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Analyzing Learning Mode Preferences Using Machine Learning

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I. INTRODUCTION

Education has been greatly transformed with modern technology, giving rise to remote education along with traditional education system in schools and colleges. The debate is always on if online learning is equivalent to offline learning since learning enhances with parameters like engagement, interaction, hands-on practices, and also the adaptability of the students. This paper reviews these factors based on the student's answers to a questionnaire that inquires about the satisfaction level with online education, the engagement in online lectures, asking questions free from hesitation, practical-learning opportunities, and skills improvement. Machine Learning Classification is useful for education as it can predict if the student will pass or fail and try to classify Education Learning Outcomes and hence personalize the lesson to be taken by the student - whether to skip a few chapters or to repeat a chapter.In this paper, we apply machine learning on student's responses to predict knowledge gain, using Logistic Regression, one of most popular classification techniques. Logistic Regression is good in itself in predicting two outcomes — whether a student's learning gain is high or low. The model's predicting how well learning happened based on the quantitative form responses and giving the probabilities which help in making the decision. This study is focused on comparing online to offline learning through using machine learning to assess knowledge acquisition, which can help teachers in making data-driven decisions about the way they teach.

II. DATA COLLECTION

This study was conducted through structured survey data collected from adult learners focusing on the various factors affecting their learning experience. Both online and offline learners were included in the questionnaire to obtain a balanced dataset. They were asked about their learning preferences, how engaged they felt, how comfortable they were asking questions, whether there were any opportunities for practical learning, the real-world applicability of content, and their level ofoverall satisfaction.
The survey asked both online and offline learners:
What format do you want for class instruction?
A) Online
B) Offline
How satisfied are you from the quality of online/offline education?
How engaging do you find online/offline lectures?
How comfortable are you asking questions in the setup of an online/offline class?
Yet how much practical experience do online/offline classes provide?

Do online/offline classes provide adequate coverage for real-world applications?
Would your selection on online/offline classes be as such that if they were optional, you'd still prefer them?
Is it hard to search for online/offline classes for you?
Are classes, online/offline, effective in honing your skills?
How would you rate your overall satisfaction with this online/offline class?
The survey was conducted in both an online form as well as physical copies in order to reach a wide audience.
Data Pre-processing the responses were checked for completeness and correctness.

III. DATA PREPROCESSING

The raw data collected needed to be cleaned and prepared for analysis, which involved several pre-processing steps. Responses that were incomplete or not consistent with the derivation approach were initially removed or filled in with values based on logic. Before beginning any training machine learning models, categorical variables like how user learn and satisfaction level were converted to machine readable formats using label encoding.

To normalize the response scales, application of standardization was performed. The "Knowledge Gain" Variable was divided into binary values, high or low, based on the median response. To normalize our numerical values we used StandardScaler, so that variables with wider ranges of numerical values will not dominate other variables in the performed training of the model.
The first step is pre-processing and is important for preparing the data for analysis. The following procedures were done to clean and organize the data:
Handling Missing Values Empty Columns — Removed Missing Values — removed or Imputed Based on Logical Assumptions to maintain consistency missing categorical values were replaced by the mode of respective column.
Combining Columns: This involves merging data from multiple sources, usually online and offline learning responses, into a structured dataset to enable comparison and analysis.
Encoding Categorical Data: For most ML/dl algorithms, we require numbers as an input — for writing categorical responses (like satisfaction levels, engagement levels, etc.) into numbers, we use label encoding.
Standardizing Column Names: Generic column names were standardised by trimming additional spaces and cleaning up feature names.
Feature scaling: We performed standard scaling (standardScaler) to normalize the numerical variables so that all features contribute equally to the model.
Data Splitting: Dataset was divided into training and testing sets using 80-20 split with stratified sampling for fair evaluation in which class proportions were maintained.
The reasoning for these pre-processing steps was to structure the dataset into a format that is ready for machine learning analysis.

IV. ANALYSIS

Exploratory data analysis (EDA) to find patterns and trends in the dataset. Histograms, bar charts, and count plots were created to check distribution of knowledge gain against different learning strategies.
Unit analysis: The relationship between independent variables (engagement levels, comfort in asking questions, and practical learning opportunities) with the target variable (the target variable was “Knowledge Gain”) was analysed.
Lectures: High Engagement → Knowledge Gain
Ask Questions: There was a greater tendency of knowledge gains for learners who were comfortable asking questions.
Practical Learning: Sufficient practical learning opportunities land up better learning outcomes based on the respondent feedback.
Evidence: The perception of how well classes prepared students for real-world applications significantly influenced knowledge gain.
We examine different types of satisfaction in the next section.

V. CONCLUSION

This study identifies some of the most important elements affecting states of knowledge and learning, whether expressed offline or online, during an era when incorporation of information depends on whether the reader is connected to the host cyberspace. Engagement, comfort in interaction, practical real-world use are key parts of effective education — this can be seen in the results. Although online learning gives the advantage of flexibility; it needs enhancements in engagement and practical training. Offline classes is the old-school method which, even if it is organized, lacks to bridge the gap through technology to make it available for everyone. Such insights can help educators fine-tune their approaches to pedagogy, ultimately enhancing student learning processes in both modes.

OUTPUT DIAGRAM