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Using Explainable Machine Learning to Automatically Provide Feedback to Students Based on Data Analysis

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Abstract

Providing feedback to students is one of the most powerful practices that have enhanced education in the world today. Despite there being useful feedback provided by students' self-regulation and teachers' feedback provision, there is still a need for feedback that provides meaningful insights or actionable information about the reasons behind it, which is not provided by the said feedback. This paper explores how we can use explainable machine learning to compute data-driven feedback concerning students' academic performance and generate actionable recommendations which are beneficial for students and teachers. This method has been developed based on LMS (Learning Management System) data from a university course. The effectiveness of the proposed approach has been evaluated with the results demonstrating 90% accuracy.

Key words: Explainable Machine Learning, Learning Management System

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Introduction

The traditional educational paradigm often struggles to provide timely and personalized feedback to students, limiting their learning progression. The emergence of machine learning as a tool to analyze large datasets and extract patterns has opened up new possibilities for automating the feedback process. This paper examines the ways in which machine learning can enhance the quality and efficiency of feedback mechanisms in educational settings.In addition, this paper seeks to answer the following questions:

- How can explainable machine learning approaches be leveraged to provide effective and human-understandable reasoning behind conclusions about a student's academic performance?
- How can automatic data-driven feedback and actionable recommendations be derived?

Methodology

The proposed approach combines learning analytics techniques with explainable machine learning to provide automatic and intelligent feedback to students based on data analysis. The method includes the following steps:

1. Data collection: Gathering relevant data from a university course, such as student performance, behavior, and engagement. The student data is gathered from a learning management system and is used to train the artificial intelligence models. Cleaning and preprocessing of the data is done to ensure its quality and consistency.

2. Predictive modeling: Using machine learning algorithms to predict students' performance based on the collected data. The following predictive modeling techniques can be used:

   - Linear regression: This technique predicts a continuous outcome variable based on one or more independent variables.
   - Logistic regression: This technique predicts a binary outcome variable (e.g., yes/no, pass/fail) based on one or more independent variables.
   - Decision trees: This technique predicts an outcome variable by creating a tree-like structure that shows the relationship between the independent variables and the outcome variable.
   - Support vector machines: This technique predicts an outcome variable by finding the hyperplane that best separates the data into two classes.
   - Neural networks: This technique is a more complex technique that can learn non-linear relationships between the independent variables and the outcome variable.

3. Explainability: Providing transparency and human-understandable reasoning behind the predictions to help students understand their performance and identify areas for improvement. This can be done by developing methods to explain the root causes of the predictions. Such methods include:

   - Feature importance: This technique shows which features of the data are most important for the predictions of a model. This can be done by calculating the weight that each feature is given in the model, or by using a statistical test to measure the significance of each feature.

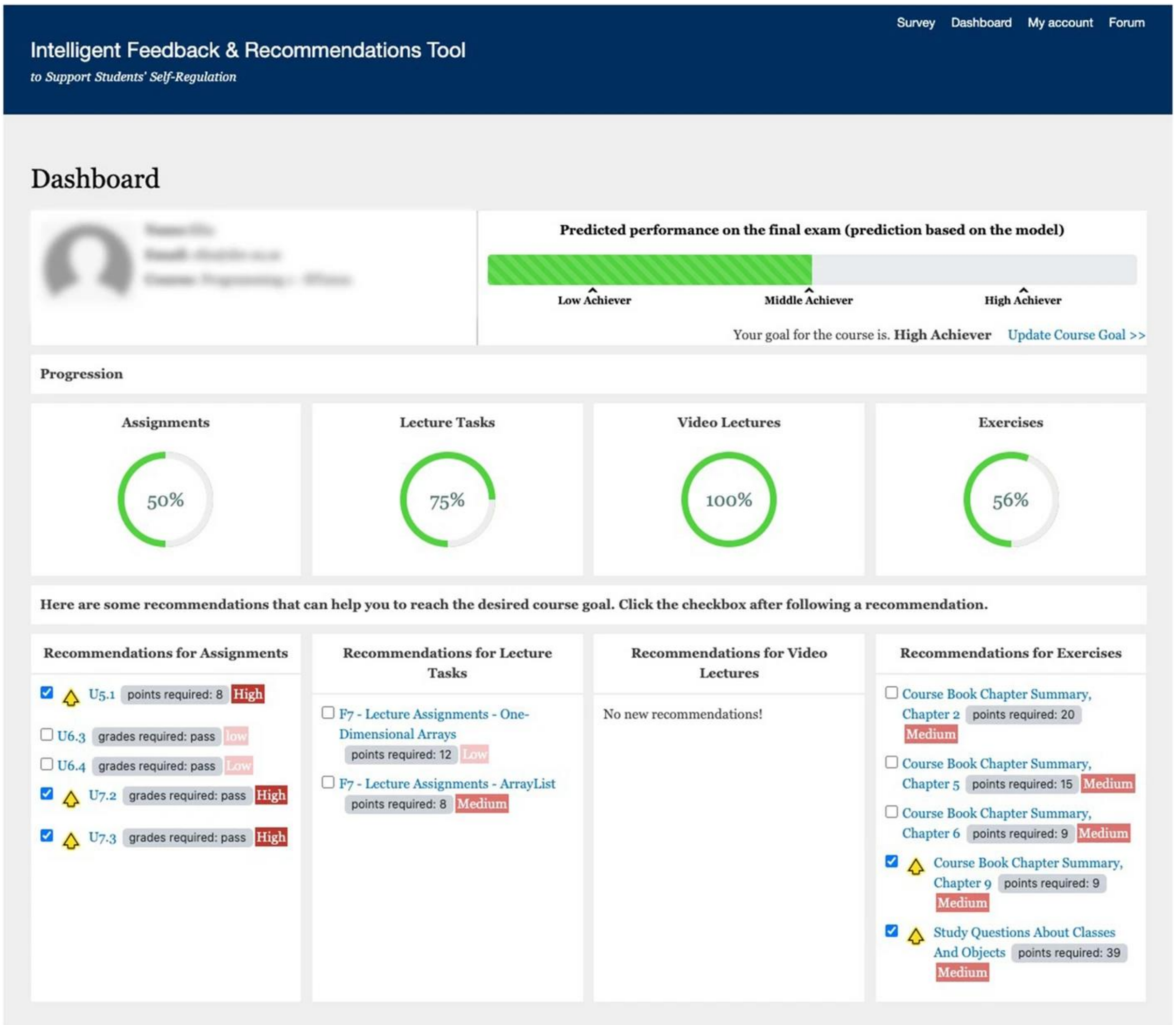
- SHAP values: This technique provides a more detailed explanation of the predictions of a model by showing how each feature contributes to the prediction. This can be done by calculating the Shapley values for each feature, which measure the contribution of each feature to the model's output.

- LIME(Local Interpretable Model-agnostic Explanations): This technique explains the predictions of a model by generating a local linear approximation of the model around the data point being explained. This can be done by creating a simplified model that only uses the features that are most important for the prediction.

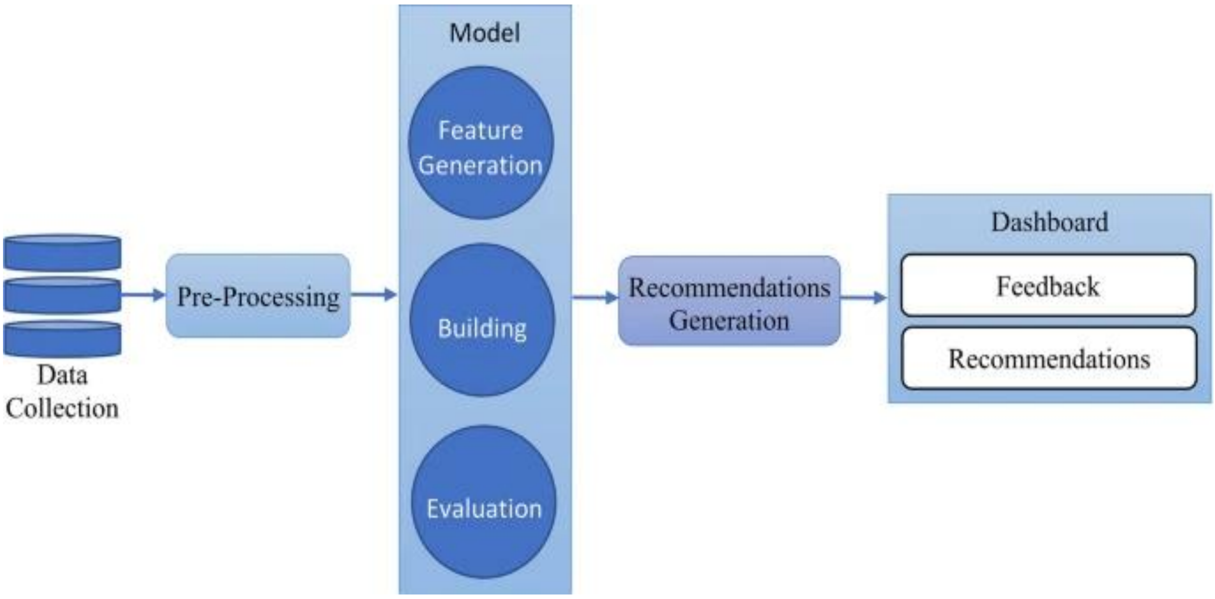
- Partial dependence plots: These plots show how the predictions of a model change as a single feature is varied. This can be done by plotting the predictions of the model for different values of the feature.

4. Actionable recommendations: Deriving data-driven recommendations for action based on the predictions and explanations. Providing personalized feedback that is tailored to each student's needs and performance.

5. Dashboard development: Creating a dashboard that presents the feedback and recommendations to students in an accessible and user-friendly manner. The dashboard can display information such as assignments covered or to be done and exercise recommendations which the student can attempt to improve scores. The following is a sample dashboard.



6. Testing and evaluation: Assessing the effectiveness and usability of the approach through testing and evaluation with students. Collecting feedback from students to improve the approach and the dashboard.



Benefits of using explainable machine learning for feedback

Machine learning algorithms bring several advantages to the feedback process in education. They can process a vast amount of student-generated data, enabling the identification of individual learning patterns and preferences. This personalization enhances the relevance and effectiveness of feedback, leading to improved learning outcomes. Additionally, automation reduces the burden on educators, allowing them to allocate more time to teaching and mentoring.

Challenges and considerations

Despite the potential benefits, integrating machine learning into educational feedback systems presents challenges. Ensuring the accuracy and fairness of feedback generated by algorithms is crucial. Biases within training data can lead to skewed results, disproportionately affecting certain groups of students. Striking a balance between automation and human oversight is essential to maintain the educational value of feedback.

Future directions

The field of automated feedback using machine learning is rapidly evolving. Future research could focus on refining algorithms to better understand context and nuance in students' work, thereby improving the quality of feedback. Additionally, investigating hybrid models that combine machine-generated feedback with human insights could leverage the strengths of both approaches.

Conclusion

This research paper presents an approach that utilizes explainable machine learning and learning analytics techniques to automatically provide feedback and actionable recommendations to students based on data analysis. By combining predictive modeling, explainability, and actionable recommendations, the approach aims to support students' self-regulation and improve their performance in courses. The developed dashboard serves as a platform for delivering the feedback and recommendations in a user-friendly manner. Further testing and evaluation are needed to assess the effectiveness and usability of the approach.

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