the phenomena of using and implementing information technology in tourism as digital tourism or smart tourism. This definition of smart tourism, which incorporates mobile digital connection technologies to foster more intelligent, meaningful, and long-term relationships between visitors and cities [19], also serves to emphasize the practical benefits of smart tourism in smart cities. Gretzel et al. [20] thoroughly sorted out the theoretical foundation of smart tourism based on past research outcomes. Using data from infrastructure, social relations, governments, organizations, and individuals in a place to create a smart tourist experience is a key component. By combining these data with cutting-edge information technology, the tourism industry is able to gain practical experience and economic benefit.

Dams et al. [21] pointed out that smart tourism is a ubiquitous tourism information service, that is, this service has or seems to have the ability to exist anywhere at the same time. This means that the Internet has been integrated into people's lives and enables tourists to obtain ubiquitous travel information at any time, place, and according to any personal needs. According to Hunter et al. [22], smart tourism's technology features include ubiquitous infrastructure, information systems with increased mobility and situational awareness, dynamic connection mechanisms, and the ability to collect and synthesize enormous amounts of data. It can be seen that changes in information and communication technologies have promoted fundamental changes in tourists' travel patterns, tourism demands, and tourism patterns and structures [23]. Xiang et al. [24] define a smart tourism destination as a tourist destination. It ensures the sustainable development of the scenic area by using the most advanced technology, promotes the interaction and integration of visitors, and enhances the quality of life of the residents. Buhalis and Amaranggana [25] and Tu and Liu pointed out that smart tourism also contains three levels embedded in these smart components. One is the smart information layer designed to collect tourism data. The second is the smart switching layer that supports data interconnection. Therefore, under the interconnection and mutual support of the three smart levels, each part of the smart components can operate effectively and realize the intelligence of tourism activities.

According to Morabito [26], smart tourism has affected all or part of the following five market elements: exchange items, market structure, market institutions, market players, and market practices. Öberg and Graham [27] believe that smart tourism relies on massive tourism information and open technology platforms to transform value propositions. The infrastructure of smart tourism can form information asymmetry, which is conducive to new business development. Vargo and Lusch [28] argue that the labels assigned to roles such as tourists, travel companies, and travel intermediaries are no longer valid in the smart service ecosystem. This means that to re-examine the relationship between producers and tourists, new models of cooperation must be initiated. Yoo et al. [29] described the means and strategies adopted to build a trip advisor service ecosystem,

including identifying different stakeholders, the types of resources involved in the exchange, and the types of value jointly created through interactions.

3. Personalized Recommendation of Tourist Attractions with Domain Adaptation

Data sparseness and cold start issues currently plague tailored tourism attraction recommendations. And in order to construct a personalized recommendation system for tourist sites that performs well, a huge amount of labeled training data are needed. However, the personalized tourism attraction suggestion system's efficacy will be substantially diminished if only a tiny amount of labeled data are available. To circumvent the problem of a dearth of labeled data in the target dataset, we are considering creating an auxiliary data set using prelabeled data from the target data set. Owing to this, it is necessary to minimize any distribution discrepancies before training a tailored trip recommendation system using an auxiliary data set and the target data set. The goal of this chapter is to develop a domain-adapted recommendation model for tourist attractions that can successfully reduce the distribution discrepancies between different data sets in order to make more tailored recommendations. Domain adaptation-based personalized recommendation model for tourism sites is illustrated in Figure 1.

3.1. Classification of Tourist Attractions with Domain Adaptation. How to quickly and efficiently employ effective samples and information from the source domain task to assist with the target domain task is a challenge worth investigating. By adapting transfer learning to the target domain, the current issues can be effectively addressed. To put it another way, domain adaptation can address the issue of using labeled samples from the source domain data set to help classify data from the target domain when the distribution of data between the two data sets is different but similar. If you wish to avoid the cold start and scant data issues that plague classic personalized tourist attraction recommendation systems, try implementing domain adaptation, which is essentially a method of changing data sets based on the task of a source domain. Differences in data set distribution provide a challenge. However, in the field of personalized recommendation of tourist attractions, there have been few research outcomes and most recommender systems still require a considerable amount of labeled data as training support for classification approaches based on domain adaptation. As a result, the focus of this part is on developing a method for categorizing tourist attractions based on their style, one that considers domain adaptation. Classifying tourist destinations based on their style can be accomplished in the absence of labeled data using a domain-adaptive classification framework, even when there is a shortage of labeled information.

The total model can be separated into two modules: classification and recommendation. The main goal of the classification module is obtaining the style of attractions that users are interested in through classification, that is, user preferences. The recommendation module's major purpose is to assess the relationship between the target user and other users based on the user preferences gained through categorization, in order to provide customized scenic place recommendations for the target user.

The data set preparation, feature extraction, feature transfer, and classifier classification components of the framework for style categorization of tourist attractions based on domain adaptation are divided into four parts. The first step is to prepare the data set, obtain photos of various tourist attractions uploaded by users from social media, and use the photos of scenic spots uploaded by users as the target data set, denoted as $U = \{u_1, u_2, \ldots, u_n\}$. Only a small number of photos of attractions are tagged, most of them are untagged. Then, according to the properties of the target data set, images that have a certain correlation with the target data set are obtained from the search engine. And think that these are all labeled images, and use it as the source domain data set, denoted as follows:

$$S = \{S_n\}_{n=1}^{N}. \tag{1}$$

Second, after the data set preparation is completed, feature extraction is performed on the target data set and source data set. The features are denoted as follows:

$$F_u^n = F_{\mathrm{ul}}^n \cup F_{\mathrm{uu}}^n, \tag{2}$$

where F_{ul}^n represents labeled feature data with labels and F_{uu}^n represents the unlabeled feature data without labels.

The features extracted from the source domain data set are denoted as follows:

$$F^n = \{F_n^n, y_n = n\}_{n=1}^{N}, \tag{3}$$

where F_n^n represents a feature of the image of the nth scenic spot type and $y_n = n$ represents that the feature vector of the ith scenic spot type is marked as n.

Then, migrate features. The distribution discrepancy between the target domain data set features and the source domain data set features necessitates the usage of domain adaptation at the feature level to bridge the gap. Domain adaptation is at its most fundamental when it minimizes the largest mean distribution discrepancy between source and target domain data. The highest mean difference between source and target domain data is used in a tourist attraction style classification based on domain adaptation, as demonstrated here:

$$D_k(U, S) = \frac{1}{M}\sum_{n=1}^{M} \varphi\left(F_u^n\right) - \frac{1}{N}\sum_{n=1}^{N} \varphi\left(F^n\right)_H. \tag{4}$$

When D_k is smaller, it means that the distribution difference between the scenic spot-type data set and the user album data set is smaller. If $D_k = 0$, it means that the distribution of the scenic spot-type data set and the user album data set is the same. Therefore, by minimizing D_k, the distribution difference between the features of the attractions type data set and the features of the user album data set is reduced.

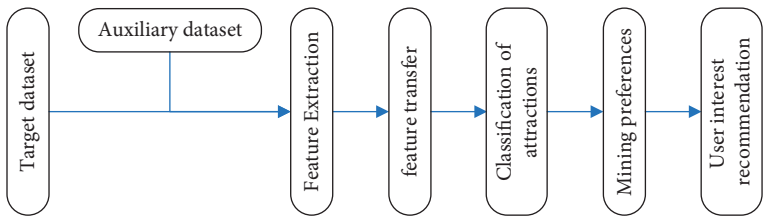

Figure 1: Personalized recommendation of attractions based on domain adaptation.

Finally, the features are input into the SVM classifier for classification on the basis of lowering the distribution difference between the features of the scenic place type data set and the characteristics of the user album data set. An auxiliary classifier $f^a(x)$ is obtained by training the labeled scenic spot-type data set feature F^n, and the goal is to obtain a classifier $f(x)$ that can accurately classify the target data set U based on the auxiliary classifier $f^a(x)$. In the regenerated kernel Hilbert space, reducing the data distribution difference between the feature of the scenic spot-type data set, and the feature of the user album data set can be achieved by minimizing the regular expression of the SVM.

Through the aforementioned method, the target classifier can accurately classify the user data set, that is, the style of the scenic spot that the user is interested in is obtained.

3.2. Personalized Tourist Attraction Recommendation. On the basis of getting the style of the scenic spots that the user is interested in, by analyzing the relationship between the target user and other users, the relevant scenic spots can be recommended to the target user. First, calculate the similarity between the target user and other users. Cosine similarity is used to measure similarity between two users. Let $N(A)$ denote the set of attraction types that user A likes and $N(B)$ to denote the set of attraction types that user B likes. Then the cosine similarity between user A and user B can be expressed as follows:

$$\mathrm{Sim}(A,B) = \frac{|N(A) \cap N(B)|}{\sqrt{|N(A)| \times |N(B)|}}. \tag{5}$$

Assuming there are m users in total, a similarity moment M can be constructed, where the larger $\mathrm{Sim}(A,B)$ is, the higher the similarity between user A and user B is. Therefore, through the similarity matrix, the K users most similar to the target user A can be obtained, which is represented as a set $T(A, K)$. Then classify the attractions that users like in the set T, and remove the types of attractions that user B already likes. For each candidate attraction type, user A interest in it is calculated as follows:

$$p(A,n) = \sum_{B} \mathrm{Sim}(A,B) \times r(B,n), \tag{6}$$

where $r(B,n)$ is user B's preference for attraction type n.

Finally, according to interest in candidate spot types, the recommendation is implemented for the user.

4. Personalized Recommendation of Attractions with Deep Migration

In recent years, with the exponential growth of network information data and the substantial improvement of hardware computing power, artificial intelligence technology has gained immeasurable development potential, especially an important branch of artificial intelligence, that is, deep learning algorithms. The fields involved in deep learning algorithms have sprung up. At the same time, the application of deep learning algorithms in these fields has made major breakthroughs compared with traditional technologies. With the continuous expansion of the application field of deep learning, deep learning has been applied to the personalized recommendation of tourist attractions, and it is expected that certain breakthroughs can be made in improving the recommendation performance of personalized recommendation systems.

4.1. Deep Migration. The deep learning approach uses a convolutional neural network to extract many levels of visual feature information from the original image, including low-level, intermediate, and high-level semantic features. Abstracting multilevel image features yields sample image features with great completeness. The most important distinction between machine learning and deep learning algorithms is this. Both deep learning techniques and machine learning require a large number of labeled samples for training and optimization, which is similar. When there is not enough training data, models learned using deep learning algorithms perform worse than models learned using traditional machine learning techniques. In the realm of personalized recommendations of tourist sites, the target domain data set typically contains only a limited quantity of labeled data for the problem that needs to be done. There is a considerable amount of labeled data in the source domain that has some connection with the target domain data, but this limits the model's performance to a large extent. It was thus proposed by Tzeng et al. [30] a novel convolutional neural network architecture, the domain confusion-based, and deep transfer learning framework (DDC). The adaptive layer has been added to the basic convolutional neural network structure, and it may be used to obtain the difference in data distribution between the source and target domains. It is able to handle the issue of a shortage of labeled data in the target domain by minimizing the distribution difference between the two. Because of the paucity of labeled data in the target domain data set, this chapter offers a

personalized recommendation model based on deep transfer. Tourist venues can now be recommended to visitors based on deep migration with the use of properly labeled data from the original source domain.

4.2. Attraction Style Classification with Deep Transfer. The personalized recommendation model of tourist attractions with the deep transfer is solved. The style classification model for tourist attractions with the deep transfer is shown in Figure 2.

The first stage is to input the data set and then the source domain data set, which is the labeled scenic spot style image data, into the deep transfer convolutional neural network, on the assumption that all layers in the convolutional neural network share weights. The main task of the first five convolutional layers is to learn the features of the source domain data and then get an output after going through the fully connected layer and the adaptive layer, and then get output through the classifier. The output obtained by the classifier is the classification loss of the source domain data. Then, the target domain data set, that is, the user's scenic spot album image data, is input into the deep transfer convolutional neural network. The first five convolutional layers are mainly to learn the features of the target domain data, and output through two fully connected layers and adaptive layers. Then, the difference between the output from the adaptive layer obtained from the input of the source domain data and the target domain data, respectively, is called the domain loss. In the end, it is only necessary to consider minimizing the classification loss and the domain loss at the same time, transforming the original complex problem into a problem of optimizing the loss function. Therefore, the distribution difference between the source domain data and the target domain data is subtly solved, and the convolutional neural network is also guaranteed to accurately classify the target domain data.

In order to eliminate the distribution difference between the scenic spot-type data set S and the user album data set U, the maximum mean difference (MMD) is used as the criterion to measure the distance between the scenic spot-type data set S and the user album data set U data distribution. This is achieved by minimizing the maximum mean difference. In essence, the maximum mean difference is to quantify the data distribution difference between the feature of the attraction type data set and the feature of the user album data set by the mean of their probability distributions in the regenerated kernel Hilbert space. Let the scenic spot-type data set S and the user album dataset U be subject to probability distributions p and q respectively, and the data sets are independent and identically distributed. Then the maximum mean difference between the scenic spot-type data set S and the user album data set U can be expressed as follows:

$$\mathrm{MMD}(F, p, q) = \sup\left(E\left[f\left(x^s\right)\right] - E\left[\left(\left(x^t\right)\right)\right]\right). \tag{7}$$

The smaller the MMD, the higher the similarity of the two distributions p and q. When MMD is 0, the two distributions p and q are considered equal. The scenic spot-type

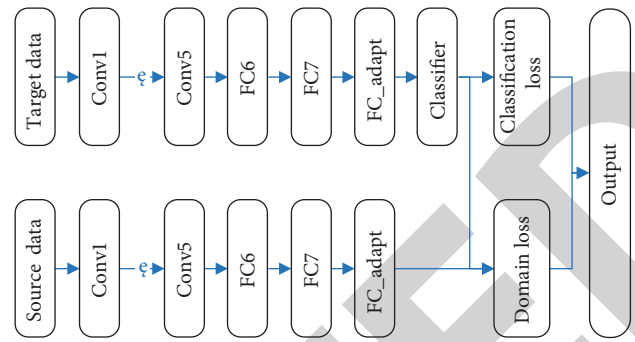

Figure 2: Attraction style classification based on deep transfer.

data set S and the user album data set U are subject to two independent distributions p and q, respectively. Therefore, an empirical estimate based on the scenic spot-type data set S and the user album data set U can be obtained, which can be expressed as follows:

$$\mathrm{MMD}(F, U, S) = \frac{1}{M}\sum_{n=1}^{M} f\left(x_n^s\right) - \frac{1}{N}\sum_{n=1}^{N} f\left(x_n^t\right)_H. \tag{8}$$

The difference in distribution between the scenic place type data set and the other data sets S and the user album data set U can be eliminated by minimizing the MMD. On the basis of reducing the distribution difference between the scenic spot-type data set S and the user album data set U, the scenic spot-type data set can be used to assist in training the target classifier.

The deep transfer-based tourist attraction style classification model is trained on convolutional neural networks. The convolutional neural network selected in this paper is the ImageNet weight loaded by the AlexNet network. The AlexNet network structure contains five layers of convolution layers and three layers of fully connected layers. Owing to the need to reduce the distribution difference between the attraction type data set and the user album data set, the first seven layers of the AlexNet network are fixed, and adaptive metrics are added on the eighth layer. The adaptive measure uses the maximum mean difference MMD criterion. The optimization goal of deep transfer neural networks is to minimize both domain loss and classification loss at the same time. Thus, the deep transfer neural network can learn more shared features between the scenic spot-type data set S and the user album data set U through training.

By minimizing the loss, the classification of tourist attractions style based on deep migration is realized, that is, the distribution difference between the data set of scenic spots type and the data set of user albums is reduced, and the style of scenic spots can be accurately classified. The use of deep feature transfer technology can effectively solve the problem of scarce labeled data in the target domain data set, that is, the cold start and data sparsity problems faced by travel recommendation systems. Then, through the training of a convolutional neural network, the user's potential scenic spot style preferences can be classified more accurately.

Finally, the same method as in Chapter 3 is used for personalized recommendations of attractions.

5. Experiment and Discussion

5.1. Data Set and Detail. In this paper, the selected experimental data come from search engines, covering a total of three villages. The composition of the target domain data set is shown in Table 1. At the same time, the source domain data set was crawled from search engines, totaling 4000 images of eight different types of attractions. They are natural scenery, historical monuments, art and culture, shopping, sports, entertainment, food, and night scenery, and there are 500 pictures for each type of attraction.

The first comparison algorithm is the classification algorithm of tourist attraction style based on domain adaptation, which is the method proposed in Chapter 3 of this paper. First, the bag-of-words model features of the source domain data set and the target domain data set are extracted. Second, at the feature level, domain adaptation is used to reduce the distribution difference between the source domain data set and the target domain data set, that is, to minimize the maximum mean difference. Finally, on the basis of reducing the distribution difference between the source domain data set and the target domain data set, the feature data are input into the support vector machine (SVM) classifier. In this way, the style classification of tourist attractions is realized, and the first comparison algorithm is abbreviated as DASVM.

The second comparison algorithm is to use a typical convolutional neural network model to train the source domain data set and the target domain data set directly on the convolutional neural network. The original image is directly input into the input layer of the convolutional neural network, and the features of the original image are extracted through the convolution kernel of the convolutional layer, and the output of the convolutional layer is the high-level semantic features of the image. Then the output of the convolutional layer is input to the fully connected layer, and after the fully connected layer, the style classification of tourist attractions is realized. The second comparison algorithm is abbreviated as CNN.

The third comparison algorithm is to use a deep transfer neural network based on domain confusion, that is, a new adaptive layer is added before the output layer of a typical convolutional neural network. The training method is the same as the general convolutional neural network, and the original image is directly input into the input layer of the deep transfer neural network. The features are extracted from the original image through the convolution check of the convolution layer. The output of the convolution layer is the high-level semantic feature of the image, and then the output of the two fully connected layers enters the newly added adaptive layer. The distribution difference between the source domain data set and the target domain data set is reduced by the adaptive layer, and finally, the output from the adaptive layer enters the softmax layer. In this way, the style of tourist attractions can be classified, and the second comparison algorithm is abbreviated as DTSoftmax.

5.2. Classification Result of Tourist Attractions with Domain Adaptation. The experiment adopts the method of cross-validation and randomly selects 80% of the data as the training data and 20% of the data as the test data. The domain adaptation algorithm and the comparison algorithm were used to classify the target domain data, and a total of five cross-validation experiments were conducted. Finally, the average precision and recall of five cross-validation classification experiments are taken as the result. The classification results of attraction types are illustrated in Table 2.

Table 1: The details of the target data set.

Rural community	Number
Village 1	15,056
Village 2	13,562
Village 3	25,836

According to the classification results of attraction types, the traditional SVM classifier lacks a large amount of labeled training data during the training process. As a result, the classification effect of the classifier on the test data set is poor. For the cross-domain support vector machine (CDSVM), it can help classify the target domain data set with the help of the labeled data in the source domain data set. Compared with the traditional SVM, the classification effect of the CDSVM is more excellent. However, CDSVMs cannot solve the distribution difference between the source domain data set and the target domain data set very well. With the help of the linear combination of various basic kernel functions, multikernel learning MKL can also solve the problem of scarcity of training data sets to a certain extent. And it can be seen from the classification results that its classification performance is slightly better than that of a CDSVM. However, the disadvantage of multikernel learning is that it does not resolve the distribution difference between the source domain data and the target domain data. Therefore, the domain adaptive DA method adopted in this paper can eliminate the distribution difference between the source domain data and the target domain data well, and then achieve accurate classification of the target domain data, and the classification effect is good. Thus, the problem of scarcity of labeled training data is effectively solved, and finally, the category of the target data, that is, the scenic spot style of the user data, is obtained by classification.

5.3. Recommendation Result of Attractions with Domain Adaptation. Based on the style of scenic spots obtained from user data, that is, the style of scenic spots that users are known to be interested in, the user-based collaborative filtering recommendation algorithm is compared with the recommendation algorithm in this paper. Taking precision and recall as evaluation indicators, the obtained recommendation results are shown in Figure 3. Among them, CF represents the user-based collaborative filtering recommendation algorithm, and DAR represents the recommendation algorithm used in this chapter.

From the analysis of the trend of the recommendation results, with the increase of the number of nearest-neighbor users, the precision and recall rate of the user-based collaborative filtering recommendation algorithm and the domain adaptation-based tourist attraction personalized

Table 2: The result of classification on spot-style.

Method	Village 1		Village 2		Village 3		Average	
	P	*R*	*P*	*R*	*P*	*R*	*P*	*R*
SVM	44.60	42.90	43.70	42.00	43.30	41.90	43.90	42.70
CDSVM	62.70	61.70	63.10	62.30	61.90	61.30	62.60	58.80
MKL	66.10	65.30	66.70	64.90	65.00	64.20	65.90	64.80
DASVM	67.20	66.10	66.60	65.40	67.80	67.00	67.20	66.20

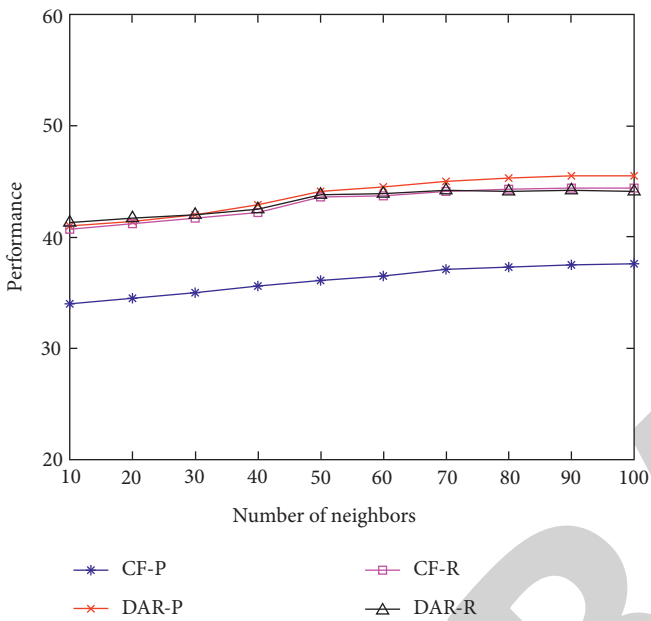

Figure 3: The comparison of recommendation results diagram.

recommendation algorithm adopted in this paper both increase. When the number of nearest-neighbor users reaches 80, the precision and recall tend to be stable. From the numerical analysis of the recommendation results, the recommendation precision and recall rate of the personalized recommendation algorithm for tourist attractions based on domain adaptation is better than those of the user-based collaborative filtering recommendation algorithm.

5.4. Attraction-Style Classification Result with Deep Transfer. The deep migration-based tourist attraction-style classification algorithm proposed in this chapter is similar to the third comparison algorithm, that is, a new adaptive layer is added before the output layer of a typical convolutional neural network. The training method is the same as the general convolutional neural network. The original image is directly input into the input layer of the deep transfer neural network, and the features are extracted from the original image through the convolution kernel of the convolutional layer. The output of the convolutional layer is the high-level semantic features of the image, and then the output of the two fully connected layers enters the newly added adaptive layer. An adaptive layer is used to reduce the distribution difference between the source domain data set and the target domain data set, and finally, the softmax layer is replaced by an SVM classifier. That is, the output of the adaptive layer is input to the SVM classifier for classification. The style classification algorithm of tourist attractions based on deep transfer proposed in this chapter is abbreviated as DTSVM.

Figure 4 shows the performance comparison of scenic spot-style classification under different algorithms. The horizontal axis represents different classification algorithms, from left to right are DASVM, CNN, DTSoftmax, and DTSVM. The vertical axis represents the evaluation index, that is, the average classification accuracy mAP.

First, comparing the domain adaptation-based tourist attraction classification algorithm DASVM with the typical convolutional neural network CNN, the average classification accuracy of the DASVM algorithm is slightly higher than that of the CNN algorithm. Second, comparing the DASVM algorithm with the deep transfer convolutional neural network DTSVM proposed in this chapter, the average classification accuracy of the DTSVM algorithm is higher than that of the DASVM algorithm. Finally, comparing the deep transfer convolutional neural network DTSVM proposed in this chapter with the DTSoftmax algorithm, the average classification accuracy of the DTSVM algorithm is higher than that of the DTSoftmax algorithm. In summary, the deep migration-based tourist attraction-style classification algorithm DTSVM proposed in this chapter has better classification performance and applying it to classify user data can more accurately obtain the attractions styles that users are interested in. Then, by analyzing the relationship between the target user and other users, personalized recommendations of tourist attractions can be realized.

5.5. Recommendation Result of Attractions with Deep Migration. The user data are classified by a deep migration-based tourist attraction-style classification algorithm, so as to obtain the user's interests and preferences. This can effectively solve the problems of cold start and data sparsity when making personalized recommendations. Therefore, on the basis of obtaining the scenic spot style of the user's album, that is, the known scenic spot style that the user is interested in, the personalized recommendation of tourist attractions is realized. Comparing the user-based collaborative filtering recommendation algorithm with the deep migration-based tourist attraction recommendation algorithm proposed in this chapter, with precision and recall as evaluation indicators, the recommended results are shown in Figure 5. Among them, CF represents the user-based collaborative filtering recommendation algorithm, and DTR represents the recommendation algorithm used in this chapter.

The horizontal axis represents the number of nearest neighbors of the target user, and the vertical axis represents the evaluation indicators, namely recommended precision and recall. Among them, the accuracy rate represents the probability that the user is interested in the recommended attractions, and the recall rate represents the probability that the user's interesting attractions are recommended. It can be seen from the figure that the recommendation accuracy of the personalized recommendation algorithm for tourist

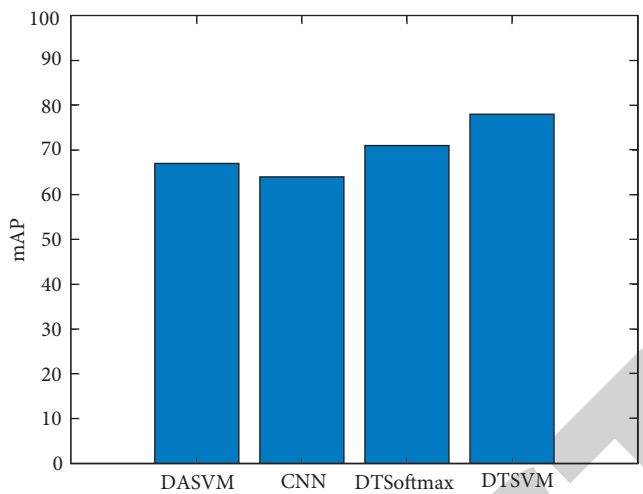

Figure 4: Comparison of classification with different algorithm.

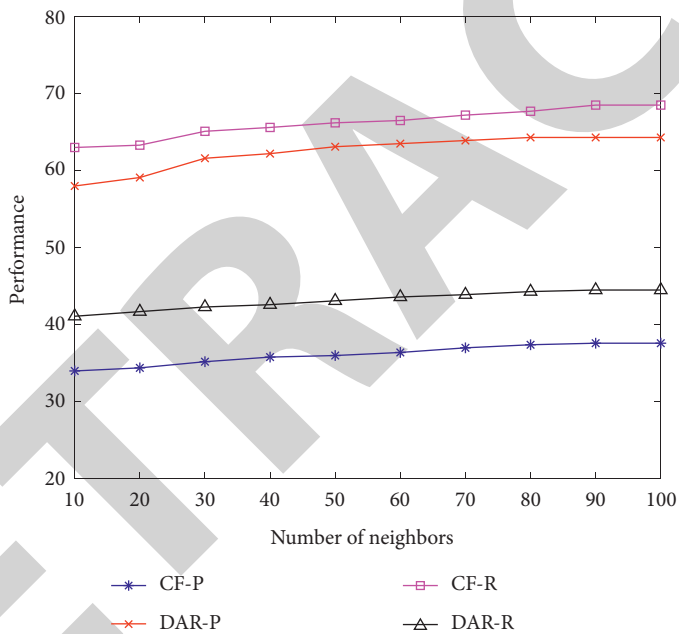

Figure 5: The comparison of recommendation results.

attractions based on deep migration proposed in this chapter is significantly better than that of the user-based collaborative filtering recommendation algorithm. Through the experimental verification, the recommendation performance of the personalized recommendation algorithm for tourist attractions based on deep migration proposed in this chapter is better.

6. Conclusion

The IoT and rural smart tourism have become a popular topic of discussion, and all regions have joined the army of smart tourism builders. Theoretical study on the use of IoT technology in tourism and the development of smart tourism, on the other hand, is still in its infancy. It is critical to figure out how to maximize the rural smart tourist service model using IoT technologies. This paper takes the personalized recommendation for tourist attractions with transfer learning as the research object, applies the transfer learning and deep learning in machine learning to the recommendation system of rural smart tourist attractions, and then realizes the optimization of the rural smart tourism service model. Main research results include the following: (1) A new algorithm for recommending tourism destinations based on domain adaptability has been suggested. Domain adaptation in transfer learning reduces the disparity between source and target information by introducing data that might help identify prospective user interests and preferences from the target data. Personalized recommendations for tourist sites can be achieved by decreasing the distribution gap between the source and target domain data. (2) A

personalized recommendation algorithm with deep migration is designed, and the deep learning algorithm is applied. The advantage for deep learning algorithms is that the use of convolution kernels in convolutional neural networks can extract more complete, robust, and discriminative data features. To solve the problem of cold start as well as data sparsity, source domain data are introduced for assistance. To reduce dispersion, a new adaptive layer has been added. More complete and accurate user potential attractions of interest are mined from the target data with the help of source data, resulting in tailored tourist attraction recommendations.

Data Availability

The data sets used during this study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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