CHAPTER 1

INTRODUCTION

1.1 Introduction

In the current higher education teaching quality guarantee system, student evaluation of teaching has emerged as a vital constituent for gauging course quality, optimizing teaching content, and assessing the teaching efficacy of teachers. With the incessant escalation of the demand for high-quality education, the function of student evaluation of teaching is becoming increasingly salient. Traditional teaching evaluation modalities mainly rely on quantitative scales, conducting quantitative analyses by awarding scores to aspects such as teachers' attitudes, course content, learning difficulty, and knowledge acquisition. Nevertheless, such approaches have certain constraints in reflecting students' subjective experiences and emotional feedback. By contrast, the open-ended text comments in student evaluation of teaching furnish a considerable amount of unstructured data resources, capable of revealing students' subjective sentiments and emotional attitudes towards the teaching process, teaching methods, and teacher-student interaction in a more profound manner, and embodying their overall learning experiences and satisfaction. (Shaik, T., Tao, X., Dann, C., Xie, H., Li, Y., & Galligan, L. 2023)

However, due to the inherent attributes of unstructured text, such as complex semantics and uneven information density, traditional manual analysis methods encounter issues such as low efficiency and subjective outcomes when dealing with large-scale student reviews. (Wang, Y., Liu, X., Zhang, H., Wang, T., & Xu, J. 2019) Hence, resorting to intelligent technological means such as Natural Language Processing (NLP) and Machine Learning (ML) for systematic information extraction and emotion recognition from student evaluation texts has become an inevitable tendency in the intelligent development of teaching quality evaluation. (Kastrati, Z., Dalipi, F., Imran, A. S., Pireva Nuci, K., & Wani, M. A. 2021)

In recent years, sentiment analysis, as a significant research area within natural language processing, has been extensively employed in multiple domains such as public opinion surveillance, product assessment, and financial forecasting. This technology, by excavating the emotional characteristics in texts and integrating machine learning and deep learning models, can effectively identify sentiment tendencies, quantify attitude intensities, and even predict users' behavioral intentions. (Elnagar, A., Al-Debsi, R., & Einea, O. 2020) The introduction of sentiment analysis technology into the higher education evaluation and teaching system not only enables the automatic classification and interpretation of students' opinions but also, through the integration with structured quantitative data, facilitates the modeling of multi-modal teaching satisfaction, thereby offering more explicable decision support tools for the quality management of teaching in colleges and universities.

This study selects authentic student course evaluation data from an open education platform and comprehensively applies text mining and machine learning methods, with the aim of constructing an intelligent analysis framework that integrates sentiment recognition and satisfaction modeling. Through techniques such as emotion recognition, keyword extraction, and feature construction, an intelligent satisfaction prediction model applicable to the quality evaluation and management of teaching in colleges and universities is established. This research not only expands the application scenarios of sentiment analysis in the educational field at the practical level but also provides theoretical support and technical guarantees for colleges and universities to enhance the scientificity, objectivity, and personalized service capabilities of teaching evaluations.

1.2 Background of the Problem

With the rapid advancement of higher education, the contents of courses, teaching approaches, and the patterns of interaction between teachers and students have been increasingly diversified. How to assess teaching quality scientifically and impartially has emerged as a core topic in the teaching management and educational quality guarantee of colleges and universities. In the current higher education quality assessment system, student evaluation of teaching, serving as a crucial means for gauging teaching effectiveness, optimizing course design, and improving teaching methods employed by instructors, holds an irreplaceable position. Presently, the majority of colleges and universities mainly rely on structured questionnaires (such as Likert scales) to gather student feedback. Although this approach is conducive to quantification and statistical analysis, it has limitations when it comes to expressing students' genuine learning experiences and individualized opinions. (Li, Smith, & Brown, 2025) Structured scoring frequently only reflects certain dimensions of the evaluation and is deficient in capturing subjective experiences, course participation, and other profound contents, making it challenging to comprehensively present students' overall satisfaction and authentic feelings. (Quansah, F., Cobbinah, A., Asamoah-Gyimah, K., & Hagan Jr., J. E. 2024)

To compensate for the deficiencies of structured data, an increasing number of colleges and universities have begun to incorporate open-ended text evaluations into their teaching evaluation systems, encouraging students to express their viewpoints on courses and teachers through free writing. These unstructured text data are more information-rich compared to scoring data and can disclose specific feedback from students regarding teaching processes, course contents, and teaching styles. For instance, Deshpande et al. analyzed 5,000 pieces of student feedback in engineering courses and compared the effects of various machine learning models. They discovered that the random forest model performed optimally in terms of accuracy, precision, and the F1 score, attaining 91%, 94%, and 89% respectively. (Deshpande, K., Deshmukh, N., & Tanna, D. 2025). Additionally, Sohel et al. utilized the Coursera course review dataset and compared six machine learning techniques. They found that the logistic regression model performed best in the sentiment classification task, with an accuracy rate reaching 97.31%. (Sohel, M. S., & Mahmood, M. 2024) In the domain of deep learning, Baqach and Battou proposed a hybrid model integrating BERT, LSTM, and CNN for extracting emotions from student feedback, demonstrating superior performance compared to traditional methods. (Baqach, M., & Battou, A. 2024) Nevertheless, the high-dimensional, complex, and heterogeneous nature of text data poses considerable challenges to their automated processing and effective analysis.

Consequently, how to effectively employ advanced sentiment analysis and machine learning methods to automatically extract emotional tendencies, key themes, and core factors influencing teaching satisfaction from a vast amount of teaching evaluation texts, and construct high-precision and interpretable evaluation models, constitutes a key path for promoting the intelligent and precise development of teaching quality assessment in colleges and universities.

1.3 Statement of the Problem

The conventional teaching evaluation approaches primarily depend on structured scale scoring, emphasizing the quantitative assessment of aspects such as teachers' teaching attitudes, course content arrangements, learning difficulty, and knowledge acquisition. Despite the certain convenience these methods offer in data processing and result aggregation, they tend to fall short in comprehensively reflecting the "soft feedback" such as students' genuine learning experiences, individualized requirements, and emotional attitudes in practical applications.

(Heffernan, T. 2022) Hence, this research aims to expand the means of teaching evaluation in higher education institutions and explore an intelligent teaching feedback mechanism that is both generalizable and scalable, thereby providing theoretical support and practical pathways for the scientific and personalized development of educational evaluation.

1.4 Research Questions

(a) How can we intelligently predict students' satisfaction from the evaluation data?

(b) Which emotional and contextual features have an impact on satisfaction?

(c) Which machine learning model is the most efficacious for this task?

1.5 Objectives of the Research

(a) Carry out preprocessing and extract sentiment features by means of natural language processing techniques.

(b) Construct satisfaction prediction models through the utilization of machine learning (such as random forests and long short-term memory networks).

(c) Employ SHAP and LIME to identify the key influencing factors.

1.6 Scope of the Study

(a) Choose the student teaching evaluation data from public educational evaluation platforms (e.g., RateMyProfessor), encompassing structured data (quantitative indicators such as course ratings, teacher ratings, and course difficulty) and unstructured data (students' textual comments on courses and teachers).

(b) Eliminate missing values and outliers in the collected initial data to guarantee the quality and reliability of the data.

(c) Adopt conventional natural language processing approaches, including word segmentation, stop word removal, and word vector representations (e.g., TF-IDF), and carry out three-class sentiment analysis (positive, neutral, negative).

(d) For the modeling section, traditional machine learning algorithms such as random forest and deep learning methods like LSTM will be utilized to control computational resources.

(e) Incorporate interpretability tools such as SHAP and LIME to identify the key factors influencing satisfaction prediction, with an emphasis on explaining the top five major features.

1.7 Significance of the Research

This study, with natural language processing and machine learning as the core technologies, is intended to explore the application feasibility and practical efficacy of text mining methods in student course evaluation data, and thus holds crucial theoretical value and practical significance. On the one hand, the research broadens the interdisciplinary application boundaries of sentiment analysis techniques in the education domain, promotes the in-depth development of multi-source data fusion modeling approaches in educational data mining, and enriches the research perspectives of educational quality assessment. On the other hand, the outcomes of this research are anticipated to offer more scientific data support for university teaching management. Through constructing intelligent prediction models and precisely identifying the key factors influencing student satisfaction, it can contribute to the continuous optimization and personalized improvement of the teaching process and enhance the overall teaching quality and student learning experience.

1.8 Structure of the Thesis

The structure of this thesis consists of seven chapters, and each chapter adopts a systematic and elaborate approach to address the research questions based on the thesis title "Intelligent Prediction of University Course Satisfaction Using Text Mining and Machine Learning". The following is the specific format arrangement of each chapter.

Chapter 1: Introduction

This chapter will introduce the background and motivation of this research. Although traditional structured scoring is conducive to statistical analysis, it is difficult to comprehensively reflect the true feelings of students. Therefore, an increasing number of universities have adopted students' open-ended text comments. However, such unstructured data is difficult to analyze due to its complex language and diverse emotions. This study combines natural language processing and machine learning techniques to extract the emotions and key information from students' comments and build an intelligent model that can predict course satisfaction.

Chapter 2: Literature Review

This chapter will review the current research status of teaching satisfaction assessment in higher education and focus on the relevant applications of text mining, sentiment analysis, and machine learning in educational data analysis. The literature indicates that sentiment analysis technology has been widely used in scenarios such as e-commerce reviews and social media public opinions, but its application in educational evaluation scenarios is still relatively limited. In addition, this chapter will also review previous studies on course satisfaction modeling, including text feature extraction methods, the use of classification and regression models, and the practical application of explainability techniques (such as SHAP and LIME), providing theoretical support and technical references for this study.

Chapter 3: Methodology

This chapter introduces the methods and technical processes employed in the research. The data is sourced from the RateMyProfessor platform, and English evaluations of courses related to computer and data science are selected. Preprocessing encompasses cleaning structured data and denoising, tokenizing, and vectorizing text data. Sentiment analysis utilizes models such as Naive Bayes or LSTM to classify students' comments. Subsequently, combined with the scores and text features, Random Forest or LSTM is utilized to construct a satisfaction prediction model. Finally, SHAP and LIME are employed to explain the model results, facilitating the understanding of the key factors influencing the prediction.

Chapter 4: Exploratory Data Analysis

This chapter aims to conduct a comprehensive exploratory analysis of the dataset utilized to deeply understand the data characteristics, variable relationships, and the basic structure of text comments, laying the foundation for subsequent sentiment modeling and satisfaction prediction. Exploratory data analysis includes preliminary observations and visualization analysis of structured data (such as ratings, difficulty levels) and unstructured data (student comment texts), identifying potential data issues, patterns, and correlations.

Chapter 5: Experiments and Results Analysis

This chapter will present the experimental process and the evaluation results of model performance. Through experiments, the advantages and disadvantages of traditional machine learning models and deep learning models will be compared, and their predictive capabilities under different feature combinations will be analyzed. Additionally, this chapter will showcase the key influencing factors revealed by SHAP and LIME, further analyzing which teaching elements (such as teacher expression, course structure, interaction methods) have a significant impact on student satisfaction, providing actionable feedback for educational administrators.

Chapter 6: Discussion

This chapter will conduct an in-depth discussion of the experimental results and analyze their significance in higher education practice. Additionally, this chapter will explore the limitations of this study, such as the single data source, language limitations, and model generalization ability. Based on the research findings, it is proposed that universities should pay greater attention to the collection and utilization of unstructured student feedback in teaching management.

Chapter 7: Conclusion

This chapter will summarize the core achievements and academic contributions of this research. Through constructing a hybrid model integrating text mining and machine learning, the study achieved the automatic prediction of university course satisfaction and verified the effectiveness of unstructured text data in teaching evaluation. Simultaneously, the use of explainable AI technology enhanced the transparency of the model, providing data support for educational management decisions. Finally, this chapter will point out the potential directions for future research.

1.9 Summary

This research commences from the teaching evaluation mechanism within the higher education quality assurance system, concentrating on the structural limitations present in the current student evaluation of teaching approaches. Although the traditional evaluation method relying on quantitative questionnaires holds advantages in data collection and processing, it is conspicuously inadequate in reflecting the individualized learning experiences, emotional attitudes, and in-depth feedback of students. As universities gradually incorporate open-ended text comments, unstructured data has emerged as a significant supplementary resource for teaching quality assessment. Nevertheless, such data proves challenging to analyze effectively through conventional means due to its complex semantics and loose structure. Grounded on this, this study proposes an intelligent analysis framework centered on natural language processing and machine learning, with the aim of achieving automatic prediction and interpretation of student satisfaction. Focusing on the core query of "how to intelligently predict student satisfaction", the study poses three specific research inquiries: how to predict satisfaction intelligently from evaluation data, which emotional and situational characteristics impact satisfaction, and which machine learning model proves to be the most efficacious. The research objectives encompass: employing natural language processing techniques to extract emotional features, constructing a satisfaction prediction model integrating structured and unstructured data, and utilizing explainable methods to identify key influencing factors. The significance of this study lies in its innovative application of sentiment analysis and machine learning methods to higher education teaching evaluation, broadening the research perspective of educational data mining. Through the intelligent processing of unstructured student evaluation texts, the study enhances the scientificity and interpretability of satisfaction prediction. Simultaneously, the constructed explainable model offers a practical teaching feedback mechanism for universities, assisting in precisely improving teaching content and methods, and elevating the overall teaching quality and student learning experience.

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