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Original Research Article

Spatiotemporal Information Fusion Method of User and Social Media Activity

Chao Yang*, Liusong Yang, Kunlun Qi

School of Geography and Information Engineering, China University of Geosciences, Wuhan 430074, China

ABSTRACT

Social media check-in data contains a lot of user activity information. Understanding the types of activities and behavior of social media users has important research significance for exploring human mobility and behavior patterns. This paper studies the user activity classification method for Sina Weibo (a very popular Chinese social network service, referred to as "Weibo"), which combines image expression and spatiotemporal data classification technology to realize the identification of the activity behavior represented by the microblog check-in data. Firstly, the user activities represented by the Sina Weibo check-in data are divided into six categories according to POI attribute information: "catering", "life services", "campus", "outdoors", "entertainment" and "travel"; Then, through the Convolutional Neural Network (CNN) and K-Nearest Neighbor (KNN) classification methods, the image scene information and spatiotemporal information in the check-in data are fused to classify the activity behavior of microblog users. The experimental results show that the proposed method can significantly improve the accuracy of microblog user activity type recognition and provide more effective data support for accurately exploring human behavior activities.

Keywords: *Social Media Informatio; Microblog Check-in Data; Classification of User Activities; Machine Learning*

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***CORRESPONDING AUTHOR**
Chao Yang
yangchao@cug.edu.cn;

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1. Introduction

With the development of the Internet and the popularity of social networks, more and more users obtain and share all kinds of social media information on social networks[1]. Social networking software such as Facebook, Twitter and Sina Weibo have more than 3 billion active users worldwide[2], generating and disseminating massive amounts of social media data every day[3]. Sina Weibo is one of the main social media applications in China, by the first half of 2018, the number of Weibo users had reached 337 million, of which 316 million were using smart phones, accounting for 93.5%[4].

Social media data can provide a large amount of information at the level of human and social interaction, especially smart phone users. It can provide social media check-in data with geographical location information, including short text messages, photos, time and location of message release and their corresponding points of interest (POI) information, which can reflect or infer the users' activity content at a certain time and space location to a certain extent[5-6].

Massive social media check-in data can provide data support for tracking and analyzing human movement patterns and behavior patterns in a long time and space scale[7]. Compared with previous location data (such as mobile phone location data), check-in data includes not only time and location information, but also users' behavior information, that is, information related to social media user activity content; Secondly, the spatiotemporal information sequence of check-in data can be regarded as the spatiotemporal trajectory of users. For example, the check-in point map of 500 million users on four-square clearly shows the distribution of global human activities[8]. Based on this, more researchers began to explore social media data from different angles. Duan *et al.* proposed a spatiotemporal theme model considering continuous time and regional influence factors, which can more accurately find the evolution of microblog event theme in continuous time[9]; Wang *et al.* proposed the concept of co-word network, extracted the key words of time type to describe different microblog topics, and proved its effectiveness through experiments[10]; Cheng *et al.* explored the activity preference and activity time of Twitter users through the analysis of twitter check-in number in New York City[11]; Rizwan *et al.* used Sina Weibo check-in data to observe the individual check-in behavior and activity intensity in Shanghai[12].

However, social media data is a kind of user generated content (UGC), which is subject to the objective constraints of data acquisition technology, data users' understanding of data and data operation specifications, as well as the subjective influence of location, time and published content. There is uncertainty in data quality[7]. Therefore, when using social media check-in data to analyze the activity category of users, the quality of check-in data needs to be considered[13]. Due to the lack of verification means for the correctness and reliability of social media data, when analyzing user behavior for social media check-in data, we only consider one assumption of data quality: is the POI location of user check-in consistent with the content displayed by users? That is, whether the activity category represented by the POI information is consistent with the multimedia content (text and picture) in the check-in information. As shown in **Figure 1**, we list the cases where the spatiotemporal information and multimedia content contained in Sina Weibo check-in data do not match the activity category represented by the check-in POI information. Therefore, only using the POI information of social media check-in data will directly affect the results of user behavior analysis.

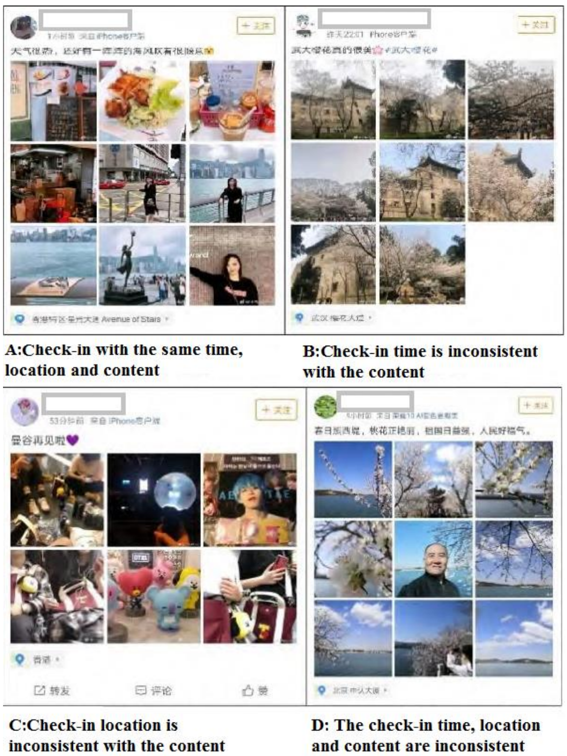

Figure 1. Examples of Sina Weibo check-in data quality problems.

In the research on the behavior classification of microblog users, based on the POI category definition of sina microblog platform, aiming at the main daily activities and contents of social media users, this paper divides the activity types of users into six categories: "catering" "life service", "campus", "utdoor", "entertainment" and "travel". By comprehensively analyzing the spatiotemporal information and image scene information of microblog check-in data[14], the behavior classification of microblog data is realized, so as to improve the accuracy of behavior data classification.

This paper proposes a user activity classification method combining K-Nearest Neighbor (KNN) and Convolutional Neural Networks (CNN). The method determines the temporal and spatial distribution of each check-in data in the three-dimensional space according to the time and space information of the check-in data of Weibo. Based on the theory of KNN model, we believe that the sign in points with similar distribution in time and space are more likely to have the same activity category; according to the image characteristics of microblog check-in data, the scene information in the image is extracted by using the pre-trained CNN model[15]. We believe that the images uploaded by most users have certain practical expression significance, and the scene information contained in the image can reflect the spatial information or activity state of users. Finally, we use the method of logistic regression to distinguish the type of user activity by combining the probability distribution vector obtained from the above spatiotemporal features and image features. Experiments show that integrating the spatiotemporal information and image scene information of microblog check-in data can significantly improve the accuracy of microblog user activity classification.

2. Microblog check-in data and user activity types

2.1 Microblog check-in data

Every time a microblog user signs in, a microblog check-in data with geographic location information will be generated, including time, location, image, short text and other information; at the same time, when checking in, users will choose to carry the POI information near their location, which not only contains the spatial location information, but also carries the relevant location semantic information, such as the category and name of the POI.

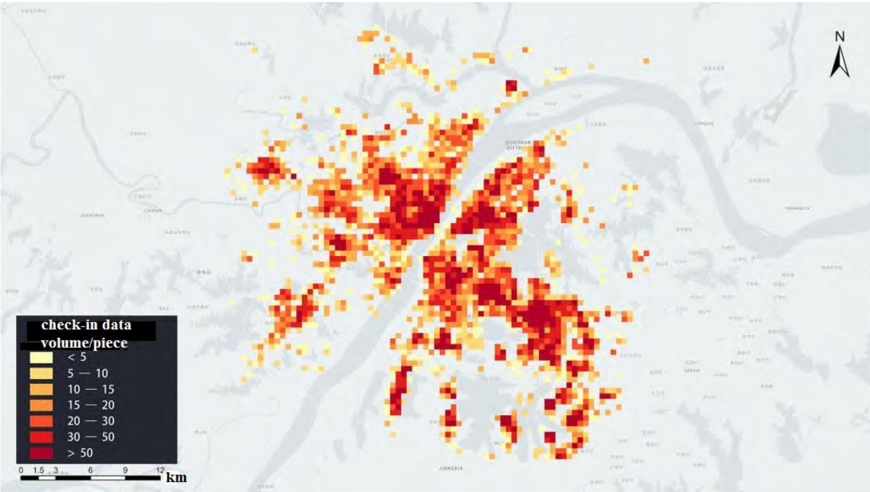

Figure 2. Distribution of Weibo check-in data during January 2015 and June 2015 in Wuhan.

The data set studied in this paper is the check-in data of microblog users in Wuhan from January 2015 to June 2015. As shown in **Figure 2**, the overall data adopts a grid size of 500 m × 500 m to construct a square grid covering the urban area of Wuhan, which is spatially connected with the data of check-in points. The number of check-in points in the grid is used as the classification standard, and the natural breakpoint grouping method is used to select different color bands for each grid according to the sample density; it can be seen that the user's activity area basically covers the main urban areas of Wuhan, while the number of check-in is obviously scarce in the surrounding suburbs and areas with low population activity density.

2.2 Activity types of microblog users

Although the activity type of microblog users' check-in data cannot be obtained directly from the check-in data, most users will choose to carry POI information with high relevance to their activities when signing in. Therefore, it is feasible to classify user activities based on the POI information of check-in data[16]. Sina Weibo officially has 200+ POI categories, such as cafes, cake shops and seafood restaurants, etc. Although this division method is very detailed, for this study, we focus not on the specific activity content of each data, but on the macro activity distribution of user groups. According to the land use regulations and the types of human daily activities, we redefined the original POI types into six categories: "catering", "life service", "entertainment", "outdoor", "campus" and "travel", among which the POI types corresponding to each activity category and the proportion of microblog data of each category in the check-in data set are shown in **Table 1**.

Table 1. The activity classes of POIss in Weibo check-in data

Activity category	Check-in POI point category	Proportion (%)
Restaurant	Coffee shop, tea shop, dessert shop, fast food restaurant, Chinese restaurant, foreign restaurant, leisure restaurant, pastry shop, cold drink shop, catering food, buffet, barbecue, cooked food, snacks	29.32
Life service	Residential area, community service, dry cleaning shop, photo studio, bank, telecommunications business hall, beauty salon, bath and massage, class III hospital, clinic, drugstore, specialized hospital, 4S store, express, museum, exhibition hall, convention and Exhibition Center	13.38
Entertainment	KTV, billiards hall, bar, game hall, disco, chess and card room, Internet cafe, cinema, theater, nightclub, casino	22.18
Outdoors	Amusement parks, parks, zoos, botanical gardens, city squares, campsites, aquariums, water sports centers, golf related, fitness centers, sports venues, tennis courts, badminton halls, taekwondo halls, natatoriums, basketball venues, football fields, national scenic spots, general scenic spots, scenic spot gates	11.01
Campus	Colleges and universities, adult education, vocational and technical schools, middle schools, primary schools, kindergartens, university centers, school gates, scientific research institutions, libraries	5.01
Travel	Ticket office, airport, railway station, port wharf, long-distance bus station, subway station, hotel guest house, star hotel, Youth Hostel, toll station	19.08

3. Microblog user activity classification model

3.1 Spatiotemporal characteristics based on microblog check-in data

Study the types of user behavior activities, in which time and space factors are very important characteristic factors. Set $S=\{a_1, a_2, \cdots, a_n\}$ as the collection of check-in data samples, where n is the total number of samples in the data set. Each check-in record $a_i (1 \le i \le n)$represents a user's microblog check-in record. For example, after a user completes a microblog check-in behavior, it produces $\{<114.35, 30.14>, 19:23:11, Catering\}$ such a microblog check-in record, we can understand that the user's time in Beijing is $<19:23:11>$, location $<114.35, 30.14>$ carried out catering related activities; we denote it as $a_i=\{(l_i, t_i), c_i\} (1 \le i \le n)$, which represents a user's check-in record. Among them, (l_i, t_i)represents the spatiotemporal information of the check-in data, and c_i represents the user activity category information of the check-in data.

Because geographical things or attributes are related in spatial distribution, the closer things in space are more closely related; and in real life, human activities often show a specific time pattern[17]. For example, people often carry out catering activities at a fixed time every day. Therefore, this paper attempts to explain and analyze the user's activities from the perspective of time and space by taking hours as the basic scale and combining with the geographical distribution of spatial features. Based on the above ideas, this paper uses KNN method to model the temporal and spatial characteristics of microblog check-in data, and calculates the classification results of user activities based on the temporal and spatial characteristics of microblog check-in data.

3.2 Image features based on microblog check-in data

In addition to the above-mentioned spatiotemporal characteristics, the microblog check-in data also includes the image features uploaded by users, which can provide feature information related to user activities to a certain extent, supplement and assist decision-making for information that cannot be directly expressed by spatiotemporal characteristics. For example, for a microblog check-in data whose activity category is unknown and whose space is located around ordinary streets, if the images it carries are mainly images closely related to the catering category, such as dishes, restaurant interior or restaurant door face, we have reason to think that this check-in data probably reflects a user's ongoing catering activities, rather than outdoor category or resident category.

Based on the above ideas, we use the places 365 data set[18] published by MIT in 2015 and its places365 CNN model based on alexnet network training[19]. For each input picture, the model calculates its corresponding scene category probability distribution. Based on the pre-trained places 365 CNN model, combined with manual annotation, this paper maps its original 365 scene categories to the microblog user activity categories described in **Table 1** (as shown in **Figure 3**). For example, we divide the airport and bus station in the original category into travel activities. Cafeteria and bakery are divided into catering activities. Finally, the above model is used to calculate the user activity classification results corresponding to the images in the microblog check-in data (some examples are shown in **Figure 4**).

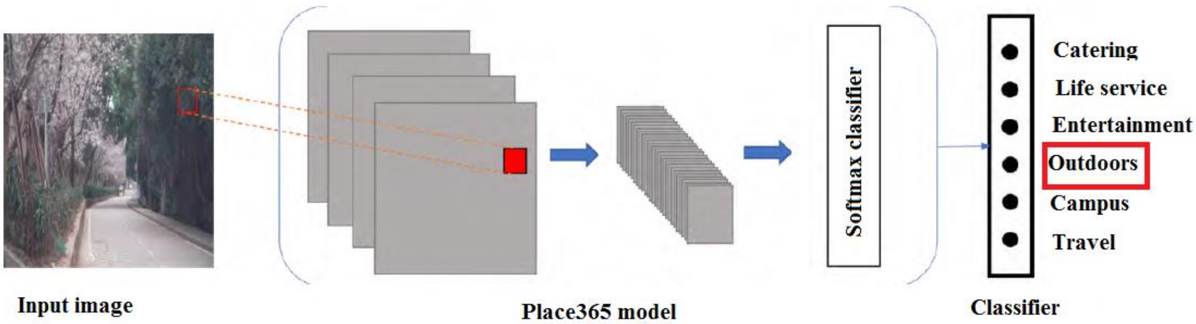

Figure 3. Framework of the image-based user activity classification model.

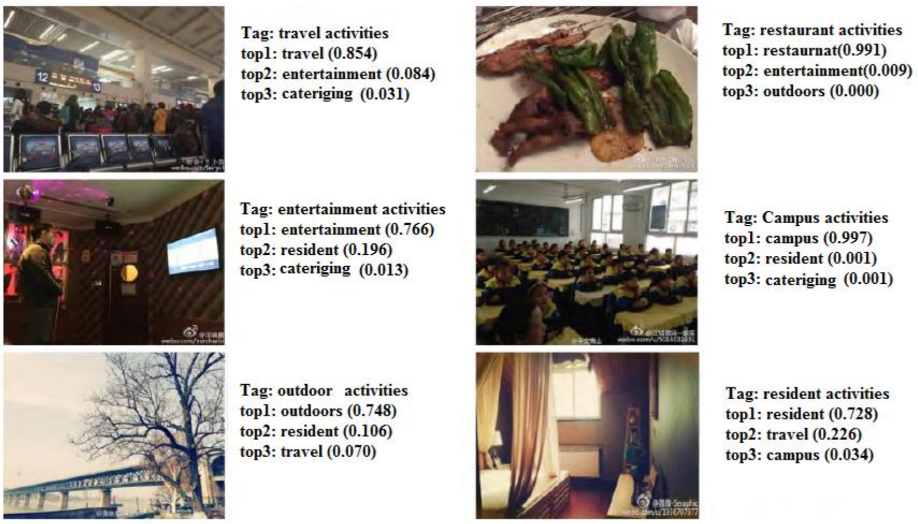

Figure 4. Examples of image-based user activity prediction results.

3.3 Activity classification method based on multi features

For real human activities, most activities will show high aggregation and reciprocation in time and space, such as people's behavior atterns such as three meals a day or working from nine to five, that is, the activity category distribution of a time and space point can be roughly determined through spatio-temporal characteristics. However, for social media check-in data, there is a lag problem, that is, microblog users may sort out activity photos and publish microblogs after catering or entertainment activities, resulting in the space-time information of check-in data cannot accurately represent the space-time period of activities, resulting in misjudgment of user activity categories based on spatiotemporal characteristics.

We think about two situations: (1) user A has a catering activity in a commercial body at noon, but he only publishes the check-in information in the afternoon. Then, through the obtained spatiotemporal characteristics, we are more likely to think what kind of activity he is doing? (2) User B goes to a KTV in a business at noon to get together with his friends, and clocks in on his social media at the same time. Then, through the obtained spatiotemporal characteristics, we will be more likely to think what activities he is doing? It's not hard to figure out that if we try to judge the user activities behind the social media check-in data only through the spatiotemporal characteristics, we will be more likely to misclassify the above situation (1) into entertainment activities and (2) into catering activities. In view of the above situation, this paper attempts to fuse image features for improvement.

Based on this idea, we propose an activity classification method based on the multidimensional characteristics of social media check-in data:

1) The preprocessed spatiotemporal features are input $\{l_i, t_i, c_i\}$ into the KNN model in the form of triples. For each microblog check-in data, the model based on spatiotemporal characteristics is used to calculate the corresponding probability distribution vector of user activity s_{vector} category;

2) Using the user activity classification model based on image features, the probability distribution vector of user activity category corresponding to the image in each microblog check-in data is p_{vector} calculated;

3) Integrating the probability distribution vector s_{vector} and p_{vector} sum of user activity categories based on spatiotemporal characteristics and image features, a logistic regression equation based on multi-dimensional features of social media check-in data is established: $F = w_1 \times s_{vector} + S_{vector} + w_2 \times p_{vector} + b$;

4) Solve the logistic regression equation to obtain the classification results of user activities based on the multidimensional characteristics of social media check-in data.

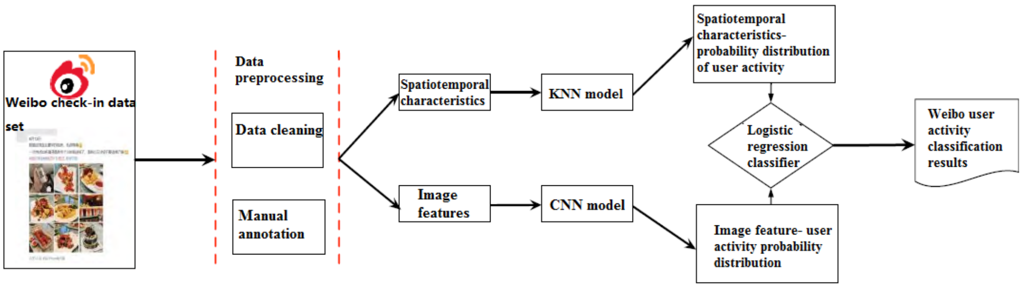

Figure 5. Framework of user activity classification using Weibo check-in data.

4. Experiment and analysis

4.1 Experimental data

The experimental data selected in this paper comes from the microblog check-in data in Wuhan in the first half of 2015, with a total of more than 100,000 pieces of data, which are distributed in all districts of Wuhan. We manually label the data according to the POI, image, timestamp and other information contained in the original data to remove the meaningless or unclear data

Figure 6 shows two microblog check-in data with POI information of different spatial scales. According to the POI information, the microblog data in **Figure 6**(b) can be correctly divided into outdoor activities, but the data in **Figure 6**(a) cannot make a correct judgment. This shows that the POI information contained in the user's sign in microblog data may affect the judgment of their activity category.

Figure 6. The effect on categories of POI at different spatial scale.

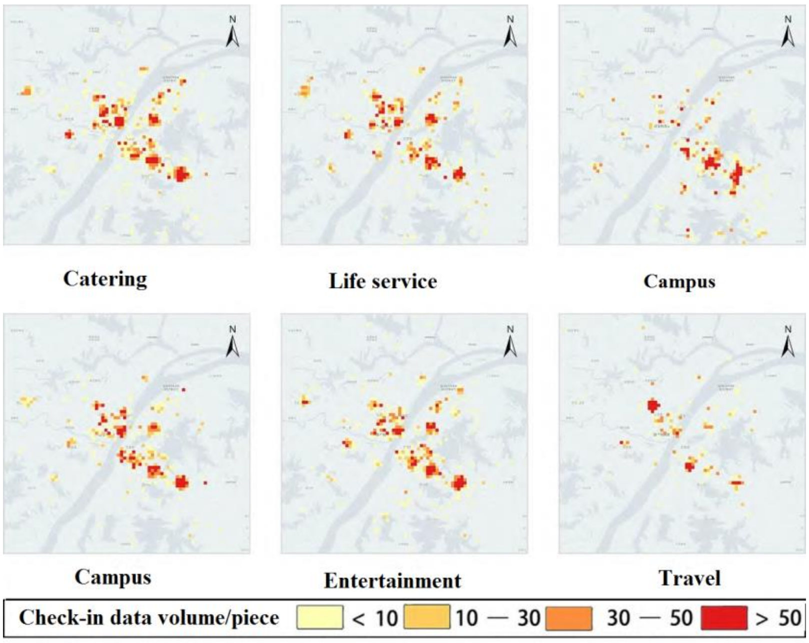

Figure 7. Distribution of user activity classes in Weibo check-in data.

After data preprocessing, there are more than 20,000 effective experimental data used in this paper, of which the data of each activity category accounts for as shown in **Table 1**. **Figure 7** shows the data distribution of different user activity types. It can be seen from the figure that there are a large number of check-in activities in transportation hubs such as Wuhan Tianhe Airport and Wuhan Station, as well as hot areas such as campus and commercial complex, indicating that microblog users prefer to check-in activities when traveling and dining; moreover, the main body of such activities is mainly young people and students, which is in line with the results of microblog user survey that most of them are highly educated people and young people.

In order to ensure the effectiveness of precision comparison, the data set is randomly divided in this experiment. The proportion of training data and test data is 4:1. The experimental results in this paper are the average value calculated by 10 times of random division.

4.2 Experimental results

According to the above ideas, this paper compares three different methods based on the spatiotemporal characteristics, image characteristics and multi feature fusion of microblog check-in data to verify the effectiveness of the method in the activity classification task of microblog check-in users. As can be seen from **Figure 8**, the overall accuracy of the method based on spatiotemporal characteristics is basically the same as that of the method based on image features; the model based on image features should be relatively robust, and its precision and Kappa coefficient have been significantly improved; the performance of the multi-feature fusion method proposed by us is significantly better than that of the single feature method using only spatiotemporal characteristics or image features. Its accuracy has been improved by nearly 10%, and the recall rate, F1-Score and Kappa coefficient have also been improved by 7%~9% The above results show the effectiveness of this method for the activity classification task of microblog check-in users.

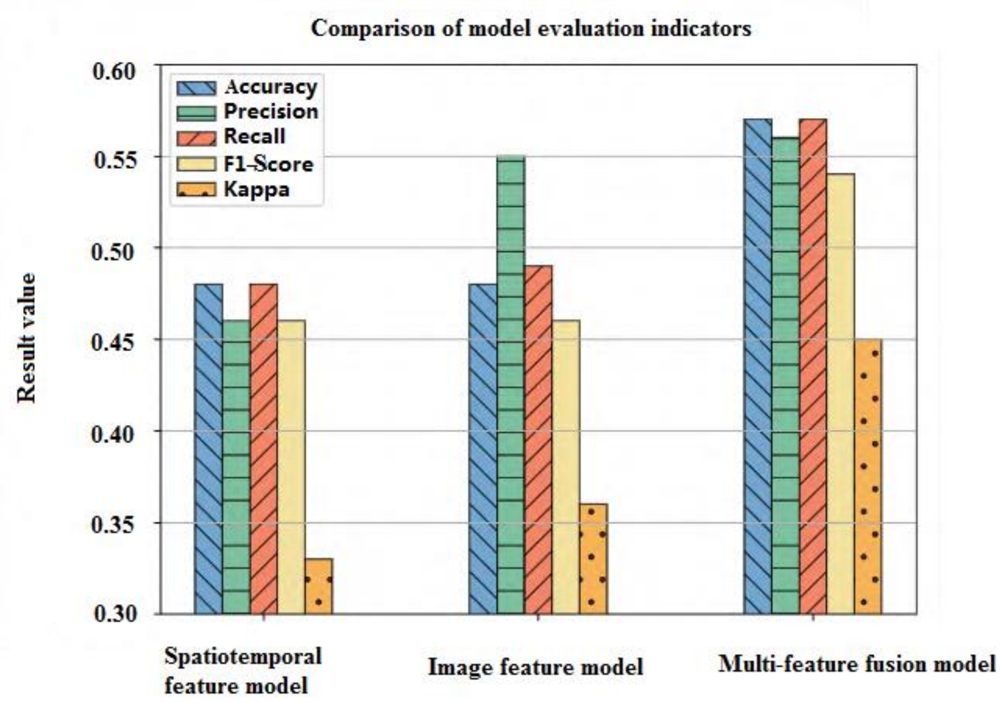

Figure 8. Comparison of three models on different evaluation indicator.

As shown in **Figure 9**, we give the confusion matrices of the three models in each subdivision category. The results show that the three methods show obvious differences in different user activity categories. For the method based on spatiotemporal characteristics, it has nearly 90% accuracy rate in the category of travel activities, which may be because most of the target locations related to travel activities are concentrated in railway stations, airports and other places, which are generally unique in cities. Secondly, the method based on spatiotemporal characteristics also has an accuracy rate of nearly 60% in catering categories. It can be seen from the confusion matrix that a considerable part of the data is misjudged as catering categories. The reason for this phenomenon may be related to the distribution of urban catering industry. The catering industry is mostly distributed in the interior of major businesses, around major scenic spots or near major universities in order to seek stable passenger flow or more potential customers; however, this also leads to a problem. Assuming that most people choose to release check-in data related to food in a business or around a scenic spot, some data belonging to other categories, such as entertainment or outdoors, will be misjudged as catering activities due to the temporal and spatial aggregation.

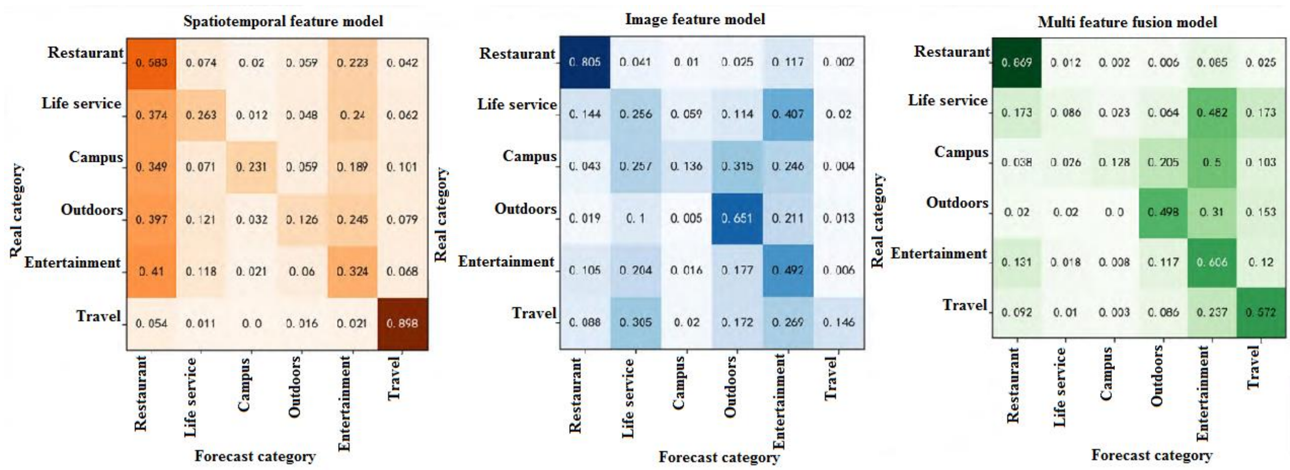

Figure 9. Comparison of the confusion matrix of models.

For the method based on image features, it has shown considerable results in catering category and outdoor activity category, and the accuracy of catering category has reached 80%. This is because most of the images carried by microblog check-in data are related to user activities, such as dishes in catering category, restaurant interior or sky and grassland in outdoor category. The images of these categories have high discrimination and can also provide more information related to user activities; for campus, travel and other categories, the image information carried by these categories, such as the appearance of campus roads and railway stations, does not contain clear feature points and cannot provide strong activity category related information, which also leads to low accuracy of these categories and more misjudgments and misjudgments.

This method can integrate the advantages of different features by integrating space-time and image scene information. While ensuring the classification accuracy of catering category and travel category, it also achieves an overall accuracy of more than 50% in outdoor category and entertainment category. Compared with the single feature method, the accuracy of the multi-feature method in catering and entertainment categories has been improved by 5% and 10% respectively, which shows that this method can alleviate the impact of lag in microblog check-in data to a certain extent; on the other hand, for some microblog check-in data, the single spatiotemporal characteristics image features may not be able to fully express their scene semantics, but the integration of different features can make up for the lack of semantic expression ability of single features in some scenes, so as to improve the accuracy of user activity classification.

By comparing the confusion matrix, we find that although the method based on multi-features has achieved quite good improvement in the overall accuracy compared with the single feature method, its accuracy in some activity categories has decreased to varying degrees. For example, the accuracy of travel categories has decreased by up to 30%. In addition, the method based on multi-features has no significant effect on some activity categories, such as campus category and resident category. This may be because the main influencing factors of these activities are the spatiotemporal characteristics of their activities. For example, the microblog check-in data corresponding to the travel activity category are mostly located in railway stations or airports, so there is a high correlation in time and space; however, these categories of microblog images are often not the image information corresponding to the activity type, and are often expressed as images of landscape, food or some scenes, such as photos on the subway, at the station or at the airport entrance. These images may be identified as other types, which may interfere with their judgment on the user activity category and affect their classification performance on these user activity categories

Although the classification method based on multi-features cannot comprehensively improve the performance of all user activity types, on the whole, this method can better express microblog user activities, significantly improve the classification accuracy of user activities based on microblog check-in data, and provide more effective data support for accurately exploring human behavior activities.

5. Conclusion

Aiming at the user activity category information hidden in the social media check-in data, this paper uses the machine learning method to decompose the problem, tries to look at and analyze the problem from different angles, and realizes the user activity classification model integrating image and spatiotemporal information. The experimental results show that the method of integrating the spatiotemporal characteristics and image characteristics of microblog check-in data can significantly improve the recognition accuracy of user activity types and provide more effective data support for the research of accurately exploring human behavior activities.

In the future, it will be considered to combine the POI information of microblog check-in data, design a user activity classification model integrating the temporal and spatial characteristics, image characteristics and POI information of check-in data, and realize the end-to-end model from microblog check-in data to user activity category classification, so as to further improve the accuracy of user activity classification method.

Conflict of interest

The authors declare that they have no conflict of interest.

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