WiFi LOG-BASED STUDENT BEHAVIOR ANALYSIS AND VISUALIZATION SYSTEM

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ABSTRACT:

Student behavior research can improve learning efficiency, provide decision evidences for infrastructure management. Existing campus-scale behavioral analysis work have not taken into account the students characteristics and spatiotemporal pattern. Moreover, the visualization methods are weak in wholeness, intuitiveness and interactivity perspectives. In this paper, we design a geospatial dashboard-based student behavior analysis and visualization system considering students characteristics and spatiotemporal pattern. This system includes four components: user monitoring, data mining analysis, behavior prediction and spatiotemporal visualization. Furthermore, a deep learning model based on LSTNet to predict student behaviour. Our work takes WiFi log data of a university in Beijing as dataset. The results show that this system can identify student behavior patterns at a finer granularity by visualization method, which is helpful in improving learning and living efficiency.

1. INTRODUCTION

As an important component of society, campus is characterized by demographic diversity, spatiotemporal pattern diversity and activity trajectory complexity (Youzeng, Li et al 2018). Exploring student behavior patterns provides decision evidences for improving learning efficiency, campus infrastructure planning and management, and building smart campuses (Yang, Liu et al. 2020). At present, there is still a lot of space to explore the behavior research on campus scale. This paper explored the spatiotemporal pattern of student behavior and predicted the distribution of mobility flow in campus from a microscopic perspective, finally realizing the analysis and visualization of student behavior.

Traditional research on student behavior is often achieved through questionnaires, student interviews, or by requiring students to install location-related APP software (Shenglan, Du et al 2017). However, traditional questionnaire surveys are often influenced by human subjective factors, and the survey results are mostly recalled records, lacking accurate temporal attributes, making it difficult to match the data quality with the researcher's real spatial and temporal trajectory. While location APPs are easy to cause students' sensitivity, and most students are unwilling to install them, resulting in a small sample size and difficulty in capturing students' behavioral patterns. With the development of wireless communication technology, wireless access technology has gradually matured, and WLAN, as a kind of wireless access technology, is loved by the majority of mobile users because of its advantages of easy installation, flexible use and easy expansion (Rekimoto, J et al.2007). With the continuous development and popularity of the Internet, people have become dependent on WiFi technology in their daily lives. Due to the advantages of wide coverage, fast transmission speed, high security and simple use (Zheng, Wang.2019), WiFi has become the primary choice for users to access the network, and demands such as video conferencing, online classes and artificial intelligence are constantly put forward, WiFi technology is used in traffic monitoring and prediction (Traunmueller et al 2018), indoor positioning and behavioral trajectory WiFi technology is widely used in various scenarios such as traffic monitoring and prediction, indoor localization and behavioral trajectory research (Yuan, Li et al 2020). However, the current research results on campus student behavior are relatively few, and the existing studies are monotonous in analyzing the spatiotemporal patterns of student behavior, without a comprehensive mining and analysis of student behavior patterns from a multi-scale and multi-perspective idea, and lacking a practical and comprehensive visualization system for student behavior analysis (Qi Pan 2015). In addition, in the field of prediction, Transformer has a better performance than the traditional model LSTM in the field of time series prediction, but the Multi-Head Attention mechanism that Transformer relies on brings a huge number of parameters and computational overhead to the model (Box, G. E et al 2015), which makes it difficult for the model to meet the demand of campus tasks with high real-time requirements. In contrast, the LSTNet deep learning framework adopted in this paper adds a temporal attention mechanism to the LSTM model to accomplish accurate prediction by mining temporal periodicity (Lai, Chang et al. 2018), which achieves perfect prediction results in campus applications with obvious periodicity patterns and high demand for real-time.

Students have to meet the needs of dining, shopping, accommodation, study, leisure and sports within limited time and space, so compared with urban residents, students' behaviors have obvious regularity, small scope of activities, stable groups and similar behavioral characteristics. How to analyze and accurately predict students' behavioral patterns in time and space at microscopic scale is one of the existing problems (Buqing, Li. 2021). In addition, traditional visualization methods can no longer meet the needs of smart campus (Hu, He et al. 2020). How to explore student behavior patterns more intuitively and flexibly

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and present them to users in an easy-to-understand visualization form is the biggest problem to be solved in this paper.

To address the above issues, this paper proposes a framework for analyzing and predicting student behavior based on WiFi log data, considering that WiFi is highly popular and WiFi logs can record users' online time and location in real time, which can accurately reflect students' activity trajectories. The framework explores the patterns of student behavioral activities from user group characteristics and spatiotemporal perspectives, respectively, and predicts student behavioral patterns based on time series, solving the challenge of fine-grained analysis and prediction of student behaviors at the microscopic scale. In this paper, taking into account the superiority of geospatial dashboards in the direction of spatiotemporal data visualization, mining and analysis (Jing, Du et al. 2019), we design and implement a behavior analysis visualization system based on WiFi logs. The system inherits the design idea of geospatial dashboard, integrates data management and real-time monitoring, data mining and analysis, and spatiotemporal prediction and visualization, and makes an important contribution to the accurate perception and visualization of students' behavioral characteristics.

This paper designs and develops a visualization system for student behavior analysis inspired by geospatial dashboards, and the adopted multi-perspective and multi-dimensional spatiotemporal analysis approach takes into account the periodicity, aggregation and stability of student behavior, and explores the student behavior patterns from user characteristic differences, time and space. Finally, the effectiveness of the LSTNet deep learning model incorporating temporal attention mechanism in student behavior prediction is explored, and it is found that this model achieves better results than traditional models in long time series prediction of student behavior applications.

There are five sections in this paper. Section 1 introduction introduces the background significance of student behavior analysis, briefly summarizes the current status of research and problems based on WiFi data behavior analysis, and presents the key elements and contributions of this paper's research. Section 2 introduces the three solutions proposed by the authors for the current problems. Section 3 introduces the data sources and contents from the data perspective and outlines the data processing process. The results and discussion in Section 4 present practical examples of the systems developed in this paper and analyze student behavior patterns. Section 5 summarizes the entire paper.

2. METHOD

Traditional analysis of student behaviour usually focuses only on the statistical analysis of data, but ignores the importance of its spatiotemporal characteristics, and the depth of data mining is not deep enough, the level of refinement is not enough, moreover, the lack of accurate prediction of behaviour, which cannot meet the current needs of smart campus construction. In terms of visualisation methods, traditional research is a separate display of feature patterns, which greatly increases the difficulty for users to access the full range of student behavioural features.

Based on the existing research in the field of student behavior analysis, this paper proposes the following three research methods to further deepen the research on student behavior analysis by addressing the problems in the process of mining, analysis, prediction and visualization of student behavior.

2.1 Geospatial dashboard-based visualization system for behavior analysis.

Geospatial dashboard is a system that integrates data collection, analysis and visualization in the form of a dashboard, which is widely used in the analysis, mining and visualization of geospatial big data in cities and parks because of its multi-screen linkage, dynamic interaction and multi-scale view visualization (Xiao, N et al. 2017).

In response to the problem that current visualisation methods for student behaviour analysis are too monotonous in presentation and users cannot intuitively access data information and behaviour patterns, this paper designs a multi-view multi-functional visualisation system based on a geospatial dashboard that can be linked and interacted with. The system integrates a user monitoring module, a mining analysis module, a spatiotemporal visualisation module and a user prediction module. Through the intelligent interaction between users and the system, the system realises the dynamic linkage of all functional modules of the whole system and accurately displays the user demand information.

2.2 Spatiotemporal mining analysis of WiFi data based on multi-perspective and multi-dimensionality.

In view of the significant differences in group characteristics between campus and urban residents, resulting in the current incomplete and unrefined analysis of students' behaviors at the campus microscopic scale. This paper explores the characteristics of students' behaviors around spatiotemporal multidimensionality from two perspectives, namely, the differences in user group characteristics and campus functional areas, in order to achieve accurate perception of students' behaviors.

In the analysis of the spatiotemporal pattern of student behavior, this paper first analyses the spatial cold hotspot distribution of student behavior by using spatial hotspot map; then analyses the cycle evolution pattern and reasons of student behavior by different time intervals respectively, and finally analyses the spatiotemporal characteristics of user behavior comprehensively from the spatiotemporal perspective with the visualization method of spatiotemporal cube (Jing, C et al 2020). In addition, the characteristics of behavioral differences among different students are also analysed according to the differences in the characteristics of student users.

2.3 Behavior prediction based on LSTNet deep learning framework.

The emergence of LSTNet can be considered as an improvement for researchers to enhance the temporal prediction ability of LSTM model through attention mechanism, which is a great advancement for solving long time series prediction as well as improving prediction efficiency and real-time. Since the WiFi data used in this paper has long time series, complete data, large data volume and strong periodicity, there is good applicability between the data and the model.

To address the problems of information forgetting in LSTM long time series prediction and the difficulty of Transformer to meet the demands of campus tasks with high real-time requirements. This paper adopts the LSTNet deep learning framework and adds a temporal attention mechanism to the LSTM model to accomplish accurate prediction by mining temporal periodicity (Lai, Chang et al. 2018). Achieves perfect prediction results in

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campus applications with clear periodicity patterns and high demand for real-time.

3. DATASET

This paper takes a university in Beijing as the study area, which has achieved full wireless network coverage. By cooperating with the campus network information canter, WiFi logs and wireless AP location information of each AP-connected end-user in the campus are successfully obtained. The time range of the data is from zero 0:00 on November 5, 2021 to zero 0:00 on December 15, 2021, with a total of 41 days of WiFi logs. WiFi logs contain information on the time students logged into WiFi, online status, device number, and AP number accessed, etc. Through pre-processing of the data, the demand for analysis and mining of student behavior patterns is solved.

The data pre-processing includes WiFi log data processing and wireless AP location analysis. As shown in Figure 1, workflow diagram for data pre-processing, the pre-processing of WiFi log data mainly includes data desensitization, data cleaning and time discretization; the pre-processing of campus wireless AP location information includes location analysis and coordinate picking. Then the AP fields of the data table are connected to obtain a WiFi user login information database containing the required fields and location coordinates. Finally, the data are discretized according to the time interval according to the requirements to prepare for the subsequent analysis and visualization of student behavior.

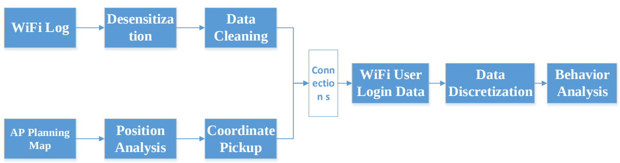

Figure 1. Data pre-processing flow chart.

3.1 Data Desensitization

In order to protect the privacy and security of student users, we have desensitized the data of WiFi logs. The database does not contain information related to student name, student number, cell phone number and internet browsing history, but the MAC address of the terminal device connected to WiFi is used as the unique identifier of the user. MAC address is a randomly generated encrypted address on each cell phone, computer or iPad, and the MAC of each device is unique, so the MAC address can be used as the identity ID of the student user. The data just records the status of user A, B, C, D... when and where they use WiFi, which does not cause privacy and security issues and still meets the experimental requirements.

3.2 Data Cleaning

Data cleansing is to remove those incomplete data, wrong data, abnormal data, duplicate data and other non-compliant data from the database to improve the accuracy of the data and the credibility of the study. Since the student WiFi login log data obtained in this study is informative and complex and contains many fields, and the fields that are really valuable for this paper's research are: user MAC address (unique identifier), user login time, user login AP number, user login location and latitude and longitude coordinates, so the information of other useless fields need to be deleted to reduce redundancy. In addition, there are some incomplete, duplicate and abnormal data in the data, such as the phenomenon of a user connecting to multiple APs in a short period of time, so it is necessary to apply iteration and add time threshold in the cleaning algorithm to clean the data.

3.3 AP Location Analysis

The most critical aspect of the visual display of the spatiotemporal location is the display of the spatiotemporal location on the map. Although the original data recorded the AP number of the campus location when the user logged in, it was only a textual record value and could not be spatially located on the map. Here we need to parse the geographic location codes of these APs into the map, firstly parse out their corresponding specific buildings on the campus, and then use the coordinate picker tool provided by Amap API to obtain the spatial location of specific buildings, i.e., latitude and longitude information.

With the continuous development and progress of WiFi technology, WiFi positioning technology has gradually matured and has now reached a positioning accuracy below the meter level. The university under study has achieved full WiFi coverage, and each classroom is equipped with more than one AP. When the device enters a room, it will automatically connect to the nearest AP, so the accuracy of this paper is guaranteed with the AP location coordinates as the user's location.

3.4 Data Discretization

Discretization is the process of dividing the value range of continuous attributes into some discretized intervals according to a number of division points within a specific value range, and finally representing the attribute values falling in each subinterval with different values or symbols. The essence is the process of dividing the space composed of continuous attributes by using the selected breakpoints, thus achieving the purpose of simplifying the data structure. The user login time of the original data in the study is accurate to the second, and the amount of data is huge. At the same time, in order to facilitate the dynamic display of spatiotemporal changes in the visualization platform at a later stage, the time values of the original data must be simplified according to the needs of the research object.

4. RESULTS AND DISCUSSIONS

Using WiFi logs of a university in Beijing as experimental data, the geospatial dashboard-based student behavior analysis system designed and implemented in this paper has achieved good results in data mining analysis and visualization. It provides a query platform for the students of the university to accurately perceive the density and regularity of people in various places and reasonably plan their time schedule; it also provides support for the campus administrators to grasp the student dynamics and trends and formulate management policies. The system has been well received by the students of the university and the university administration.

The system framework designed in this paper is shown in Figure 2, which is divided into three levels overall: user layer, functional layer and data layer. The user layer includes student users, teacher users and school administrator users, and gives different permissions to different users. Students have only viewed privileges; teachers can view the visual charts in addition to the underlying data tables for more detailed information on student behavior, but do not include specific student privacy; and administrators, in addition to the above privileges, also have the privileges to maintain the system to modify and control the data layer. The functional layer includes four modules of user monitoring, spatiotemporal patterns, user feature differences and behavior prediction, which realize a comprehensive and integrated analysis of student behavior. The data layer is a dataset built in MySQL database, which contains campus WiFi log data, AP location data, Amap API and campus topographic map.

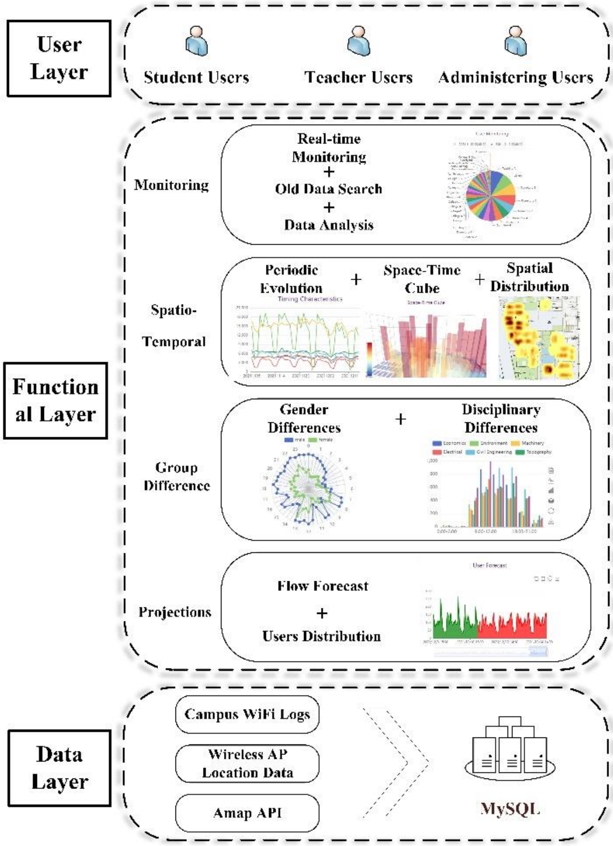

Figure 2. System Framework.

The WiFi log-based student behavior analysis and visualization system focuses on four modules: user monitoring, spatiotemporal patterns, user feature differences and behavior prediction to analyze and visualize. The system page is shown in Figure 3. The whole system page can display different requirement charts in the form of user interaction.

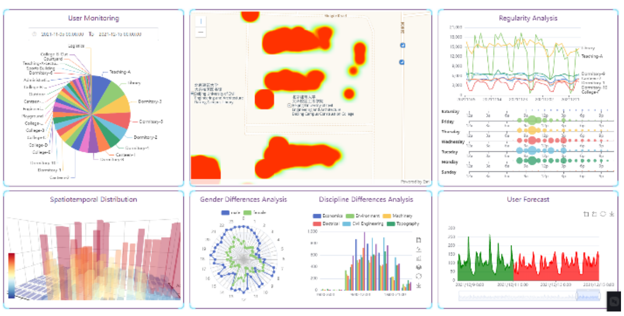
Figure 3. System Overview.

4.1 Flow Monitoring

The function of the user monitoring module is to visualize the user volume of each building on campus. It can not only realize real-time monitoring of data, but also quickly and precisely query the proportion of traffic and personnel distribution of each building at any moment or time according to different time demands and building needs. This module can be used to understand more precisely the size of the human flow in each place on campus and provide theoretical support for the distribution of resources on campus.

As in Figure 4, we inquired about the proportional information of students' activities in various places on campus during the 41-day period from 0:00 on November 5, 2021 to 0:00 on December 15, 2021, and we could find that student behaviors in the dormitories accounted for the largest proportion, followed by more student behaviors in the library and various college buildings, which is consistent with the daily study habits of the school.

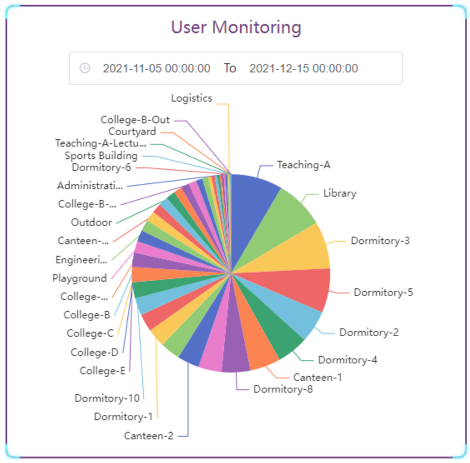

Figure 4. User Monitoring.

4.2 Spatiotemporal

Spatiotemporal pattern analysis is the focus of this paper. In the system built in this paper, the spatiotemporal pattern module is subdivided into three parts for analysis, which are the three system modules of spatiotemporal hotspot, cycle evolution law and spatiotemporal cube.

4.2.1 Hot Spot Analysis

The hot spot analysis can visualize the hot and cold spots of spatial distribution of student behaviors in order to analyze the spatial distribution pattern of students. As shown in Figure 5, the left figure shows the heat map of spatial distribution of student behavior during weekends, and the right figure shows the heat map of spatial distribution of student behavior during weekdays.

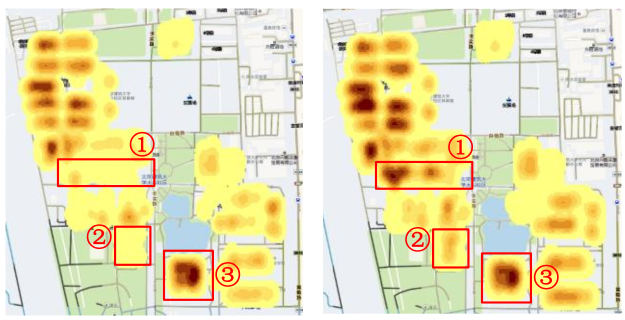

Figure 5. Hotspot Map.

In the figure, ① is the basic teaching building, ② is the administrative office building, ③ is the library. We found that there are hotspots of student behavior in both the teaching building and the administrative office building on weekdays, while there are few student activities in the teaching building and the administrative building on weekends, which is due to the fact that students do not attend classes and office workers do not work on weekends. It is worth noting that the library has slightly more student behavioral activity on weekends than on weekdays, indicating that students at the university prefer to study in the library on weekends when classes are not in session.

4.2.2 Analysis of cycle evolution pattern

In this paper, we analysed the patterns of student behavior changes over time using moments and days as time granularity, respectively. As shown in Figure 6, the Library, Classroom Building A, Dormitory Building 1, Dormitory Building 9, Dormitory Building 10, Dining Hall 2, and College Building F were selected in this paper. We found that the student behavior pattern has a certain periodicity, taking 7 days a week as a repetitive cycle, and the characteristics of different buildings with time change are different. For example, we found that the dormitory fluctuates less with time because students basically go back to sleep in the dormitory every night; while the classroom fluctuates more with time, which is because the school does not have classes on Saturday and Sunday, so few people will go to the classroom; the cafeteria also fluctuates with weekdays and weekends, caused by the possibility of students eating off-campus on weekends. Figure 7 also shows that student behavior patterns have great similarity from Monday to Friday, and strong similarity at the same moment on different days, which is also the most important feature in the campus behavior law.

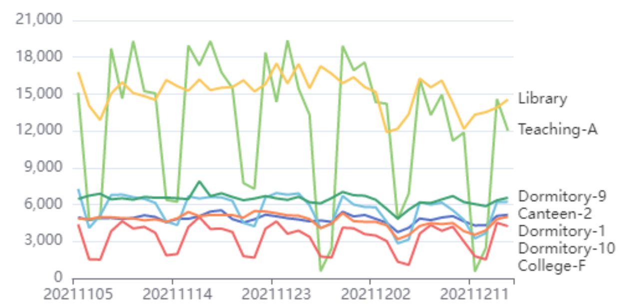

Figure 6. Timing Characteristics(day).

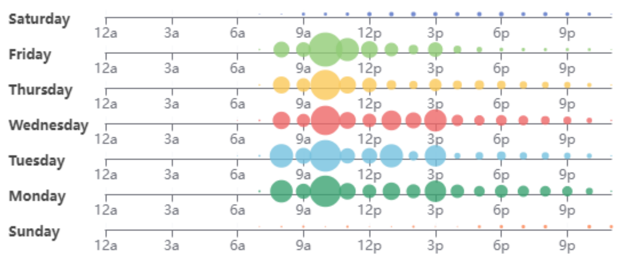

Figure 7. Timing Characteristics(hour).

4.2.3 Space-Time Cube

The Space-Time Cube integrates temporal and spatial elements to analyze and visualize student behavior from a spatiotemporal perspective. This module not only analyses the pattern of student behavior over time, but also visualizes the spatial distribution of student behavior, which is one of the indispensable methods in current spatiotemporal pattern research. In the spatiotemporal cube module of this system, the image can follow the rotation of the mouse to change the viewpoint arbitrarily, and the best viewpoint can be found according to the demand. In this paper, the campus is divided into seven functional areas according to functional areas: classroom, research building, dormitory, library, administration building, outdoor and dining hall. As shown in Figure 8, the X-axis represents the moment, the Y-axis represents the campus area, and the Z-axis represents the number of users. We find that the distribution of different places at different times is different, such as classrooms and laboratories where student behavior is mostly concentrated in the daytime and declines rapidly after 20:00; while the dormitory area is just the opposite, mainly concentrated in the evening time period, in addition to the lunch break time period.

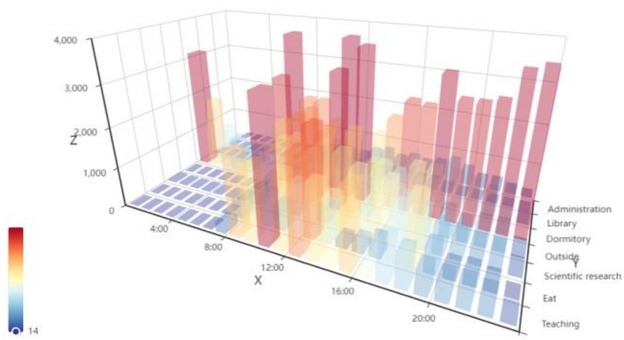

Figure 8. Space-Time Cube.

4.3 Differences in user characteristics

In the analysis of students' behavioral characteristics, the differences among different students cannot be ignored. Exploring the behavioral patterns of different students can provide decision support for school authorities to comprehensively grasp students' behavioral characteristics and formulate relevant management policies. In this paper, we analyze the influence of their characteristic variability on students' behaviors by using two examples, gender difference analysis and subject difference analysis, respectively. It is found that students of different genders and different disciplines have significantly different life patterns. As shown in Figure 9, from the perspective of work and rest patterns, it is more common for male students to stay up late, and the proportion of those who are still on the Internet at odd hours or even later is significantly higher than that of female students; among students of different disciplines, students of surveying and mapping disciplines work the longest overtime, but on the whole, the behavioral patterns of students of all disciplines are also relatively similar, mainly concentrated between 9:00 and 18:00.

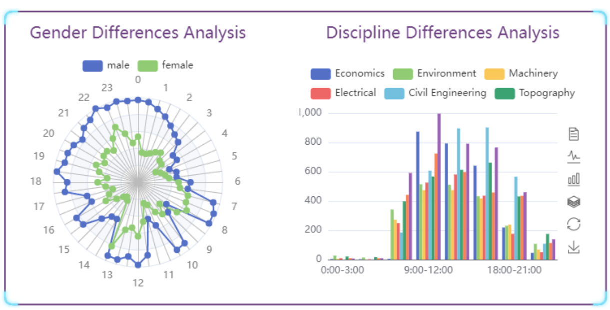

Figure 9. Differences in user characteristics.

4.4 Behavior prediction

Since the campus student behavior pattern has significant periodic patterns and high demand for real-time, the traditional LSTM long time series prediction can no longer meet the demand, this paper adds a temporal attention mechanism to the LSTM model to complete the accurate prediction of student behavior. As shown in Figure 10, red represents the predicted value, blue represents the real value, this paper uses dormitory building 1 as an example, with 12 days of data 1 day of data. Through the results we can find that the prediction results of this paper obtained good prediction results compared with the real values, so the LSTNet model can be applied to the system.

The system prediction module is shown in Figure 11, where the green part is the true value and the red part is the predicted value. It can be found that the characteristics between the predicted value and the true value are very similar and there is a significant periodicity, which achieves a good prediction effect. And the roll bar below the prediction module can be used to select the time period of interest in the long time series for viewing. Through the accurate prediction of student behavior, we can understand the evolution trend of student behavior and provide theoretical support for the school administration to coordinate management and budget.

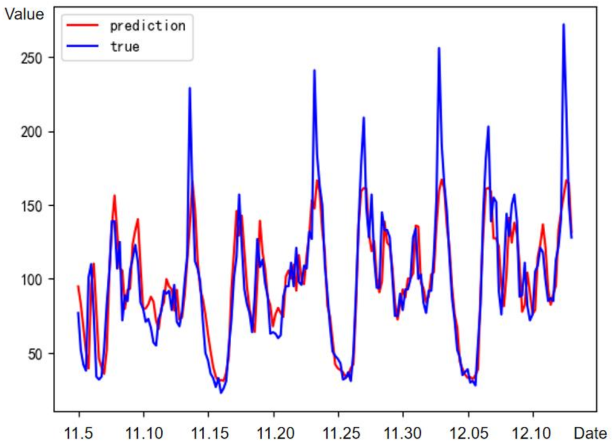

Figure 10. Comparison of predicted results and true values.

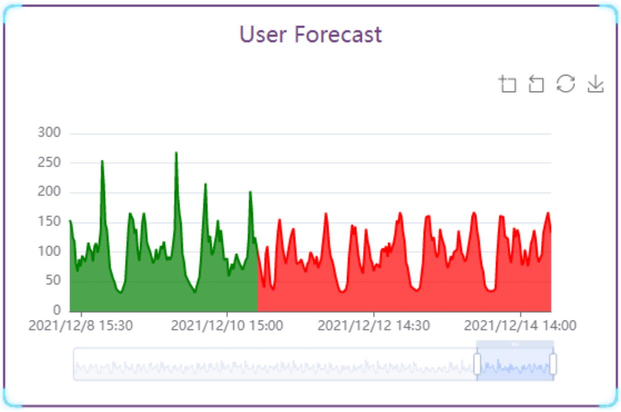

Figure 11. Behavior prediction.

5. CONCLUSIONS

In this paper, we design and implement a WiFi log-based student behavior analysis and visualization system to mine and analyze the behavioral characteristics of students' daily activities and visualize them according to user requirements. The system adopts the design idea of geospatial dashboard and integrates the multi-view and multi-dimensional spatiotemporal mining method and the behavior prediction framework based on deep learning LSTNet, which remedies the shortcomings of the unrefined process of student behavior analysis, low accuracy of prediction and monotonous visualization. The system has been put into use in a university in Beijing, and the results show that the system is outstanding in improving the efficiency of learning and living, and that administrators can understand student behavior patterns more intuitively, accurately, and comprehensively compared with traditional methods.

The interactive behavioral analysis system designed and developed in this paper can provide multidimensional behavioral analysis and prediction of student behavior for students, schools and management; provide reference for students to avoid peak periods such as dining and shopping to improve their life efficiency; provide technical support for the current prevention and control of the new crown epidemic to control the gathering of people and the investigation of student behavior trajectories; provide support for campus managers to grasp student dynamics and formulate relevant policies and facilities deployment; realize the informationization of student management means, improve the scientific level of student education and management, and promote the construction of smart campus.

This system is not limited to the analysis of students' behavior. Based on the research framework and ideas in this paper, this system can be applied in different scenarios such as shopping malls, companies and parks to achieve accurate sensing and visualization of user behavior characteristics and help the rapid development of smart life.

However, our system does not consider the correlation between behavioral influences and the relationship between student behavior and other factors such as student achievement, and in the future, the mechanisms of student behavior influence may be our next step.

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