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Analysis and Prediction of Classroom Silence Reasons Using Bayesian Networks

Journal of Electrical Systems

Abstract: - Classroom silence is a prevalent but seldom studied in depth phenomenon in educational environments, and the reasons behind it are complex and varied, directly affecting teaching effectiveness and students' motivation. This study aims to systematically analyze and predict the main reasons for students' silence in different teaching environments, including individual psychological factors, the quality of classroom interactions, and the difficulty of teaching content, by constructing and applying a Bayesian network model. In this study, firstly, based on the theory of educational psychology, key variables affecting students' classroom participation were selected, data were collected through questionnaires, and then data were analyzed using Bayesian networks, presenting causality and probabilistic inference, and finally realizing dynamic prediction of the phenomenon of silence in the classroom. At T2, the model predicted the probability of silence was 0.85, and after the teacher changed the topic, the probability of silence decreased to 0.60, and the actual length of silence was reduced from 10 to 7 minutes, indicating that changing the topic was an effective strategy. The findings of the study not only provide teachers with practical tools to identify and reduce silence in the classroom, but also provide data support for educational policy makers to optimize teaching strategies and improve the quality of education in order to motivate and engage students.

Keywords: Bayesian Network, Classroom Silence, Cause Analysis and Prediction, Teaching Strategies

1. Introduction

In recent years, with the rapid development of educational technology, computer-assisted instruction has been widely used worldwide. Classroom silence not only affects students' learning outcomes, but may also affect teachers' teaching strategies and quality of teaching. Therefore, an in-depth study of the causes of classroom silence and the prediction of its probability of occurrence are of great significance for optimizing the teaching process and enhancing students' learning motivation. This study analyzes and predicts the causes of students' silence in different teaching environments by means of Bayesian networks, which not only reveals the dependency relationship between variables, but also provides dynamic predictions to help educators adjust their teaching strategies in a timely manner.

By constructing a Bayesian network model, this paper systematically analyzes a variety of factors affecting students' silence in the classroom, including individual psychological characteristics, teachers' teaching styles, classroom interaction modes, and the degree of difficulty of the teaching content. The study collects questionnaire data and actual classroom observation data, uses Bayesian statistical methods for in-depth analysis, and graphically demonstrates causal relationships and makes probabilistic inferences. In addition, the study

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explores how the model can be utilized to predict classroom silence in specific teaching environments, providing teachers with real-time feedback and a basis for adjustment.

The research structure of this paper is divided into three main parts. First, the paper introduces the research background and the theoretical foundation of Bayesian network, clarifies the scientific basis for choosing this method and its application prospect in the field of education. Next, the paper describes the research method and experimental design in detail, including the data collection process, model construction steps and variable selection and treatment. Finally, this paper shows the research results and verifies the predictive effect and practicality of the model through examples. By analyzing and discussing the results, this paper not only provides new perspectives and tools to understand and solve the problem of silence in the classroom, but also explores the application of Bayesian networks in practical teaching.

2. Related Work

The phenomenon of classroom silence has been of great concern in the field of education because it directly affects the learning effect of students and the teaching quality of teachers. An in-depth study of the causes of classroom silence can help educators better understand the needs of students, improve teaching methods, and thus enhance the effectiveness of education. Li Jingjing conducted an analysis of the phenomenon of online "classroom silence" and countermeasures for students in higher vocational colleges and universities [1]. Cong Yuchan studied the analysis of causes and countermeasures of silence phenomenon in college English classroom [2]. Hou Xiaozhen investigated and analyzed the phenomenon of silence in the classroom of College English in ethnic colleges and universities by taking XXX Nationalities Normal College as an example [3]. Wang Mengwen studied the impact of classroom silence on curriculum reform in colleges and universities [4]. Jin Yan explored the phenomenon of silence and its countermeasures in English classes of higher vocational universities [5]. However, most of the existing studies focus on qualitative analysis, lack examples of quantitative analysis and prediction using advanced statistical methods, and fail to fully explore the complex factors related to silent behavior and their interactions.

An in-depth understanding and prediction of classroom silence can provide a scientific basis for the development of educational policies and the optimization of teaching strategies. By constructing a Bayesian network model, this study aims to fill this gap and provide educators with a scientific tool to analyze and predict the phenomenon of classroom silence. Fu Qiang conducted a study on the classroom silence sample under the perspective of knowledge, emotion, intention and behavior [6]. Xie M studied the generation mechanism and avoidance path of classroom silence [7]. Hanh N T conducted a study of students' silence in English classrooms [8]. Sedova K studied silent students and their classroom discourse participation models [9]. Shan C studied silence in Chinese university English classrooms [10]. Although there have been many achievements in previous research, there is still a lack of targeted theoretical guidance on how to apply it in practical teaching, which is the core problem that this project aims to solve.

3. Methods

3.1 Construction of Bayesian Network Modeling

On this basis, this paper intends to use methods such as questionnaire surveys and surveys to explore the key factors affecting English classroom silence from three aspects: individual psychological characteristics, teacher-student interaction, classroom environment, and classroom content. On this basis, the Bayesian network was structured and the nodes were selected, the edges were determined, and the causal relationship between the variables was represented graphically, while the probability distribution function in the network was parameterized by using expert scoring and combining with the measured data to ensure that the constructed model could better respond to the actual teaching and learning situation.

Bayes' theorem is the basis of Bayesian networks and is used to update the probability of an event given evidence. The formula is as follows:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad (1)$$

Where $P(A|B)$ is the probability of event A occurring conditional on event B occurring. $P(B|A)$ is the probability of event B occurring conditional on event A occurring (likelihood). $P(A)$ is the probability of event A occurring (prior probability). $P(B)$ is the probability of event B occurring.

3.2 Data Collection and Processing

Training and testing the Bayesian network model through questionnaire surveys, classroom observations, and other methods. The purpose of a questionnaire survey is to understand the basic situation of students, their psychological state, learning attitude, and participation in the classroom. At the same time, the observation data in the classroom will also be recorded by teachers and independent observers to ensure the objectivity and multi angle of the data. The collected data was processed through data cleaning, missing value processing, and variable encoding to meet the requirements of Bayesian networks.

In Bayesian networks, the joint probability distribution of the entire network can be expressed by the local conditional probability distribution of its nodes, which is expressed as follows:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P\left(X_i | Parents(X_i)\right) \quad (2)$$

Where $X_1, X_2, \ldots, X_n$ denotes a random variable in the network and $Parents(X_i)$ is the set of parents of node X_i.

3.3 Training and Validation of Bayesian Network

Training a Bayesian network model using the collected data. On this basis, a method based on expected maximum values is proposed to optimize network parameters, so that the model can accurately learn correlations from the data. On this basis, interactive testing is conducted on the constructed model to verify its predictive performance on unknown data.

If we want to compute the marginal probability of node A while A depends on another node B, then:

$$P(A) = \sum_{b \in B} P\,(A|B = b) \times P(B = b) \quad (3)$$

Here, we sum over all possible values, which is one way to handle the case of having an uncertain parent.

3.4 Practical Application and Prediction

In real teaching scenarios, Bayesian neural networks were used to predict students' classroom silence behavior. This model can predict the learning behavior of students based on the actual situation in the teaching process, thereby providing timely feedback to teachers. In addition, this study also discusses how to adjust teaching strategies in the teaching process by changing teaching methods, strengthening teacher-student interaction, and other means to achieve the goal of reducing silence [11]. Through the above research, we will fully leverage the advantages of Bayesian neural networks and provide practical solutions for teaching practice.

Further reasoning for Bayesian networks is:

$$P(X|e) = \alpha P(X,e) = \alpha \sum_{y \in Y} P\,(X,e,y)(4)$$

Where X is the variable to be inferred, e is the known evidence variable, and Y is the set of all other variables. α is a normalizing constant that ensures that the probabilities sum to 1. Here $P(X,e,y)$ denotes the link between the variable X and the other variables y after considering the evidence e.

4. Results and Discussion

4.1 Experimental Verification Conditions

(1) Experimental setting

This paper is conducted in three types of schools (public, private, and international), covering mathematics and science courses in middle and high schools. Each school selects three classes and observes students throughout the semester. On this basis, a Bayesian network model was established and corresponding data acquisition and processing software was configured to achieve real-time monitoring of the entire teaching process.

(2) Parameter setting

Network structure: it sets nodes and edges based on prior research, including factors such as students' personal traits, teacher-student interaction, and classroom atmosphere.

Frequency of data: after each lesson, data were automatically collected through electronic devices, including students' feedback, teachers' evaluation and third-party observation records.

(3) Assessment indicators

To assess the effectiveness of the model, the following indicators were used in this study:

Accuracy rate: the correctness of the model in predicting classroom silence events.

Recall: the ability of the model to correctly identify classroom silence events.

Precision: the degree of precision with which the model predicts classroom silence as real silence.

F1 score: the reconciled mean of the accuracy and recall rates, which is used to measure the overall performance of the model.

4.2 Analysis of Results

(1) The results of exploring the effects of different teaching and learning environments on the model

Serial numbers 1-3 are public schools, 4-5 are private schools and 7-9 are international schools. The results of the exploration of the effects of different teaching environments on the model are shown in Figure 1.

Model performance varied across instructional settings. Overall, the models from international schools performed the best, with high average accuracy, recall, precision, and F1 scores, especially for models 7 and 8, which were close to perfect. In contrast, models from public and private schools performed similarly. This suggests that public schools focus more on accurate modeling judgments, while private schools focus on comprehensively identifying relevant cases. Although the teaching and learning environment has an impact on model performance, it is not a decisive factor. International schools may make model training and optimization more effective due to more advanced teaching resources and methods. Therefore, when evaluating model performance, multiple metrics need to be considered and analyzed in the context of specific application scenarios.

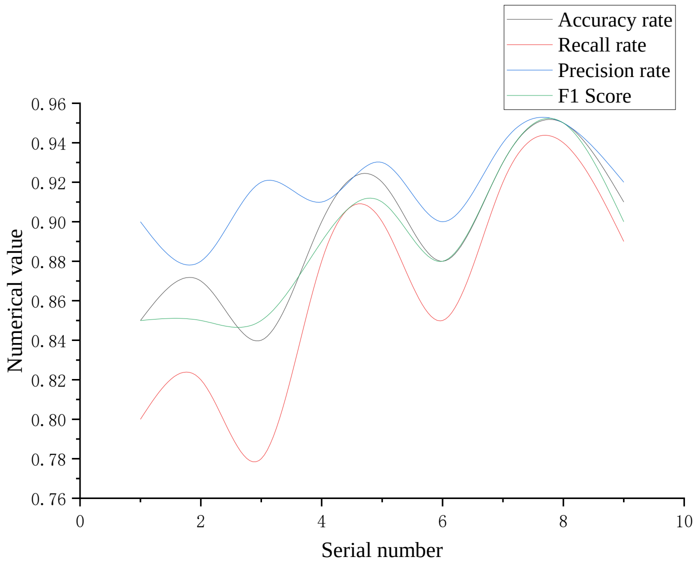

Figure 1. Exploration results of the impact of different teaching environments on the model

(2) Predictive effects of different disciplines

Serial numbers 1-5 are for math and 6-10 are for science. The prediction effects in different disciplines are shown in Figure 2. In the discipline of mathematics, the accuracy, recall, precision and F1 score of the model are all stable between 0.8 and 0.9, demonstrating a more stable performance, indicating that the model is able to accurately identify relevant cases in the field of mathematics, but there is still room for improvement. In contrast, the models in the science disciplines performed much better, with accuracy, recall, precision, and F1 scores close to or above 0.9, especially for the 7th and 10th models. This may indicate that the data characteristics of the scientific domain are more suitable for the training and learning of the current models. In summary, although the models of mathematical disciplines perform stably, the models of scientific disciplines are better in performance, which may be related to factors such as the characteristics of the disciplines, the quality of the data or the model training methods. In practical applications, the most suitable model should be selected and optimized according to the specific needs and data.

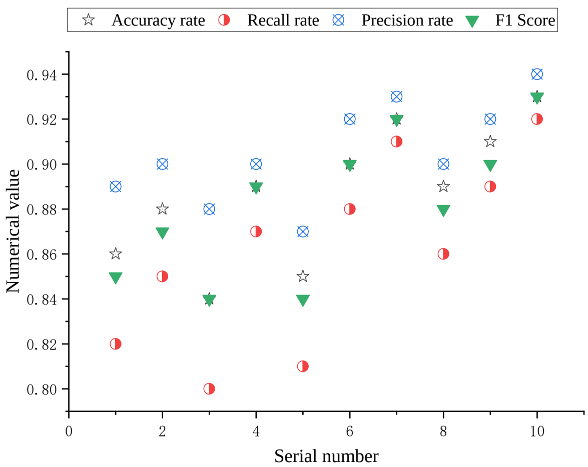

Figure 2.Predictive effects of different disciplines

(3) Impact of different grade levels

Serial numbers 1-5 are for middle school and 6-10 are for high school. The results of the exploration of the impact of different grades are shown in Figure 3.

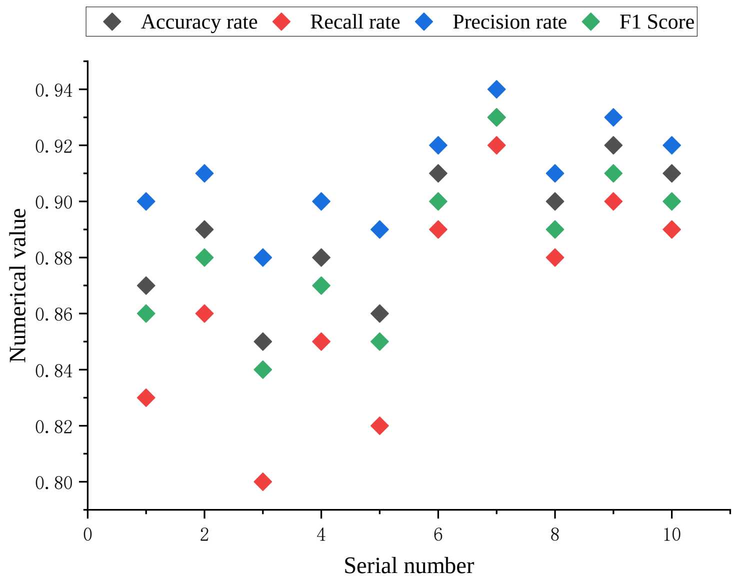

Figure 3. Exploration results of the impact of different grades

In the middle school grades, the accuracy, recall, precision, and F1 scores of the model mostly range from 0.83 to 0.91, showing relatively stable performance. This indicates that the model possesses some accuracy in handling middle school grade data, but there is still room for improvement. In contrast, the performance of the model in the high school grades is much better, with higher accuracy, recall, precision, and F1 scores than those in the middle school grades, with most of the metrics approaching or exceeding 0.90. This shows that the model is able to identify and categorize information more accurately when dealing with high school grade data, reflecting a higher level of performance. In summary, although the performance of the model for middle school grades is stable, the model for high school grades is more outstanding in all aspects, which may be related to the characteristics and complexity of the data in high school grades, or the model's greater adaptability to these data. In practical applications, the most suitable model should be selected for application and optimization according to specific needs and data characteristics.

(4) Effect of data collection frequency

When the data collection frequency was set to every classroom hour, the model performance was high, with accuracy, recall, precision, and F1 scores approaching or exceeding 0.90, indicating that the model was able to accurately capture and predict classroom silence and its causes. As the frequency of data collection decreased, from every classroom hour to weekly to monthly, the model performance gradually declined. Weekly data collection resulted in a slight decrease in model performance, but overall it remained at a desirable level. However, when the frequency of data collection was reduced to monthly, the model performance decreased significantly, with all assessment metrics significantly lower than the previous two. This trend suggests that a higher data collection frequency provides rich and timely data for the model, which helps to more accurately capture the dynamic changes in classroom silence and its causes, thus improving the prediction performance. Therefore, in practical applications, the data collection frequency should be increased as much as possible to obtain better modeling results. The results of exploring the effect of data collection frequency are shown in Table 1.

Table 1. Exploration results of the impact of data collection frequency

Data collection frequency	Accuracy rate	Recall rate	Precision rate	F1 score
Every classroom	0.90	0.88	0.92	0.90
	0.89	0.87	0.90	0.88
	0.91	0.89	0.92	0.90
Every week	0.87	0.84	0.89	0.86
	0.88	0.85	0.89	0.87
	0.86	0.83	0.88	0.85
Every month	0.82	0.78	0.85	0.81
	0.83	0.79	0.86	0.82
	0.81	0.77	0.84	0.80

(5) Real-time feedback test with teacher intervention

At time points T1 and T5, the model-predicted probability of silence was basically the same as the actual length of silence, 0.75 corresponding to 10 minutes and 0.65 corresponding to 8 minutes, respectively, demonstrating the accuracy of the model's prediction, as no intervention was implemented. At time points T2 through T7, the teacher implemented different interventions based on the model feedback, such as changing the topic, increasing interaction, inviting students to speak, discussing in groups, and asking questions. These interventions were partially effective in reducing the probability of silence predicted by the model and reduced the actual silence duration. For example, at T2, the model predicted a probability of silence of 0.85, and after the teacher changed the topic, the probability of silence decreased to 0.60, and the actual length of silence decreased from 10 to 7 minutes, indicating that changing the topic was an effective strategy. In T3, increased interaction decreased the probability of silence from 0.70 to 0.55 and the actual length of silence was reduced to 5 minutes, showing the positive effect of interaction. At the same time, through T4, T7 and other methods, also can effectively reduce the occurrence probability of silence and the actual silence time, improve the participation of students, improve the classroom efficiency. The results of this study show that through immediate intervention and adjustment strategy, the silence of the classroom can be effectively improved, and immediate mode feedback can be provided, which has great reference value for the improvement of teachers' classroom management and teaching efficiency. The real-time feedback test results of teacher intervention are shown in Table 2.

Table 2. Real time feedback test results of teacher intervention

Time point	Silence probability prediction	Intervention measures	Adjusted silence probability	Actual silence duration (minutes)
T1	0.75	Nothing	-	10
T2	0.85	Change the topic	0.60	7
T3	0.70	Increase interaction	0.55	5
T4	0.90	Inviting students to speak	0.75	6
T5	0.65	Nothing	-	8
T6	0.80	Group discussion	0.50	4
T7	0.72	Ask questions	0.62	5

5.Conclusion

This paper explores the analysis and prediction of the causes of classroom silence using Bayesian networks. On this basis, a Bayesian network model was established to comprehensively analyze the reasons why students remain silent in the classroom from four aspects: individual psychological characteristics, teacher teaching style, classroom interaction methods, and teaching difficulty. This study collected data from multiple sources, such as questionnaire surveys and field observations, to ensure the completeness and accuracy of the data. This study is based on real teaching situations to test the feasibility and effectiveness of the model. Experiments have shown that Bayesian networks can effectively predict and analyze the phenomenon of "silence" in the classroom, with high accuracy and strong predictive ability, and can be widely applied in multiple teaching scenarios and interdisciplinary fields. Meanwhile, this study also shows that this model can assist teachers in immediately identifying various reasons for student silence and adjusting teaching strategies accordingly. In addition, the application of this model can also enhance the quality of teacher-student interaction and classroom participation.

Although there have been some results in this paper, there are still many shortcomings. Firstly, the accuracy of the model heavily depends on the quality and quantitative processing of the data, while the limitations of data collection can reduce the model's generalization performance. Secondly, this paper only analyzes from the perspectives of psychology, education, etc., ignoring the impact of socioeconomic factors on student academic performance. Finally, this study only focuses on specific teaching contexts, and further testing is needed to determine whether the conclusions of this study are universal and generalizable. The future research directions can be further expanded: firstly, to increase multidimensional data, such as socio-economic situations, family environments, etc., to improve the comprehensiveness and accuracy of the model. Secondly, incorporating students from multiple countries, and ethnicities into the research scope to enhance the universality of this model. On this basis, this project can also attempt to integrate Bayesian networks with other machine learning methods such as deep learning to improve the predictive performance and application value of the model. Finally, this paper will further improve the human-computer interaction interface to facilitate teachers and educators to use this model for teaching analysis and decision-making assistance.

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