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Article

Research on the Trend of Students' Ideological Dynamics in Civic Education Based on Time Series Prediction Modeling

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Abstract: This paper takes students' daily behavioral habits as the entry point to explore the changes of students' ideological dynamics in ideological education through behavioral analysis. The behavioral trajectory of students' school life is divided into five modules: course learning, school life, social interaction, employment and ideology and politics, and this is used to form a behavioral dataset of the research sample. After fusing the data from multiple sources to obtain the spatial and temporal fine-grained daily activity trajectories of the samples, the mathematical formulas for students' daily activities, daily behaviors and daily behavioral habits on campus are designed on the basis of which, as well as the calculation method for the intensity of the habits, the modeling method for students' daily behavioral habits is proposed. The extracted behavioral time feature sequences are input into the multivariate time series classifier, and the MLSTM-FCN model is determined to be the best model. Since its FCN branch has the problem of small sensory field and only supports single-item operation when extracting the sequence features, the Transformer encoder is used to replace the FCN unit, and the model sensory field is enlarged by introducing the form of multi-attention mechanism, so as to establish the time-series-based student abnormal behavior detection model. The model is calculated to get the intensity of the Civic Learning Resources Attention Behavior of Normal Behavior Students as 41.23% in the analysis of the change of students' ideological dynamics in Y college. It summarizes students' ideological cognition and behavioral changes through time series features, reflects students' growth patterns and effective education pathways, and points out the direction for updating and improving the model of civic education in colleges and universities.

Keywords: student abnormal behavior detection; time series; civic education; MLSTM-FCN model; daily behavior habits

1. Introduction

China is moving towards a manufacturing country, students will become the main force of social development, they are in the production line directly for the society to create wealth. To cultivate them into high-quality talents, the first problem is to study the student's ideological dynamics and the law of change, so as to find a practical way to carry out formation education, in order to achieve the goal of talent cultivation [1]. Civic education is an important part of ideological education in colleges and universities, and it is of great significance to the development of students' thoughts and enhancement of their abilities [2-3]. In the teaching of ideological education in colleges and universities, the scientific and effective application of various scientific means and the effective introduction of the theory of big ideology can not only enhance the students' ideological awareness and comprehensive quality to a large extent, but also improve the students' moral quality [4-5]. Grasping the characteristics and changing law of students' ideology in the new era is the prerequisite and key to doing a good job in ideological education, and it is necessary to review and examine the changes in students' ideology with a dynamic vision, and further summarize and sort out the formation law of students' ideology, so as to better complete the work of ideological education [6-7].

Time series forecasting, is a statistical method of predicting future trends by analyzing historical data [8]. It mainly relies on time dependence, i.e., the current values in the time series are often correlated with the past observations, and its core lies in time correlation, i.e., the current values in the time series are usually correlated with the historical observations [9-10]. Time series data is data collected in a chronological order and usually reflects the pattern of change of a variable over time [11]. It has a wide range of applications in many fields, especially important in financial market analysis, traffic flow forecasting, weather forecasting and demand forecasting [12-14].

Time series model is the earliest model used for time series forecasting, which is relatively simple in understanding and application, and its theoretical basis is mainly mathematical statistics and stochastic process theory [15-16]. At present, time series models are mainly divided into two categories: one is autoregressive sliding average (ARMA) model, and the other is autoregressive integral sliding average (ARIMA) model.ARMA model is a method proposed by American scholars Box and Jenkins in 1970 about the analysis, modeling and forecasting of time series, which mainly includes three basic types: autoregressive (AR) model, sliding average (MA) model and autoregressive sliding average (ARMA) model, such models are suitable for smooth time series modeling, while ARIMA is widely used in non-smooth time series modeling [17-18]. The identification of such models, determination of order, estimation of model parameters, diagnostic tests, and means of solving problems such as forecasting are basically perfect and mature. Time series models can well describe the linear relationships in time series, and the training and calculation process is relatively simple [19]. In many related researches, time series models are often used as reference models for verifying whether the prediction performance of some newly proposed methods is superior or not. However, many time series existing in practical applications present nonlinear and nonsmooth characteristics, which cannot be explained by linear relationships to explain their changing trends. For nonlinear problems, time series models can only be approximated by linearity, and this limitation restricts the application of such methods to practical nonlinear problems [20].

In order to adapt to the complex nonlinear relationships in time series, deep learning and machine learning methods have been widely applied to time series forecasting in different fields in recent years [21-22]. Among the nonlinear modeling methods, machine learning methods such as artificial neural networks, Gaussian process regression, decision trees, and support vector machines have adaptive and self-organizing learning mechanisms, which have good prediction ability for nonlinear time series [23-24]. In general, time series prediction models are of great help in studying the trend of students' ideological dynamics in Civic Education due to their time-dependent, trend and periodicity characteristics.

This paper describes the behavioral trajectories and contents of current college students' school life from five perspectives: course learning, school life, socialization, employment and ideology and politics. Students in college Y are taken as research samples, and multiple behavioral trajectories are collected and organized to form a sample dataset. Based on different data information attributes, multiple sources of data are fused to form the spatial and temporal fine-grained daily activity trajectories of students in college Y. The data framework lists students' behavioral trajectories and their content. Combined with this data framework, the mathematical expressions of students' campus daily activities, daily behaviors and daily behavioral habits, as well as the calculation of the intensity of behavioral habits, are enumerated as the modeling method of students' daily behavioral habits. Meanwhile, for the phenomenon of abnormal behavior, all the feature sequence data are subjected to multi-temporal classification experiments, the best model is screened out, and the algorithm optimization is launched for the problems of this model to obtain the students' abnormal behavior detection model. Using the proposed daily behavioral habit modeling method, we analyze the behavioral trajectories of the experimental subjects and mine their behavioral habit information to construct a daily behavioral habit model that meets the characteristics of Y college students. Within the framework of the model, the proposed model for detecting students' abnormal behaviors is used to calculate and summarize the time characteristics of students' daily behaviors in college Y, so as to detect students' abnormal behaviors, summarize the rules of behaviors, and analyze the changes in students' ideological dynamics and the corresponding measures in the ideological education.

2. Trajectory of the student's life at school

According to the specific indicators of students' trajectory in school life, they can be divided into a total of five aspects: curriculum learning, school life, socialization, employment and ideology and politics:

(1) Curriculum. This part is the main investment of students' energy during school, so the study focuses on study time, study intensity, and study effect. Study time includes the average daily study hours, the time and number of participation in research projects; study intensity includes the intensity

and source of pressure felt, the degree of adaptation to research and study and specialization, etc.; study effect focuses on students' credits and GPA in each semester. In addition, there is a second classroom learning: aimed at cultivating students' communication skills and team leadership skills in addition to their professional qualities.

(2) Life. Students' living status and adaptation to life during school, including diet, work and rest, exercise, use of funds and so on. Dietary habits include whether the diet is regular, the main source of diet, etc.; work and rest habits include the average daily sleep time, staying up late, etc.; exercise includes the frequency of exercise; the use of funds includes the source of funds, etc.

(3) Socialization. In the socialization module, the study focuses on students' experiences of participating in student clubs, getting along with various types of friends, and social adjustment. The experience of students' participation includes the type of work and tenure of various types of clubs; the getting along with various types of friends includes the number, experience and relationship of male and female friends, roommates, same-sex friends, etc.; and the social adaptability includes the adaptation to socialization, etc.

(4) Career planning. Employment situation as a more concerned part of the student's career, specifically including participation in work placement experience, job-seeking intentions and choices. Work experience includes the length of various types of annual internship experience; job search intention and choice includes job search choice considerations, and so on.

(5) Ideological and political. Students' ideological situation is the key part to understand and master, including students' motives for joining the Party and their identification with their chronological identity, reasons for joining the Party, and their cognition of the “labels” of contemporary college students.

3. Modeling Students' Daily Behavior

In this paper, college Y is selected as the research object to collect multiple behavioral trajectory information under a total of five indicators, namely, course study, school life, socialization, employment, and ideology and politics, during the first academic year from 2023 to 2024. Since some of the data information involves students' privacy, sensitive data such as school number and specific indoor location are blurred. And this chapter forms a spatio-temporal fine-grained daily interaction dataset of Y college students, which provides data support for the research and analysis of this paper. Based on this dataset, the mathematical formula expressions of students' campus daily activities, daily behaviors, and daily behavioral habits and the calculation method of habit intensity are given one by one.

3.1. Spatio-temporal fine-grained daily activity trajectories with multi-source data fusion

The data in this paper's dataset is derived from the daily activities generated by 5,063 undergraduate students in the fall semester of 2023~2024 at University Y. It includes basic student data, one-card data, library access data, library checkout data, and WiFi log data. Specifically, there are 1,065,200 pieces of one-card data, 58,000 pieces of library access data, 5,379 pieces of library checkout data, and 890 million pieces of WiFi log data. In particular, this paper has encrypted the students' private data.

In order to effectively analyze the characteristics of students' daily behaviors, this paper associates students' basic data, one-card data, library access control data, library borrowing data and WiFi log data through students' school numbers, which are fused into a data table of college students' campus spatio-temporal fine-grained daily activity trajectory data, with a total of 550 million entries. In addition, this paper defines corresponding specific activities, such as eating breakfast, traveling, entering the library, consuming daily necessities, etc., for all the spatio-temporal fine-grained daily activity data with reference to data types, time attributes, location attributes, etc. in the dataset. The fusion process of multi-source data is shown in Figure 1.

Figure 1. The fusion process of multi-source data

The fusion of multi-source data allows different behavioral data to complement each other, presenting a more complete picture of students' spatio-temporal fine-grained daily activity trajectories on campus. The spatio-temporal trajectory data table of campus activities specifically records the student's school number (encrypted), start time, end time, room, floor, and activity content. This lays a solid data foundation for calculating students' daily behavioral habits on campus and analyzing abnormal behaviors on campus See Table 1.

Table 1. Example of daily activity trajectory data

Student ID	**20232890526**	**20221460402**	**20231780329**
Start time	2023/09/15 13:23	2023/10/11 08:00	2023/09/28 14:35
End time	2023/09/15 15:46	2023/10/11 09:45	2023/09/28 16:05
Building	Dormitory building	Teaching building	Teaching building
Room	14-506	5-801	3-603
Floor	5F	8F	6F
Action	Rest	Attend class	Attend class

3.2. Calculation Model of Intensity of Daily Behavioral Habits on Campus

3.2.1. Daily campus activities

College students' daily life on campus cannot be separated from various activities. Activities are the smallest units that make up behaviors, for example, eating behaviors correspond to activities such as eating breakfast, eating brunch, eating Chinese food, eating afternoon tea, eating dinner and so on. Therefore, the daily activities occurring on campus are defined as a specific behavioral activity that occurs at a point in time of a student in terms of days, and it is formally expressed as equation (1)-(2):

$$a_i = (u,t,l,d) \tag{1}$$

$$A = \{a_1, a_2, \cdots, a_n\} \tag{2}$$

where a_i denotes the ith activity, $u \in U$ denotes the performer of the activity, $t \in T$ denotes the time at which the activity was generated, $l \in L$ denotes the location at which the activity was generated, $d \in D$ denotes the specific description of the activity, and A denotes the set of all the activities that the student has done in his/her campus life.

As an example, at 18:26 on October 11, 2023, student 2**1 is having dinner in the cafeteria. Then the performer u of activity a is student 2**1, t is 18:26 on October 11, 2023, l is the cafeteria, and d is eating dinner.

3.2.2. Daily Conduct on Campus

The diverse daily behaviors occurring on campus—such as classroom conduct, reading habits, consumption patterns, and eating practices—genuinely reflect students' campus life and academic conditions. Campus daily behaviors constitute a collection of routine activities sharing common elements, united by a shared purpose and fulfilling specific functions. Their formal expression is represented by Equations (3)-(5):

$$b_i = \{S, A_{b_i}\} \tag{3}$$

$$A_{b_i} = Seq1(u, b_i) = (a_1, a_2, \cdots, a_m) \tag{4}$$

$$B = \{b_1, b_2, \cdots b_n\} \tag{5}$$

where b_i denotes the ith behavior, S denotes a specific behavioral description, A_{b_i} denotes the sequence of activities from a_1 to a_m associated with the daily campus behavior b_i, and B denotes the set of all behaviors performed by a student in campus life.

As an example, on October 11, 2023, student 2**1 eats and drinks behaviors that occur on campus during the day, specifically breakfast at 8:30 in the first cafeteria, lunch at 12:15 in the second cafeteria, and dinner at 18:10 in the first cafeteria. Then the performer u of behavior b is student 2**1, S is the eating behavior, and A_{b_i} is {(2**1, 2023.10.11 8:30, first cafeteria, eats breakfast), (2**1, 2023.10.11 12:15, second cafeteria, eats Chinese food), (2**1, 2023.10.11 18:10, first cafeteria. Eat dinner)}

3.2.3. Daily Behavioral Practices on Campus

College campuses are freer and more open than the learning environments of elementary, junior high and high school. For college students who have just transitioned from middle school to college, they are faced with not only a brand new growing environment, but also a challenge that requires them to reshape their own habits.

In order to better develop good behavioral habits of college students, the method of directly capturing students' behavioral habits is used. Therefore, combined with the definition of habit given in this paper, the sequence of behavioral activities that have been acquired in a certain environment with certain temporal and spatial repetitive characteristics, gives the formal expression of daily behavioral habits on campus as equation (6)-(7):

$$h_i = f\left(F_{b_{h_i}}, E_{b_{h_i}}, D\right) \tag{6}$$

$$H = \{h_1, h_2, \cdots h_n\} \tag{7}$$

where h_i denotes the ith campus daily behavior habit, f denotes a specific mapping relationship, $F_{b_{h_i}}$ denotes the frequency of behaviors occurring in the campus daily behavior b_{h_i} associated with campus daily behavior habit h_i, $E_{b_{h_i}}$ denotes the stability of the environment in which campus daily behavior h_i related to campus daily behavior b_{h_i} occurs in the stability of the environment, D denotes the number of days, and H denotes the set of all behaviors of students in campus life.

3.2.4. Methods of calculating customary strength

Relying on the smart campus environment, through the campus card, campus WiFi and other intelligent sensing devices, we effectively, realistically and comprehensively collect the spatial and temporal fine-grained daily behavioral activity data generated by students on campus, and quantify the stability of the daily behaviors that students have acquired and the environment in which their behaviors occur. Based on the characteristics of habit repetitiveness and periodicity, customize the length of the cycle, such as days, weeks, months, semesters, and years, and calculate the habit intensity in terms of cycles to get the habit intensity within the specified cycle. The formula for defining habit intensity is equation (8)-(9):

$$h_i^s = \frac{h_i}{D} \tag{8}$$

$$h_i = \sum_{d=1}^{D} F_{b_{h_{id}}} * E_{b_{h_{id}}} \quad (9)$$

where h_i^s denotes the habit intensity of the ith campus daily behavior habit, h_i denotes the ith campus daily behavior habit, D denotes the number of days in the cycle in which the campus daily behavior occurs, and $F_{b_{h_{id}}}$ denotes the frequency of occurrence of the campus daily behavior habit h_i related campus daily behavior b_{h_i} occurs frequently, and $E_{b_{h_{id}}}$ denotes the stability of the environment in which campus daily behavior b_{h_i} associated with campus daily behavioral habits h_i occurs on day d.

4. Construction of a Model for Detecting Abnormal Student Behavior

4.1. Multivariate time series classification

To improve the accuracy of the student abnormal behavior detection model, it is necessary to enrich the feature information and fully explore the behavioral patterns. Therefore, the main content of this section is how to input all the extracted feature sequences into the multivariate time series classifier, so as to subsequently study the degree of influence of various types of features on the model decision, i.e., the feature contribution. The multivariate time series classification models selected for the experiments mainly include the distance-based classification method KNN-DTW, the excellent classification algorithm TapNet proposed in the last two years, and the improved multivariate time series classification model MLSTM-FCN based on the unitary time series classification model LSTM-FCN.

The multivariate long- and short-term memory fully convolutional network (MLSTM-FCN) is based on LSTM-FCN by introducing the Sequeeze-and-Excitation (SENet) module and placing it after the temporal convolutional block to further improve the model classification effect, and the network structure is shown in Fig. 2. SENet learns the inputs through the fully-connected layer based on the loss training SENet learns the feature weights of each channel feature map of the tensor according to the loss training, which makes the strong correlation feature weights increase and the weak correlation feature weights decrease.

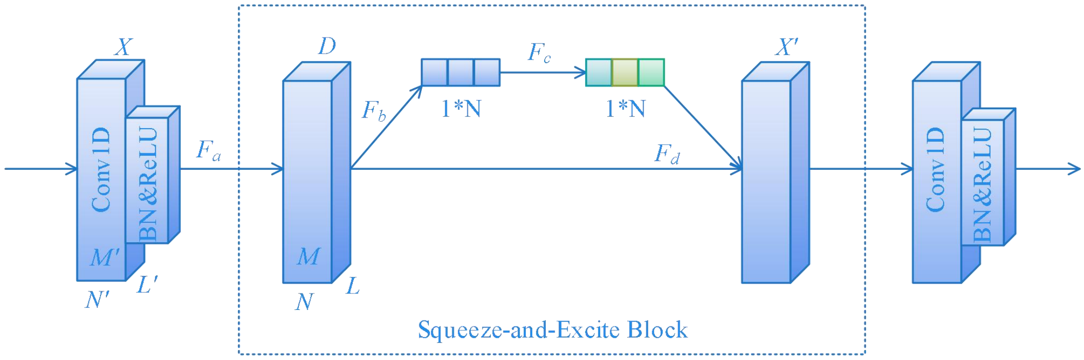


Figure 2. MLSTM-FCN network structure

By analyzing the network structure, it can be seen that before the features are input into the SENet network, they need to undergo a convolutional transformation, which can be defined as follows: $F_a : X \to D, X \in \mathbb{R}^{L' \times M' \times N'}, D \in \mathbb{R}^{L \times M \times N}$, and the related solution process is shown in Eq. (10):

$$d_n = v_n * X = \sum_{s=1}^{N'} v_n^s * x^s \quad (10)$$

Where v_n denotes the n th convolution kernel, * denotes the convolution operation, X^s denotes the sth input, and d_n denotes the nth feature map, and after processing tensor X is converted into tensor D. Subsequently, compression operation is performed, and the related formula is shown in equation (11):

$$z_n = F_b\left(d_n\right) = \frac{1}{M \times L}\sum_{i=1}^{M}\sum_{j=1}^{L} d_n(i,j) \tag{11}$$

The action is similar to global average pooling, which yields $1*1*N$ -dimensional global information. Immediately after the activation operation, in this step, the first input needs to go through the fully connected layer W_1 , and then into the ReLU layer activation, and then into the fully connected layer W_2 , and finally through the sigmoid output feature weight representation s , and the whole computation process is shown in equation (12):

$$s = F_n(z,W) = \sigma(g(z,W)) = \sigma\left(W_2\delta\left(W_1 z\right)\right) \tag{12}$$

Where W_1 and W_2 have the same dimension, both are $\frac{N}{r}*N, r$ as scaling parameters, which serves to reduce the number of channels and thus the computation. Finally, the output s is channel-multiplied with the original input to obtain the feature vector representation with variable weights, and the related expression is shown in Eq. (13):

$$x_n{}' = F_d\left(d_n, s_n\right) = s_n \cdot d_n \tag{13}$$

4.2. Algorithm Optimization

It is experimentally verified that MLSTM-FCN has the best performance among existing time series classifiers. With the same structure as LSTM-FCN, MLSTM-FCN is designed with two branches to deal with time series from different perspectives. For the set of time series $\left(N, M, L\right)$, where N represents the number of samples in the dataset, M denotes the feature dimensions under each time step, and L is the length of the sequence, the FCN branch treats the input as an M time series containing L time steps and extracts the features through three temporal convolutional networks (TCNs) and outputs a sequence vector of the same dimensions of the input, while the LSTM processes the input as an L-element sequence containing M time steps by dimension transformation. When M is smaller than L, the dimension transformation can greatly improve the computational efficiency of LSTM.

TCN is mainly composed of inflated causal convolution and fully connected networks. When performing one-dimensional convolutional operation, its working principle is similar to that of traditional convolutional networks, where the temporal information is extracted by the convolutional kernel and the expansion factor is used as a moving window, which grows exponentially with the increase of the network layer depth, so as to realize the extraction of dependencies between long sequences with a smaller number of network layers, which helps to simplify the model to avoid the problem of vanishing gradients, and the detailed process is shown in Fig. 3. where d is the expansion factor. It is worth noting that the network can only operate unidirectionally, and the computation of the eigenvalues of the l layer at the t moment must depend on the values of the previous layer before the t moment, so it is called a causal convolutional network. Because of this, FCN can only extract sequence information in one direction and has limited sensory field, which cannot fully capture the correlation between sequence segments.

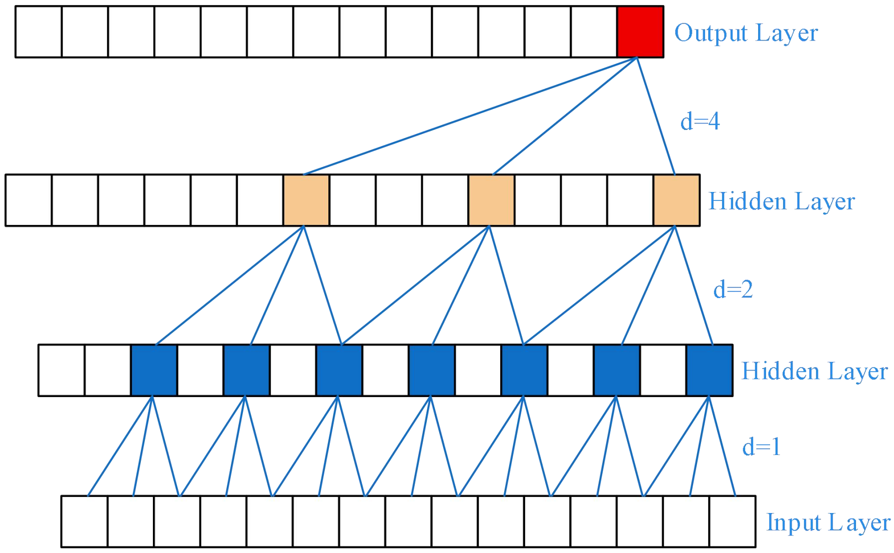


Figure 3. The working principle of temporal convolutional networks

The network runs as in equation (14):

$$E^{(l)} = max\_pooling\left(f\left(W * E^{(l-1)} + b\right)\right) \tag{14}$$

$E^{(l)}$ represents the l th layer network in the encoder, which mainly consists of a temporal convolution layer, a linear activation layer, and a maximal pooling layer, $E^{(l)} \in \mathbb{R}^{F_l \times T_l}$, L the number of layers in the encoder network, F_l represents the l th layer network number of filters, T_l represents the number of time steps of the corresponding layer, W is the set of parameter weight matrices, and b bias. So the sensory field is calculated as in equation (15):

$$r(d, L) = d\left(2^L - 1\right) + 1 \tag{15}$$

From the above equation, it can be seen that the size of the receptive field of the TCN network is jointly determined by the number of network layers, the expansion factor and the size of the convolution kernel.

In order to solve the problem that the FCN branches in the MLSTM-FCN network have a small sensory field and can only be unidirectional, this paper introduces the attention mechanism, which is commonly used in Transfomer, and replaces the TCN module to form a new Trans-LSTM network, the structure of which is shown in Fig. 4. In general, the self-attention mechanism can calculate the correspondence between all segments of a certain segment of a sequence by assigning different weights, the principle of which is similar to that of bidirectional RNN networks. In general, the self-attention mechanism can calculate the correspondence of all segments of a segment within a sequence by assigning different weights, which is similar to the bidirectional RNN network, with the difference that the self-attention mechanism can parallelize the computation; while the multi-attention mechanism can make the model split into multiple heads, with different heads focusing on different points, and extracting the features of the sequences from different perspectives, respectively. All other things being equal, the Trans branch can consider the whole sequence when extracting features, greatly expanding the field of view, and embedding the sequence position information into the model through position encoding, giving it a stronger feature extraction capability. In the Trans branch, the multi-head attention is mainly used for feature computation, while the feed-forward network is responsible for linear activation and connecting the residual network to solve the problems of network degradation and gradient vanishing as the number of network layers increases.

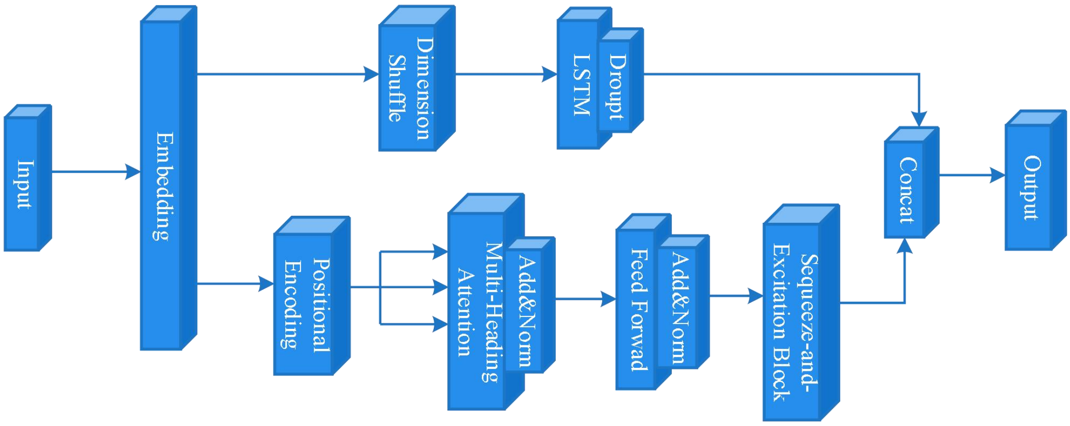


Figure 4. Trans-LSTM network structure

For location coding, the mathematical expression is shown in equation (16):

$$PE_{(pos,2i)} = \sin\left(pos / 10000^{2i/d_{model}}\right)$$
$$PE_{(pos,2i+1)} = \cos\left(pos / 10000^{2i/d_{model}}\right) \tag{16}$$

where pos represents the position where the current encoded token is located, i denotes the dimension, and d_{model} is the dimension of the processing sequence. In addition, the multi-head attention is represented as in equation (17):

$$MultiHead(Q,K,V) = Concat\left(head_1,\ldots,head_h\right)W^O \tag{17}$$

Where W^O represents the projection matrix, which is used to solve the cross-layer dimension inconsistency problem, and $head_h$ represents the h th head, which is computed as in equation (18):

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{18}$$

W^Q, W^K, W^V denote query (used to match other sequence fragments), key (used to be matched) and value (information that will be extracted), respectively. The feedforward network mainly consists of two linear transformation functions and a ReLU activation function, which is computed as in equation (19):

$$FFN(x) = \max\left(0, xW_1 + b_1\right)W_2 + b_2 \tag{19}$$

5. Analysis of Changes in Ideological Dynamics Based on Students' Daily Behavior

5.1. Analysis and Modeling of Daily Behavioral Habits

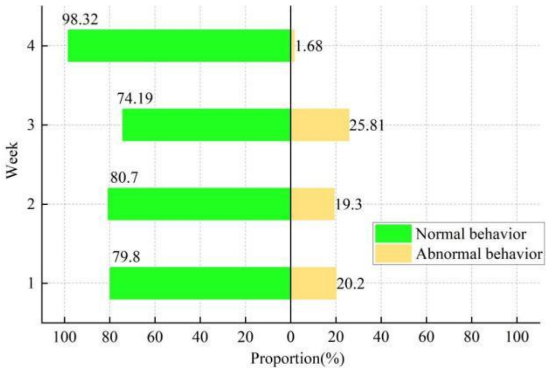
Examples of data on students' daily behavioral activities on campus in college Y are shown in Table 2. 4 of the 10 randomly selected students attended classes in the academic building and 3 studied independently in the library, which is in line with the current behavioral habits of students in colleges and universities.

Table 2. Activity data instances and behavior labels

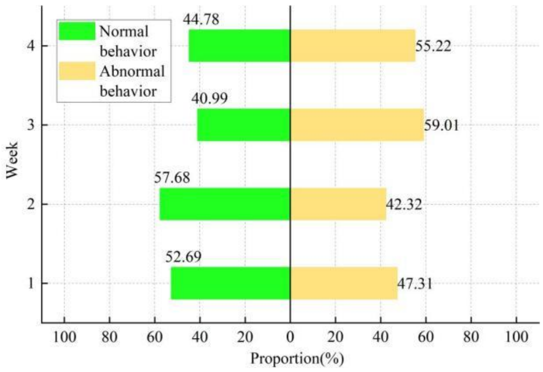
Serial number	Date	Time	Location	Behavior
A0001	2023/10/30	09:23	Teaching building	Attend class
B0012	2023/10/30	10:25	Library	Studying
D0006	2023/10/30	20:14	Library	Studying
A0108	2023/10/30	10:33	Teaching building	Attend class
B1023	2023/10/30	14:48	Dormitory building	Rest
C2895	2023/10/30	16:51	Administrative building	Work
E1653	2023/10/30	19:09	Teaching building	Attend class
E1124	2023/10/30	08:12	Teaching building	Attend class
C0786	2023/10/30	15:37	Dormitory building	Rest
B1603	2023/10/30	13:56	Library	Studying

5.1.1. Individual behavioral trajectories

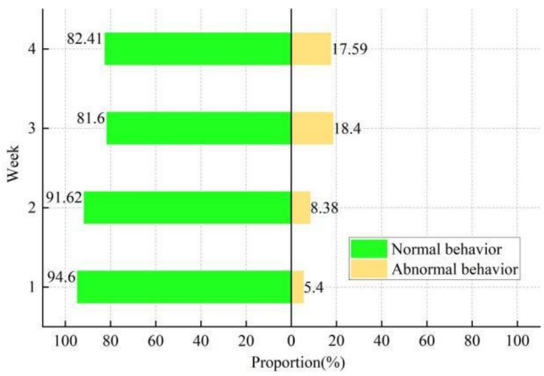
Students whose secondary school number is “B1023” were selected for further study, and using the modeling method proposed in Chapter 2, their (b1) class, (b2) life, and (b3) ideological and political behaviors during the last month (4 weeks in total) before the vacation of the first academic year from 2023 to 2024 are shown in Fig. 5 in order. (a)-(c). It can be seen that overall the student's (b1) classroom and (b3) ideological and political behaviors are at a normal level, and the percentage of their normal behaviors is 70.00% and above. The (b1) normal behavior in class reaches the highest value of 98.32% in the last week due to the proximity of the final exam, and the (b3) ideological and political normal behavior similarly decreases in the last two weeks due to the preparation for the final exam.



(a) (b1) Class behavior



(b) (b2) Life behavior



(c) (b3) Ideological and political conduct

Figure 5. The proportion of student behavior statistics in B1023

5.1.2. Mining information on individual behavioral habits

The habit intensity calculation model proposed in this paper was used to predict the behavior of student B1023 on a daily, weekly, and monthly basis, and the data correlation analysis method was used to mine his behavioral trajectory. The statistics of this student's behaviors at different times of the day in the first academic year from 2023 to 2024 are shown in Fig. 6. Due to the small amount of data, the student behaviors were subdivided from the five behaviors above in the analysis here into (b1) classroom behaviors, (b41) eating and drinking behaviors, (b42) resting behaviors, (b43) exercising behaviors, (b11) borrowing behaviors, (b12) self-study behaviors, and (b5) Other Behaviors. The student was predominantly engaged in (b42) resting behavior between 23:00 and 7:00, while (b1) classroom behavior, (b43) exercise behavior, (b11) borrowing behavior, and (b12) self-study behavior varied between 8:00 and 12:00, and the same behaviors occurred between 14:00 and 22:00, with (b1) classroom behavior, (b43) exercise behavior, (b11) borrowing behavior, and (b12) self-study behavior. Overall, the student not only has good daily behaviors, but also has a more regular routine.

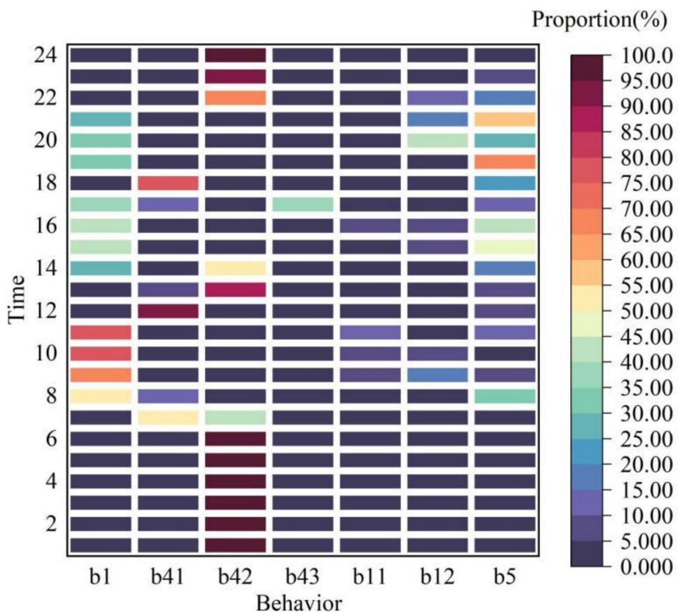


Figure 6. Analysis of Students' Daily Behavioral Habits

5.2. Detection of abnormal student behavior based on time series

5.2.1. Temporal characterization

Taking the middle of the first academic year from 2023 to 2024 as the experimental observation cycle (2023.10.16-2024.12.03), student visits in five campus buildings of college Y (c1) the second college building, (c2) the main library, (c3) the first cafeteria, (c4) the first teaching building, and (c5) the student dormitory building were selected as the subjects of observation. If the observation is carried out in a repetitive cycle of 7 days a week, there are 7 cycles as follows: W1 (10.16-10.22), W2 (10.23-10.29), W3 (10.30-11.05), W4 (11.06-11.12), W5 (11.13-11.19), W6 (11.20-11.26), and W7 (11.27-12.03), the cycle characteristics of student behavior in a total of seven campus buildings are plotted in Fig. 7. There are large differences in student attendance in different campus buildings due to their different functional attributes, and among the five buildings with high frequency of student entry and exit (peak value >20,000), there are a total of four buildings, namely, the (c2) main library, (c3) the first cafeteria, (c4) the first academic building, and the (c5) student dormitory building. There are four buildings, among which (c2) the main library and (c4) the first teaching building show obvious time change characteristics. Students need to attend classes in the middle of the week, so (c4) the first building has a higher frequency of visits in the middle of the week, (c2) the main library has a lower frequency of visits, and the weekend is a break time, so (c4) the first building has a frequency of visits <5000, while (c2) the main library has an increase in the frequency of visits.

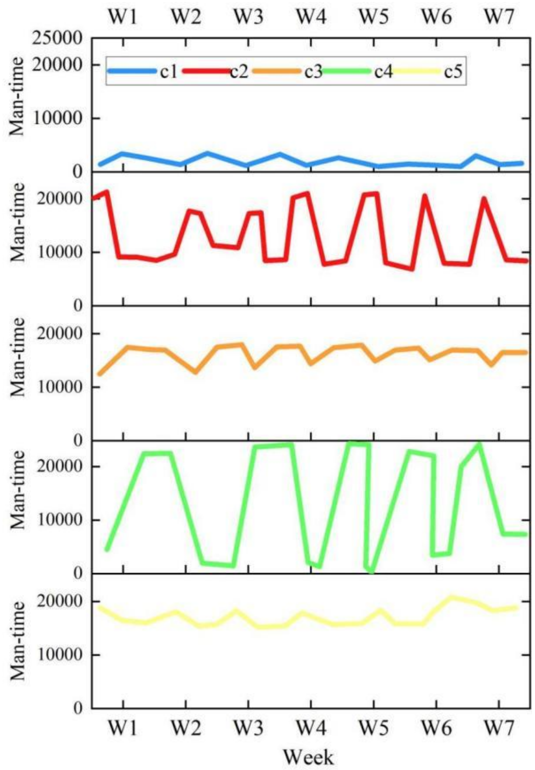


Figure 7. Periodic characteristic pattern

The pattern of time characteristics of students in the school building during the seven days of the week is shown in Figure 8. The pattern of students' behavioral activities during the weekday hours from Monday to Friday is similar, with frequent activities in the hours of 09:00-21:00, and peaks (>15.00%) in the hours of around 10:00 and 15:00-18:00. On weekends, there was less student activity behavior.

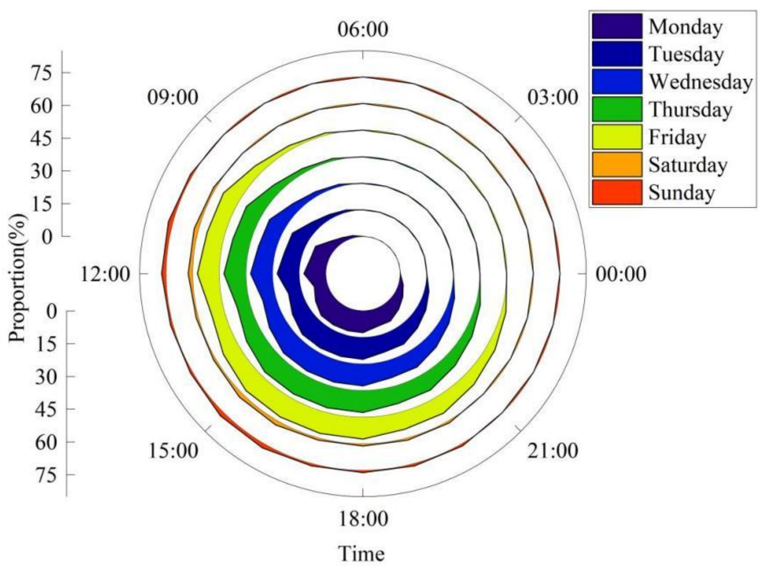
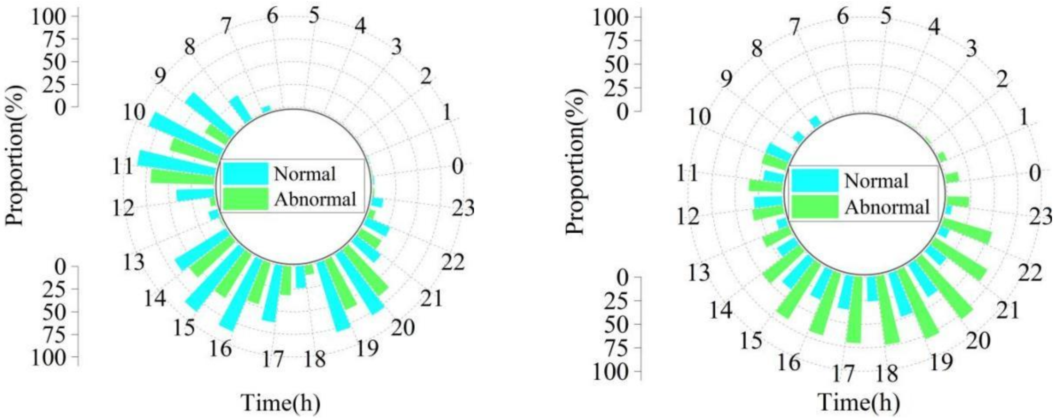


Figure 8. Time characteristic law

5.2.2. Detection and Analysis of Abnormal Student Behavior

Using the model proposed in this paper to analyze the behavioral distribution of students in college Y during the end time of the first academic year 2023~2024, the output is obtained in which 83.45% of the students belong to the normal behavioral group, and 16.55% of them belong to the abnormal behavioral group.

The comparison of the number of times that different student groups pay attention to the Civics learning resources in a day is shown in Fig. 9(a), and the comparison of the number of times that they pay attention to the entertainment resources in a day is shown in Fig. 9(b). In the time periods of 09:00~12:00 and 14:00~28:00, the proportion of the behavior of students in the normal behavior group who pay attention to the Civic and Political Learning Resources is 40.00% and above, and the maximum is up to 86.71%. In this time period, the proportion of students in the abnormal behavior group who pay attention to Civic and political learning resources is only 69.71% at the highest. On the contrary, in the concern behavior of entertainment resources, the proportion of abnormal behavior group students can reach up to 80.26%, and the proportion of normal behavior group students' concern behavior is only 47.84%, and the abnormal behavior group students still have a small amount of concern behavior of entertainment resources in the early morning from 00:00 to 03:00. This shows that students in the abnormal behavior group pay less attention to the Civic and Political Learning Resources and their work and rest time is more chaotic, while students in the normal behavior group not only pay more attention to the Civic and Political Learning Resources, but also have good behavioral habits.



(a) Learning resource (b) Entertainment resources

Figure 9. A comparison of the number of behaviors of the two groups in a day

Students' purpose behaviors have different intensities, and the intensity on different behaviors can indicate the degree of students' intention on the behavior, which is expressed by using energy consumption in this paper. Combined with the analysis of different groups of students' behavioral habits, this paper defines students' objects of concern in Civic Education as (X1) learning resources, (X2) governmental resources, (X3) vocational resources, (X4) health resources and (X5) entertainment resources. The difference between the before and after changes in energy expenditure of the two student groups in the five objects of concern is shown in Fig. 10. In the (X5) recreational resources of the change in energy expenditure of the concern behaviors, the students of the abnormal behavior group (40.25%) were much higher than the students of the normal behavior group (5.44%). On the other hand, on the change of energy consumption of attention behaviors of (X1) learning resources, students of normal behavior group (41.23%) are higher than students of abnormal behavior group (26.14%). Besides, in the three positive attention behaviors of (X2) governmental resources, (X3) vocational resources, and (X4) health resources, the change of energy consumption of the normal behavior group students is higher than that of the abnormal behavior group students.

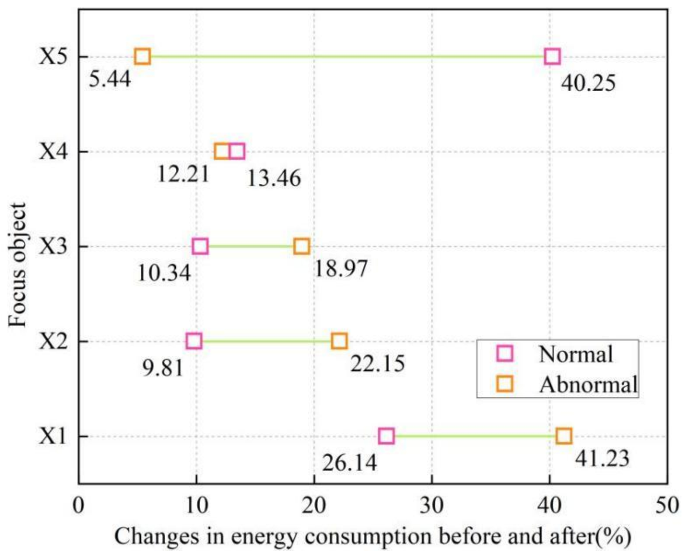


Figure 10. The comparison of energy consumption on the objects of concern

5.3. Trends in the Dynamics of Student Thought in Civic Education

Combined with the above analysis, it can be seen that most of the students in College Y are able to focus on Civics and Politics study on campus, effectively balancing the study and rest arrangements in their daily life. However, there is still a small number of students who indulge in entertainment, and these students do not have positive behaviors in Civics courses and related studies. That is to say, students who seriously participate in Civic and Political Education are able to differentiate between the primary and secondary tasks of campus life, and carry out reasonable planning and effective implementation. They are able to take advantage of the healthy concepts disseminated by the Civic and Political Education to make positive behavioral changes. Students with negative attitudes towards ideology and political education are more likely to show a lack of behavioral planning and action ability.

A brief analysis of the ideological dynamics of students in college Y reveals that the current thinking of college students is easily influenced by the environment. Therefore, in such an important period of ideological molding in college career, colleges and universities should raise the importance of ideological education and strengthen the strength of ideological education. For students who may have abnormalities, they should give timely intervention and guidance to help students shape the correct value concept of life. At the same time, it is also necessary to combine the development trend of the current era and students' thinking dynamics, respond to the development needs of students, update the content of the ideological education, innovative ideological education mode, and lead the students to a positive change in the dynamics of thought.

6. Conclusion

In this paper, from the perspective of students' daily behavior, based on the data of students' daily behavior in Y college, a campus daily behavior habit intensity calculation model is established. And combined with the time series characteristics of daily behaviors, it constructs a model for detecting abnormal student behaviors. The model was calculated to obtain that 83.45% of the students in college Y belong to normal behavior group and 16.55% of the students belong to abnormal behavior group. Among them, the behavioral intensity of the normal behavioral group is higher than that of the abnormal behavioral group in terms of Civics resources and related positive behaviors, and the intensity of attention to Civics learning resources is as high as 40.25%. This paper suggests that Y colleges and universities should combine the development needs and behavioral characteristics of students to set up more targeted Civics education courses to promote the healthy development of students' body and mind. Civic education assisted by the time-series-based student behavioral abnormality detection model can break through the limitations of the one-way output of traditional civic education, emphasize student development as the center, promote the precise and scientific development of civic education in colleges and universities, and cultivate high-quality talents in line with the needs of the times.

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