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ANALYZING GAME PLAY DATA FOR ACADEMIC PERFORMANCE IMPROVEMENT: A DECISION FOREST APPROACH

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Abstract: This study emphasizes the importance of comprehending the correlation between level_groups and questions prior to beginning the data training process. After completing stages 0 to 4, the game introduces a preliminary assessment checkpoint consisting of questions 1 to 3. The selection of training data entails matching data from specific level_groups to pertinent questions, thereby ensuring a tailored approach to model construction. Individual models were painstakingly developed for each query, and their accuracy was assessed; the average accuracy was 0.75585266561448. Due to the irregular distribution of 'correct' column values, the default 0.5 threshold for predicting classes may not optimize performance. To mitigate this, the F1 score, which is superior in evaluating imbalanced scenarios, was computed across multiple thresholds to identify the optimal threshold yielding the highest F1 score, about 0.63. This optimal threshold establishing a balance between precision and recall is crucial for accurate mapping of predicted probabilities to class labels 0 or 1. To effectively advance the discipline, future research should prioritize a clear research roadmap, the incorporation of emerging technologies, collaboration, and data quality.

INTRODUCTION

The game-based learning strategy is founded upon integrating science education with enjoyable and engaging activities. This pedagogical approach involves inviting students to actively interact with educational content inside a game-based framework, fostering an engaging and dynamic learning experience. Despite the growing utilization of game-based learning in many educational contexts, the accessibility of datasets suitable for applying data science and learning analytics concepts to enhance the efficacy of game-based learning remains constrained.

One of the challenges encountered pertains to the need for more utilization of knowledge tracing within game-based learning platforms to facilitate personalized learning advancement. Extensive research and development efforts have been dedicated to exploring and analyzing knowledge-tracking methods within online learning environments and intelligent tutoring systems. However, there needs to be more attention given to the investigation of knowledge within the realm of educational games.

Numerous investigations have been undertaken utilizing story game methodologies in education. Narrative games can serve as a potential avenue for implementing such a system. These games have the potential to offer players goal-oriented aspects that simulate real-world obstacles. Numerous studies have demonstrated the positive impact of instructional narrative games on students' cognitive development and their effectiveness in facilitating student assessment.

This study examined gamification's effect on student learning. The analysis of thirty interventions revealed that gamification positively influences motivation, engagement, and learning outcomes. The success of gamification was attributable to careful implementation and the alignment of game elements with predetermined learning objectives. (Bai, Hew, & Huang, 2020) The researchers stress the need for educators to incorporate gamification with care, considering the factors above, to maximize its benefits.

To improve the precision of forecasts regarding academic accomplishments, a thorough examination of psychological studies, the application of data mining techniques to extract valuable information, and the subsequent analysis of data findings were undertaken. Furthermore, the study prioritized the exploration of prospective avenues for enhancing performance prediction, with a specific emphasis on the potential beneficial impacts within the education domain (Ahmad, El-Affendi, Anwar, & Iqbal, 2022).

The anticipated outcome of this research is expected to yield a substantial impact by providing game producers with the means to enhance the caliber of instructional games. Furthermore, the competition is anticipated to contribute to educators' assistance by providing valuable dashboards and analytical tools. The progress above is expected to lead to a broader surge in the endorsement of game-based learning platforms as a pioneering educational instrument.

RESEARCH METHODS

The analysis of tabular data holds great significance within data analytics and machine learning, potentially bringing about a transformative impact on decision-making processes in several sectors, such as education, finance, and healthcare. TensorFlow Decision Forests is a notable tool in predictive modeling due to its notable efficiency and adaptability.

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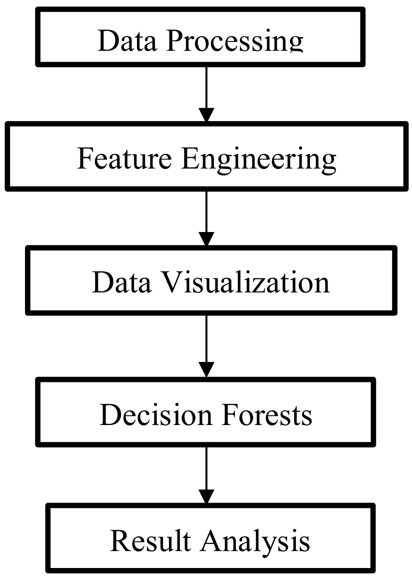
The present study systematically investigates the utilization of TensorFlow Decision Forests to augment the analysis of tabular data. The purpose of the given stages is to offer a comprehensive guide to efficiently utilizing this powerful machine-learning technology for researchers, practitioners, and hobbyists. From the careful processing of data through the evaluation of model performance, each stage is crucial in enabling a comprehensive understanding of both the method and the field of tabular data analysis.

In the following sections, we will use a methodical technique to traverse these pivotal stages. The process will commence with preparing and analyzing the dataset, followed by implementing TensorFlow Decision Forests. Subsequently, the model's performance will be evaluated, and useful insights will be extracted. The structure of each level is carefully planned to improve understanding and skill, finally enabling the proficient use of TensorFlow Decision Forests for the analysis of tabular data. Let us commence on this educational expedition to augment our capacity to extract practical observations from tabular data and further progress the field of data-driven decision-making.



Picture 1. Research Methods

RESULTS AND DISCUSSION

Before commencing the data training procedure, it is imperative to comprehend the correlation between level_groups and questions comprehensively. Within the framework of this game, the preliminary quiz checkpoint, encompassing questions 1 to 3, becomes available for access after the successful completion of stages 0 to 4. As a result, data obtained from level_group 0-4 will be utilized to train questions 1 to 3. Similarly, the data obtained from level_group 5-12 will be utilized for training questions that encompass a range from 4 to 13. Similarly, data derived from level_group 13-22 will be employed for training questions 14 to 18. The strategic alignment in question guarantees that the training data is suitably matched with the specific questions and evolution of the game.

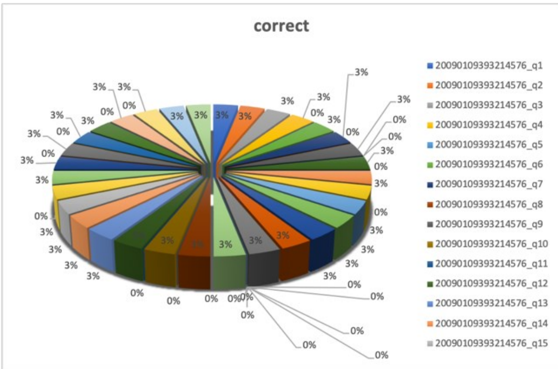
The outcomes of our model training process. Specifically, we've designed a unique model for each query. Our current objective is to evaluate the accuracy of each model separately and aggregate their accuracy by combining them. We have chosen accuracy as the principal performance metric for this evaluation.

Question	Accuracy
1	0.7286
2	0.9743
3	0.9351
4	0.7957
5	0.6319
6	0.7885
7	0.7456
8	0.6355
9	0.7632
10	0.6109
11	0.6522
12	0.8695
13	0.7218
14	0.7337
15	0.6166
16	0.7486
17	0.7027
18	0.9510
Average accuracy	0.755852606561448

Table 1. Accuracy of each question

Using the default 0.5 threshold for predicting classes 0 or 1 may lead to suboptimal performance due to the unequal distribution of 'correct' column values. In instances of this nature, it is imperative to compute the F1 score within a designated range of thresholds to optimize performance. This study aims to determine the optimal threshold, commonly known as the threshold that produces the highest F1 score. Following this, we will employ the optimal threshold to appropriately assign expected probabilities to their corresponding class labels of 0 or 1. The use of the F1 score above accuracy is justified by its efficacy in evaluating scenarios that exhibit class imbalance.

Based on the results, the optimal threshold for achieving the highest F1 score is approximately 0.63, resulting in an F1 score of approximately 0.6738. This threshold enables an optimal balance between precision and recall, making it a crucial factor in accurately translating predicted probabilities to class labels 0 or 1, particularly in cases of imbalanced data.



Picture 2. Predictions derived from the test data for each level group and level

CONCLUSION

Before engaging in data training, it is essential to comprehend the relationship between level_groups and queries. In this game, you can access the first examination checkpoint (questions 1 to 3) after completing levels 0 to 4. Consequently, level_group 0-4 data are used to educate questions 1 to 3. This strategy is consistent with data from level_group 5-12 training questions 4 to 13 and data from level_group 13-22 training questions 14 to 18. This guarantees a precise correlation between training data and game progression questions. Our procedure for training models required the creation of a unique model for each question. The objective was to evaluate and aggregate the accuracy of individual models. We selected precision as the primary performance metric for this assessment.

Due to the inconsistent distribution of 'correct' columns, it is possible that using the default 0.5 threshold for predicting classes 0 or 1 will not produce optimal results. To address this issue, we calculated the F1 score across a range of thresholds to optimize performance. Our study aimed to identify the optimal threshold that yields the greatest F1 score. This threshold allowed for the precise designation of predicted probabilities to respective class labels of 0 or 1. The choice of F1 score over accuracy was substantiated by its efficacy in evaluating class scenarios with an imbalance.

The optimal threshold, yielding the greatest F1 score, was close to 0.63. This threshold found a balance between precision and recall, essential for precisely mapping predicted probabilities to class labels 0 or 1, particularly in scenarios involving imbalanced data.

Future research endeavors should prioritize simplicity. In the first place, you must outline your research objectives and ensure that they are crystal clear. Accept emerging technologies and tools in your discipline, allowing them to shape and improve your research. Collaboration is a potent instrument; join forces with other researchers to gain access to various perspectives and skills. Always prioritize data quality and diversity; solid data is the foundation of excellent research.

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