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Article

Research on the Intelligent Construction of College Management System under the Diversification of College Students' Education and Management

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Abstract: In this paper, the trajectory data of college students are collected for preprocessing and then populated using the mean trajectory filling algorithm. The student campus trajectory prediction model is constructed to study the activity characteristics of college students in different functional areas. Three features, namely, travel distance, travel mode selection ratio, and pedestrian flow on campus main roads, are extracted to analyze the regularity of trajectory data. The variation of the number of devices in different functional areas is used as the trajectory data of college students, and the prediction model is used to visualize the clustering. 80% of the students' average daily travel distance is less than 12km, and 20% of the students' travel distance is between 12km and 22km. more than 92% of the students choose walking as their travel mode. The foot traffic on each main road has a stronger correlation with the location of their hostel area and the location of their activities. The number of students' equipment has a clear pattern of change in different functional areas. The activities in the teaching area are much higher than the other functional areas in the time period of 6:30-12:30. The frequency distribution of different functional areas in clusters can be used as a basis for predicting the behavioral trajectories of students with different characteristics and realizing intelligent student management in colleges and universities.

Keywords: trajectory data; mean trajectory filling algorithm; trajectory prediction model; student management; cluster visualization

1. Introduction

In the rapid development of China's higher education and the increasing popularization of higher education, the key role of university student education management in documenting and reflecting the educational qualifications of college students, personal achievement, social practice and other aspects of the overall quality of education guidance is becoming more and more prominent [1-4]. However, the construction of education management system for students in colleges and universities has been unbalanced with the development of colleges and universities, and cannot meet the needs of the current social development. Therefore, colleges and universities urgently need to build an intelligent management system to fully realize the high degree of integration and information sharing of student information management in colleges and universities [5-8].

Diversified governance in education management involves the participation and cooperation of multiple stakeholders within the education system, as well as outside. This governance model emphasizes the cooperation and interaction of different subjects in order to achieve the optimization of educational goals, the rational distribution of resources and the enhancement of educational equity [9-12]. In today's complex and changing social background, the importance of pluralistic governance in the intelligent construction of education management system is becoming more and more prominent [13-15]. Intelligent application can effectively integrate various resources within the university, realize information sharing and collaborative work, and improve data processing and analysis capabilities [16-18]. Through intelligent applications, universities can monitor the learning status of students in real time, find problems in time and take corresponding measures to avoid problems in the overall quality of teaching [19-21]. In addition, for colleges and universities, intelligent application can also improve the automation level of quality management, reduce human intervention, and lower the chance of error [22-24].

In this paper, the trajectory data generated by the daily activities of college students are used to study the behavioral characteristics of students, and then help educational administrators to carry out intelligent management. The trajectory data of students' daily activities are defined and preprocessed. The trajectory missing recognition algorithm is used to identify the problematic data, and the trajectory filling algorithm is used to fill the trajectory so that the trajectory data reaches the level that can be used for research. Study the change rules of students' travel distance, travel mode and pedestrian flow on the main campus road, and verify that the students' trajectory data have regularity. Further analyze the change rule of the number of students' devices in different functional areas, and use the student campus trajectory prediction model to cluster the trajectory data in different functional areas, so as to judge the characteristics of students' trajectories.

2. A spatio-temporal visualization approach to the characteristics of college students' daily activities

University campus is the main study and living place for college students, and college students, as a special social group, have both social and student characteristics. The behavioral rules of students are restricted by the school area as well as the identity of students, and have strong particularity and regularity. Visualization technology is an important way to discover and mine the potential knowledge in spatio-temporal data, and visualization technology becomes more and more important in the era of big data. The student spatio-temporal data through the visualization of the discovery of mining students' behavioral trajectory law is the core of the research in this paper. The research focus of this chapter is to construct a prediction model of students' campus trajectory.

2.1. Definition of trajectory data

Spatio-temporal trajectory is a description of different positions of moving objects, usually expressed as a series of sampling points, describing the relationship between spatial position and time. With position information, time information, according to the characteristics of spatio-temporal trajectory data, spatio-temporal trajectory is defined as follows.

Definition 1: Spatio-temporal trajectory is defined as an object of recording points, spatio-temporal trajectory is composed of a series of recording points, which are sorted according to the time, as indicated below:

$$T = \langle P_1, \cdots, P_i, \cdots, P_n \rangle,\ Which\ Pi = (x_i, y_i, t_i) \tag{1}$$

where n is the number of samples that make up the spatio-temporal trajectory, and x_i, y_i, and t_i represent the longitude information, latitude information, and time information of each trajectory point, respectively. Figure 1 shows the trajectory based on trajectory definition 1. The spatio-temporal trajectory data is generated from the points recorded during the movement of the end device, such as GPS positioning, GMS positioning, and spatio-temporal data recorded by WIFI sensors.

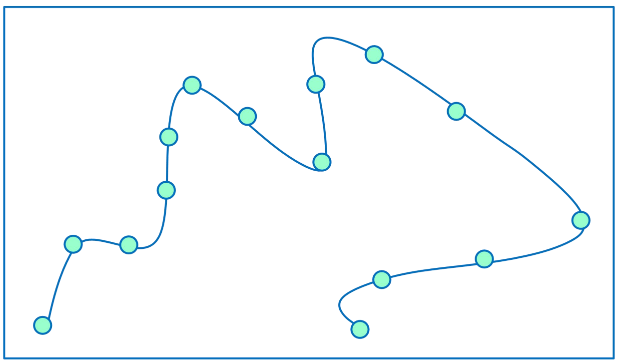


Figure 1. Defines the trajectory of 1 based on the trajectory

Definition 2: Trajectory $T = \langle P_1, \cdots, P_n \rangle$ is composed of stay and move points, where stay points are determined according to a spatial threshold and move points are represented as a maximal subsequence between two consecutive stay points. This definition is based on a semantic perspective.

Figure 2 Trajectories based on trajectory definition 2. According to the spatio-temporal trajectory definition 2, Stay1 in Fig. 2 is the point after clustering the measurement points according to the region radius, and may not be the real trajectory point, which is the reaction of the set of characteristics of the object points in spatio-temporal. The green points are the spatial distribution of the real trajectory, and the trajectory points are clustered to extract the stay points.

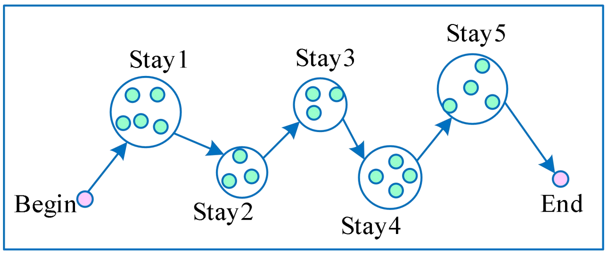


Figure 2. Defines the trajectory of 2 based on the trajectory

2.2. Trajectory data preprocessing process

Generally, the active points collected by GPS appear within a certain range of the active area, but sometimes there are data anomalies due to some uncertainties. Therefore, data preprocessing of the raw data is required before pattern analysis of the trajectory data. This is done to improve the quality of the data as well as to process the raw data into a standardized format for subsequent pattern analysis. Data preprocessing usually covers processes such as coordinate conversion, data cleaning and data normalization. One of the most critical steps is data cleaning, which greatly affects the accuracy of subsequent data analysis and stop identification.

Data cleansing is to clean up the messy code and data with missing segments during data analysis and purify the data environment. Data cleaning consists of two aspects: dealing with abnormal values and filling in missing values.

Therefore, before data mining and analysis of trajectory data, the original data should be analyzed and pre-processed first, so as to ensure the accuracy and perfection of trajectory data.

2.3. Trajectory Completion Process

2.3.1. Trajectory Missing Recognition Algorithm

When the collection object is in activity, it will affect the uploading of location information due to problems such as signal abnormality, equipment malfunction, and operability error, and cause missing trajectory data, which affects the results of data analysis. Therefore, the work of trajectory missing identification is very important.

The data acquisition software used in this paper is required to be mounted on the cell phone to use, so in the process of collecting the activities of the object between the two adjacent trajectory points may produce a time error, through the observation of the collected data found that, if the time difference between the two adjacent trajectory points is 5.5 seconds or less, it means that the distance of activities in the period of time is shorter, and will not have an impact on the subsequent results, which can be ignored. Whereas, if the time difference between two neighboring trajectory points is greater than 5.5 seconds, it means that the distance of the segment is longer, which will affect the recognition of the subsequent stopping points. Therefore, to improve the recognition of missing trajectories, it is necessary to consider both time threshold and distance threshold.

The algorithm idea is as follows:

Calculation of latitude and longitude difference of neighboring trajectory points: calculate the latitude and longitude difference of two neighboring trajectory points according to formula (2)

$$\begin{aligned} D_{lon} &= lonA - lonB \\ D_{lat} &= latA - latB \end{aligned} \tag{2}$$

Calculation of the distance between neighboring trajectory points: calculate the distance between two neighboring trajectory points according to the formula (3)

$$D_{ist} = 2\arcsin\left(\sqrt{\sin^2\left(\frac{D_{lon}}{2}\right) + \cos(LatA)\times\cos(LatB)\times\sin^2\left(\frac{D_{lat}}{2}\right)}\right) \times 6378.138 \tag{3}$$

The following is a description of the parameters in the formula: D_{lon} , D_{lat} is the difference between the longitude and latitude of two neighboring trajectory points; D_{ist} is the distance between two neighboring trajectory points.

First, the difference between the latitude and longitude of the neighboring trajectory points and the distance between the trajectory points are derived from Eq. (2) and Eq. (3). Then, according to Eq. (3), the maximum distance between two neighboring points with a time interval of 5.5 seconds can be derived as about 21 meters by choosing appropriate latitude and longitude values and bringing them into Eq. The average speed of a student's normal walk is around 1.55 meters/second, which proves the validity of the threshold. Therefore, the distance threshold in this paper is 21 meters, and the time threshold is 5.5 seconds. When the trajectory point meets the time $t > 5$ seconds and distance $d > 20$ meters at the same time, it can be judged as a missing trajectory point. Select a particular student, record the trajectory of the student's activities for a day, from which 15 representative numbers are taken to calculate the distance, and for the markers of the missing trajectories, they are recorded as Null. Accurate identification of missing trajectories can provide good data support for subsequent filling of missing trajectories.

2.3.2. Trajectory filling

Through the experimental data, it is not difficult to see that the collection object in the process of activity does appear trajectory missing situation, once the data is missing, then it is difficult to get the trajectory information at that time. Therefore, it is very important to carry out the filling of missing trajectory data. The mean value trajectory filling algorithm proposed in this paper is proposed in the case of unknown traveling road conditions, the GPS data sampling frequency in this paper is 5.5 seconds, according to the above algorithm can be derived from the maximum traveling distance of 5.5 seconds is about 21 meters, then we can set the search radius of missing trajectory as 21 meters. The specific process of the algorithm is as follows: firstly, use the mean value method to fill in to get n estimated value; then calculate the distance between the estimated value and the endpoint to ensure that the endpoint of the missing trajectory is within the search radius. Continuing to calculate the mean value of the n estimates to get the final estimate before filling can improve the accuracy of the results.

The first step is shown in equation (4), where new latitude and longitude values are computed for the candidate filled latitude and longitude.

$$\begin{aligned} Lon_j &= \frac{(LonA + LonB)}{2} \\ Lat_j &= \frac{(LatA + LatB)}{2} \end{aligned} \tag{4}$$

The second step is shown in equation (5), which calculates the difference in latitude and longitude between the candidate value and the previous neighboring point.

$$\begin{aligned} D_{lonj} &= lon_j - lonA \\ D_{latj} &= lat_j - latA \end{aligned} \tag{5}$$

The third step is to bring the newly obtained latitude/longitude difference into Eq. (6) to get the distance between neighboring trajectory points after filling.

$$D_{istj} = 2\arcsin\left(\sqrt{\sin^2\left(\frac{D_{knj}}{2}\right) + \cos\left(Lat_j\right)\times\cos(LatA)\times\sin^2\left(\frac{D_{latj}}{2}\right)}\right) \times 6378.137 \tag{6}$$

When the distance between neighboring trajectory points after filling is less than a set threshold, its value is added to the candidate data set, and the candidate data set is averaged according to Eq. (7), and the filled trajectory data is finally obtained.

$$Lon = \frac{\sum_{j=1}^{n} Lon_j}{n} \qquad Lat = \frac{\sum_{j=1}^{n} L^2 t_j}{n} \tag{7}$$

By setting the thresholds of distance and time for the missing trajectories as described above and calculating the values with the corresponding formulas, the values after the missing data are filled in can be obtained. By recognizing and filling the missing trajectories, the integrity and consistency of the data are maintained to ensure the accuracy of the subsequent clustering as well as trajectory mining.

2.4. Student Campus Trajectory Prediction Model

In this study, the aim of this paper is to predict a student's next location based on the student's historical trajectory and the collective location preferences of the group they belong to. For simplicity, the different spaces of the school are divided into N grids, with one grid representing one location. The following section describes a method to predict a user's next location by combining a student's individual behavior and collective location preference (i.e., activity distance preference). Figure 3 shows the framework of the student campus trajectory prediction model. The three main components of the model are user clustering, location prediction based on long and short-term memory of individual historical trajectories, and collective location preference extraction for each user cluster.

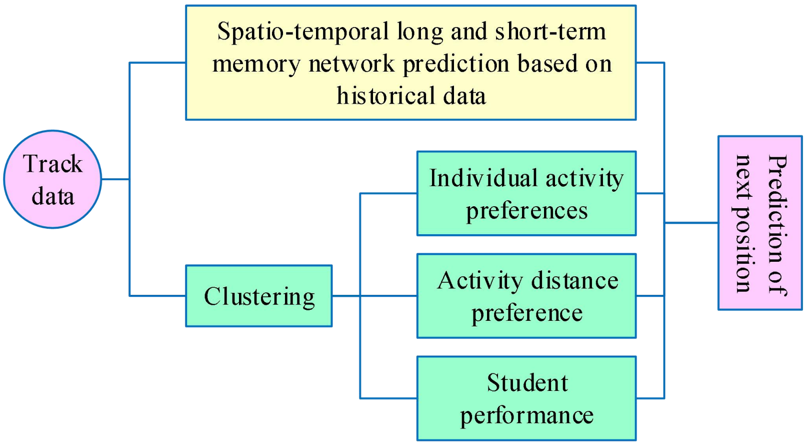


Figure 3. Trajectory prediction network framework

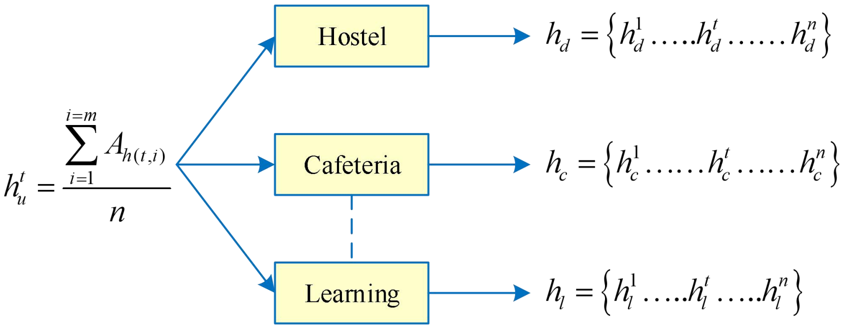
Students are clustered based on their daily activity profiles. Before clustering, the location set of student u should be converted into an activity set. Activities such as "study" and "rest" are usually identified by spatial and temporal constraints, since activity type information is not available in the movement trajectory. For the location sequence of student u on day i, usually students should be resting in the dormitory after 22:30 every night until 6:30 in the morning, and some of them will be doing experiments in the lab overnight. Similarly, most of the students are studying in the building or library or moving around in the playground as well as in various parts of the campus during the day, and most of them are in the cafeteria or dormitory during the meal time. The type of activity recorded in the remaining locations in $DL\_set(u)$ is then labeled as "Other".

After each position in $DL\_set(u)$ has been correctly labeled as "study," "rest," or "activity," "other" Calculate the frequency of each type of activity for user u at each time t in a total of m sample days. For example, the frequency of "study" activity fh_u^t is calculated as follows:

$$fh_u^t = \frac{\sum_{i=1}^{i=m} A_h(t,i)}{n} \tag{8}$$

$$A_h(t,i)=\begin{cases}1 & if\ activity\ type\ at\ time\ t\ of\ the\ ith\ day\ is\ 'home'\\ 0 & else\end{cases} \tag{9}$$

Similarly, the frequencies of “rest”, “eat”, “activity” and “other” activities are also calculated. Then, the frequency sequence of user u ’s daily activities can be represented by the following vector:



(10)

Where h_d^n is the frequency of activity in “dormitory” and h_c^n is the frequency of activity in “cafeteria”.

Finally, the frequency sequence of daily activities of all users is clustered $AF=\{AF(1),\ldots,AF(s)\}$ using the $k-means$ clustering method, where s is the number of students. The users can then be categorized into groups with different daily activity patterns.

3. Research on students' behavioral trajectory patterns on campus

The campus travel trajectory data of 25 representative student volunteers of a university in the past two weeks are selected as the research base data of this paper. This chapter analyzes the activity pattern of students' travel trajectories, extracting three features: travel distance, proportion of travel mode choices, and pedestrian flow on campus main roads. The travel distance can judge the information of students' daily activity area, the proportion of travel mode choice can judge the information of students' daily living habits, and the pedestrian flow on main roads can reflect the information of whether the layout of campus facilities is reasonable or not.

3.1. Analysis of distance traveled by students

The results of the analysis show that out of 25 people, 80% of the students' average daily travel distance is concentrated in the range of 4km to 12km, while the remaining 20% of the students are concentrated in the range of 12km to 22km.

Figure 4 shows the statistical data of the average daily traveling distance of the students. From the statistical results, it can be inferred that most of the students' trips within the school belong to “short-distance” trips, and only a few of them belong to “long-distance” trips. After matching the students' data with the road network of the school and observing the distribution of students' stopping points, it is found that the average number of stops or activity points corresponding to the distribution of average daily travel distance in the range of 4km to 10km is 7, while that in the range of 12km to 22km is 10.5, so it is obvious that the average daily travel distance is related to the number of activity points.

Students with fewer activity points focus their daily activities on the campus, and it is observed that “short-distance” students' main places of daily activities cover the dormitory area, the teaching building, the library, the cafeteria near the dormitory, the gymnasium, and recreational venues near the school. This part of the students belongs to the “regular type” of activities, and their daily activities are carried out according to the normal routine. The “long-distance” students not only covered the above activity places, but also included other “individual” activities. Among the five students in the “long-distance” group, combined with the observation of the road network, they all stopped at Of the five students in the “long-distance” category, all of them, in conjunction with the road network observation, have stops at bus stops outside the school, and stops near the school, and it is known that they have part-time jobs outside the school and need to travel to and from the school, and that they also have off-site gatherings and entertainment activities in addition to their part-time jobs. In addition to the off-campus factors mentioned above, their on-campus trips are also “irregular”, with a wide distribution of on-campus stops, indicating that these students have rich and frequent daily activities, and may wander around the same place several times in the same day. These activities make their average daily distance traveled greater than that of the "short-distance" students. However, this group is in the minority.

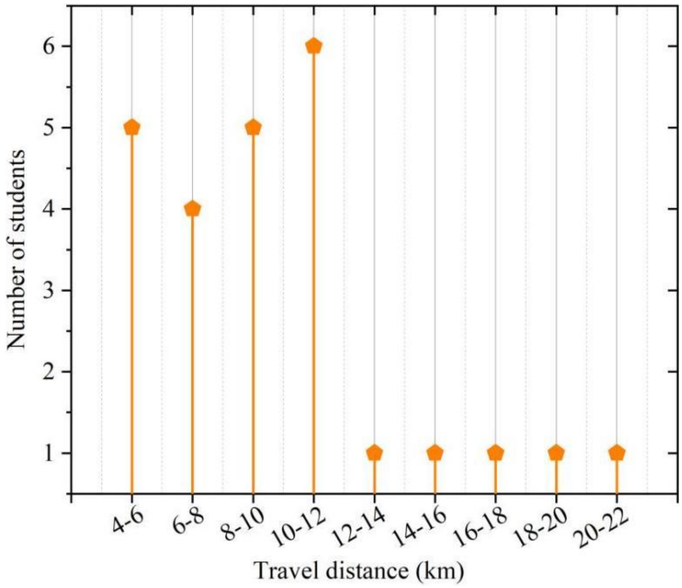


Figure 4. Statistics of students' daily travel distance

3.2. Analysis of students' travel mode choices

Campus travel mode is the daily life style of students at school, and statistical analysis of students' travel mode is important for digging deeper into the life pattern of students, which involves many aspects of factors. This study statistically analyzes the data collected from students divided into different dormitory areas and the rate of choice of one mode of transportation over a two-week period.

Out of the data collected from 25 students, 13 people live in hostel area A, 4 people live in hostel area B, 5 people live in hostel area C and 3 people live in hostel area D. The data collected from 25 students were analyzed for the mode of transportation. The mode of travel of the 25 individuals is now statistically analyzed and analogously counted for all students. The proportions of walking, bicycling, and motorized vehicles (on campus as the Circle Bus) are calculated.

Figure 5 shows the percentage of students traveling in this section. The trend presented by the data from 25 students shows that walking accounts for over 92% of all trips, bicycling ranges from 2%-5.5%, and motorized vehicles hover from 0.2%-4.9%. An analogous study of the mode share of all students at the university based on the mode share of this group of students found that walking accounted for 95% of all trips, bicycling was 3.5%, and motorized vehicles were 1.5%. Combined with the paths of the university and student trajectory data, it can be seen that the majority of students in the school travel mode is mainly walking, which may be due to the fact that most of the students travel on-campus short-distance trips, focusing on classes, meals, recreational activities, and so on, on-campus dormitory areas and activity areas are basically reasonably planned, the students can reach their destinations by walking in most cases, and the time consumed and the walking distance The time consumed and the walking distance are within the acceptable range.

Bicycle as the second choice of students' daily travel, its proportion is slightly higher than that of motor vehicles, the reason is that the bicycle is convenient, in the campus does not allow off-campus motor vehicles to travel at will is a very fast means of transportation, easy to ride on the campus roads, and fast, time-consuming, and the cost is small, the cost of a bicycle is completely within the acceptable range of college students. Motorized vehicles accounted for the smallest proportion, only 1.5%, which is due to the narrow main roads on campus, allowing fewer vehicles to pass at the same time, the number of students, the number of campus buses is small, the capacity is small, the frequency of buses is unreasonable and so on, which leads to the students do not choose the campus buses to ride on their trips, which is a little bit less convenient than biking or walking.

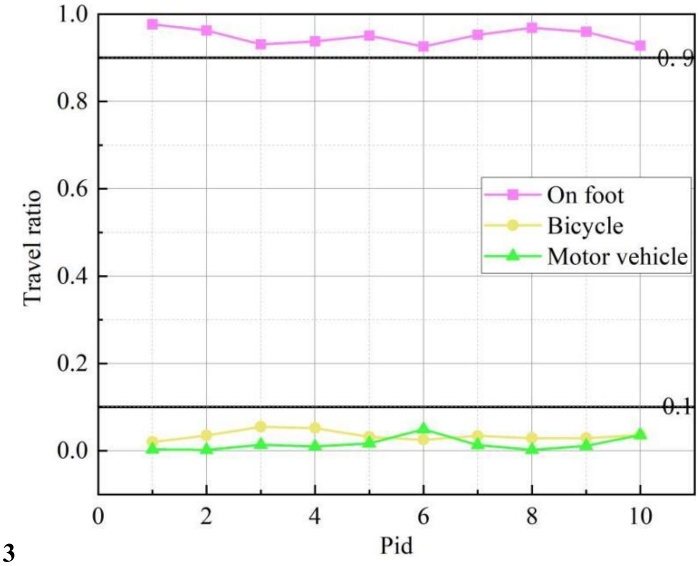


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Figure 5. Travel proportion of students

3.3. Analysis of foot traffic on main campus roads

Figure 6 shows a comparison of the average daily per capita flow of students on the main roads in the four dormitory areas of the University, namely, Area A, Area B, Area C and Area D. In this figure, the numbers 1-10 of the horizontal coordinates represent the names of 10 roads, such as School Middle Road, Student West Road, Teacher East Road, School North Road, School East Road, School North Gate Road, School West Road, Student North Road, West Gate Road, School South Road, and so on. The per capita number of passages per day on different main roads in different dormitory districts is analyzed as follows:

(1) Area A has the lowest per capita traffic in School Middle Road, Teachers' East Road, School South Road, West Gate Road, School West Road, and generally less than 2 times in each main road, the activities of students traveling in Area A every day are dispersed in the dormitory as the center, and the distance is in the acceptable range, combining with the distribution of the school's buildings, the above roads with low per capita traffic are all in the vicinity of the school's west gate, which are far away from the dormitories of Area A. There is no trajectory of Teachers' East Road and School South Road, which pull down the mean value. Combined with the distribution of school buildings, we know that students in Area A have shortcuts to their activities on campus, and do not necessarily choose the main road to go, which also pulls down the value of the average daily flow.

(2) Area C has the highest average daily flow in School Middle Road, Student West Road, School East Road, School North Gate Road, and Student North Road, generally more than 2 times, up to 3 times. Combined with the analysis of the distribution of buildings, the dormitory in Area C is located in the center of the school, and the surrounding main roads include the above roads, so each trip must first pass through the above roads with high average daily flow. In addition, the average daily flow rate of Area C on the North School Road and the South School Road is lower, respectively 1.17 times and 1.28 times, indicating that it is affected by the distribution of the dormitory area and the distance of the main roads.

(3) Zone B as well as Zone D, on the contrary to Zone A, have relatively high average daily flow rates at School Middle Road, Staff East Road, School North Road, School East Road, West Gate Road, and School South Road, generally hovering between 1.35 and 2.6 trips. The lowest average daily flows are found on North School Gate Road and North Student Road, which are generally below 1 trip. Combined with the distribution of the building complex can be seen in Area B and D distributed in the southwest of the school, the above highest flow of the main road are daily activities often through the road, and low flow are in the north of the school, the distance is far away, directly affecting the intention of the students to choose to travel.

(4) The dormitory area in the school and the school in the middle of the road and the school east of the average daily flow of similar, are in the 2 times up and down fluctuations, according to this judgment of the two main roads for the school students pass the number of times the most common road, the school in the middle of the school is the library as well as the teaching building of the main road, the school east of the school is the main off-campus subway station as well as the main access to the sports plaza road, so it is consistent with the inference.

From the analysis, it is concluded that the pedestrian flow of students' daily travel through each main road is strongly correlated with their dormitory location and activity sites. The main road with the closest pedestrian flow is the one that students must pass through for the most important activities in their daily life (e.g., study and sports activities).

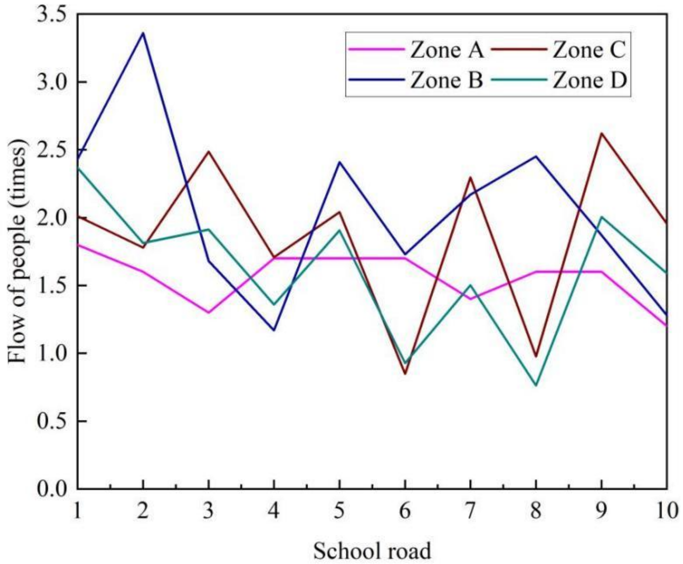


Figure 6. Comparison of daily pedestrian flow of main road in each dormitory area

4. Visualization of Predictive Models for Campus Trajectories

According to the previous section, it is known that students' campus trajectories have a certain regularity, and students' behaviors can be predicted based on the number of student devices in the campus. This part uses the student campus trajectory prediction model constructed in this paper to visualize the clustering of students' trajectories in functional areas, which is convenient for relevant educational administrators to manage students with different characteristics.

4.1. Analysis of the number of student devices

The predictability of student behavior within a typical spatio-temporal place like a university campus is very high. In this paper, the number of devices captured in different places at different times of the day can be counted to observe the student activities in each typical place on campus.

September 11 and September 12, 2024 are two weekdays. Figure 7 shows the number of devices captured at different places during different time periods during these two weekdays. Based on Figure 7, it can be seen that during the weekdays the flow of people at each venue varies in a relatively regular manner, and there are different small peaks according to the summer schedule set by the school. This can be visualized in Figure 7:

(1) Teaching building area: the first peak occurs in the teaching building first from 7:35 to 7:55 am. This is the WiFi data collected by the WiFi probe from the students who have the first class in the morning; two less obvious small peaks appear at 9:35 ~ 9:45 and 9:55 ~ 10:05, which are the students who leave the building after the first class and the students who do not have the first class in the morning but have the second class to come to the building; the second peak appears at 11:45 ~ 11:55 in the noon, which is the the number of devices that captured students who left classes; a third peak occurred at 13:45 to 13:55 in the afternoon, a small peak again at 15:25 to 15:50, and a third peak at 17:25 to 17:35, which was the same as in the morning, and insignificant small peaks occurred at 18:15 to 18:25 and 20:00 to 20:10 in the evening, which captured the evening data from students who had classes as well as those who attended self-study.

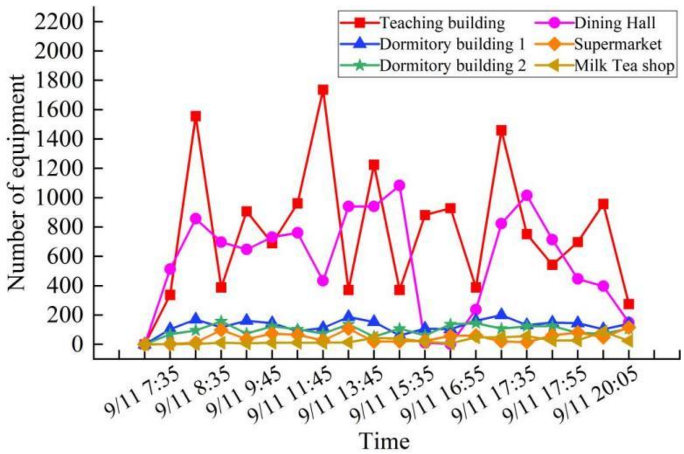
(2) Cafeteria: the first peak in Cafeteria B appeared at 7:35 to 7:45 a.m., which was the time when most of the students had their breakfast; the second small peak appeared at 9:45 to 9:55 a.m., which, according to classroom work schedules, was the large classroom interval between the end of the first large class and the beginning of the second class for some of the students; the third peak appeared at around 11:55 to 12:15 p.m., which was the students' lunch time; four peak periods occurred between 5:35 p.m. and 5:55 p.m., which was the students' dinner time.

(3) Dormitory building area: The two dormitory buildings also have different peak periods

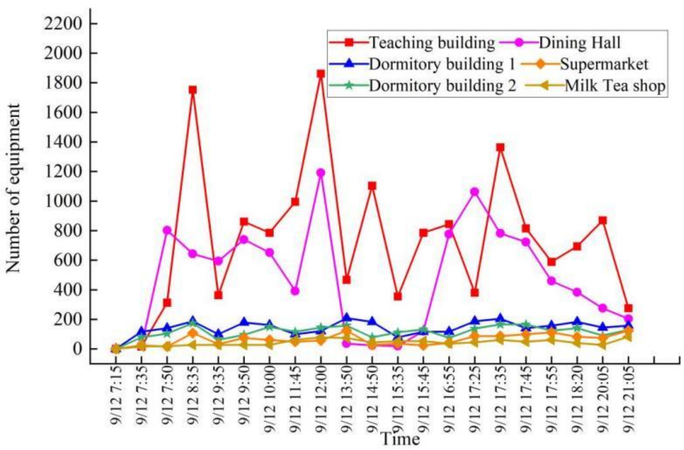
according to the work schedule.

(4) Milk tea store: no significant peak periods, slightly higher number of devices detected after meals and in the evenings compared to the school hours.

(5) Educational Supermarket: No very significant peaks were observed.



(a) Change in the volume of detection equipment as at 11 September 2024



(b) Change in the volume of detection equipment as at 12 September 2024

Figure 7. Changes in the number of detection devices within two working day

4.2. Visualization of functional area clustering by time period

Time-based trajectory clustering. Figure 8 shows the statistics of students' campus trajectories by time functional area. Among them, the number of College Building trajectories does not change much for two reasons. First, the College Building mainly distributes graduate students, and the graduate laboratories have a dedicated network and rarely connect to the on-campus WiFi network, so there is less trajectory data collected based on WiFi. Second, the College Building has a small number of laboratory classes in the morning, and there are fewer student trajectories. Comprehensive two reasons can also be analyzed to know that the number of trajectories are less in these time periods from 6:30-12:30. Library trajectory number changes, the library opens at 8:30, the number of people gradually increased, because most undergraduate students have class arrangements in the morning, a few graduate students have classes, most graduate students in the college building for scientific research activities, so the trajectory is relatively small.

Changes in the number of trajectories in the school building, the number of people in the school building gradually increased from 6:30 a.m. as more and more people attended classes and more trajectories became available.

Cafeteria trajectory according to the number of changes in the morning, some people eat breakfast, in the 6:30-8:30 time period of the cafeteria trajectory increased. After breakfast, the number of people in the cafeteria gradually decreases and the number of trajectories decreases. Around 10:30 more and more people went to the cafeteria and the trajectory increased. Regardless of which cafeteria they dine in, the number of people who dine at lunch is more than the number of people who dine at breakfast, most of the reason is due to the fact that students do not want to get up early, do not want to eat breakfast or get up late too late to eat breakfast, but almost no students do not go to lunch, so the coverage of the lunch is wider, and it provides a very good basis for the study of the regularity of the student's life.

Changes in the number of trajectories in the dormitory building, the number of students waking up in the morning gradually increased, more students came out of the dormitory, and the number of trajectories increased from 6:30 onwards. Some students go to the cafeteria, and some go to other places such as the library and the teaching building. After that time period the number of people in the dormitory gradually decreases and the number of trajectories decreases.

Overall, the activity in the teaching area is much higher than other functional areas during the 6:30-12:30 time period and the university has a good academic culture.

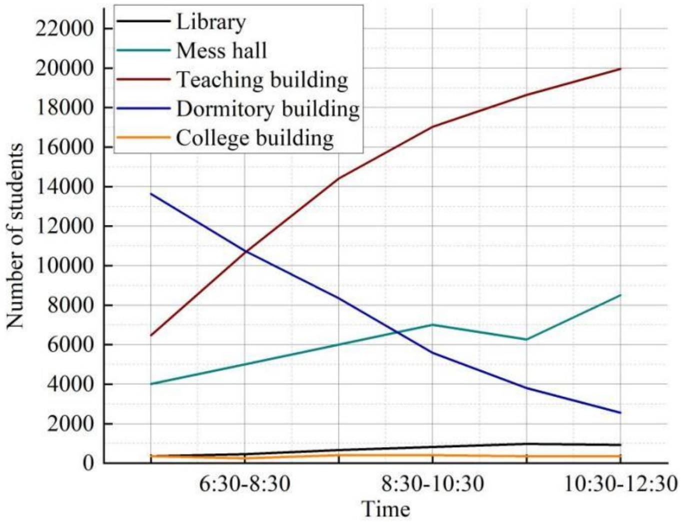


Figure 8. Clustering statistics of time segment functional areas

4.3. Visualization of the frequency distribution of functional areas in clusters

University personnel are numerous, in the functional area for trajectory distribution specificity when the statistical cost is high, time is difficult to grasp, so the model of this paper is selected for clustering. After clustering the cluster trajectory data for classification query. Select a day of the week 8:30-20:30 trajectory data, get the frequency distribution of functional areas in the cluster. Figure 9 shows the frequency distribution of functional areas in clusters, listing the top ten clusters in terms of the number of people in the cluster as a result of trajectory clustering, with 20.32% of the number of people in Cluster 1, 18.35% in Cluster 2, 6.35% in Cluster 3, 5.11% in Cluster 4, 3.76% in Cluster 5, 6.77% in Cluster 6, 4.04% in Cluster 7, 4.72% in Cluster 8, 9.74% in Cluster 9, and 10.07% in Cluster 10. 3.07%.

Among them, Cluster 1 has a higher number of trajectories in dormitory buildings and academic buildings, accounting for more than 70%, and other trajectories are also distributed in libraries and stadiums, which are students who finish the day's classes and have less time for after-school activities, and this paper speculates that they may be female students. Cluster 2 and Cluster 1 is different in that there are more stadium trajectories, more activity center trajectories, the increase in the number of around 10%, the library trajectory is less, it may be male students. Cluster 3 has more trajectories in the teaching building, followed by the library, with 56%, but with a smaller number of people, this paper speculates that the students in this category are preparing for exams. Cluster 4 trajectories are distributed in the dormitory and the library, this paper speculates that this type of students do not have courses today, in preparation for exams or more fond of studying and reading books. Cluster 5 trajectories are distributed in teaching buildings, activity centers, office areas, sports venues and the number of trajectories does not vary much, which may be the students working in the student union or the relevant personnel of student activities. Cluster 6 trajectories are mainly distributed in the college building, library, followed by the teaching building, the total share is about 60%, this paper speculates that the student finished the current day's course, the main time to participate in research activities. Cluster 7 trajectories are evenly distributed in the library, college building, teaching building, and stadium, with an average share of around 20%, this paper speculates that this category of students has a more reasonable distribution of time, and a balanced development of academics and culture and sports. Cluster 8 trajectories are mainly distributed in dormitories and sports venues, accounting for more than 60%, this paper speculates that this type of students love sports more after school. Cluster 9 trajectories are mainly distributed in the dormitory and the teaching building, accounting for an average of about 40%, almost no other activities trajectories, this paper speculates that this type of students after-school activities are mainly in the dormitory, relatively single. Cluster 10 trajectories are mainly in the teaching building and dormitory, the proportion of teaching building trajectories is 70%, this paper speculates that this type of students in the teaching building for self-study or preparation for exams.

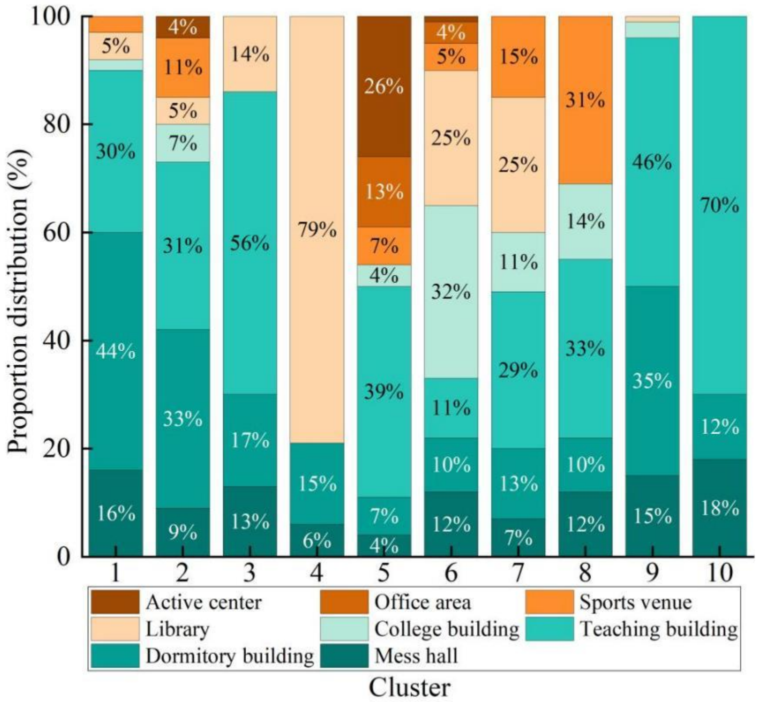


Figure 9. Frequency distribution of functional areas in clusters

5. Conclusion

This paper takes the trajectory data of college students as the object of studying their behavioral characteristics, judges the characteristics of different types of students by predicting their activity trajectories, assists education managers to optimize campus management system, and promotes the intelligent development of campus management.

Studying students' campus behavioral trajectory, 80% of students' average daily travel distance is in the range of 4Km-12Km, and only 20% of students' average daily travel distance is in the range of 12Km-22Km. Most of the students' daily activities are completed in “short distance”, and more than 92% of the college students choose to walk to complete their daily activities. In the “short distance” traveling, the pedestrian flow of each main road has a close relationship with the geographic location of the dormitory area. Therefore, relevant administrators should continue to improve the level of campus construction, so that most of the students' daily activities are more colorful and more convenient to travel.

The number of student devices in different functional zones has obvious time characteristics, and has a change situation in line with the characteristics of functional zones in different time periods, such as 7:35-8:35 and 10:30-12:30. By judging the proportion of functional areas in different clusters, it can be seen that students with different personalities and different planning have their own activity characteristics. Relevant educational administrators should target to enhance the specific functions of functional zones, so that students can achieve their own goals when using functional zones and develop their own personalities in university campuses.

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