

# Technical Note: AI-Powered Adaptive Math Learning System

## 1. Objective

This project demonstrates an AI-powered adaptive math learning prototype that dynamically adjusts puzzle difficulty based on learner performance. It combines rule-based heuristics with a machine learning (ML) model to create a hybrid adaptive system that personalizes learning for children aged 5–10.

## 2. System Architecture and Flow

The system is modular, comprising the following key components:

- **Puzzle Generator:** Dynamically creates math problems (addition, subtraction, multiplication, division) based on current difficulty.
- **Performance Tracker:** Records accuracy, correctness, and response time for each puzzle.
- **Adaptive Engine:** Decides next difficulty using both rule-based thresholds and ML predictions.
- **ML Engine:** Loads a pre-trained scikit-learn model to predict whether to increase, maintain, or decrease difficulty.
- **Progress Summary:** Displays end-of-session accuracy, average time, and recommended next level.

\*\*Flow Summary:\*\*

1. User starts and selects initial difficulty.
2. A math problem is generated and solved.
3. Performance is logged (correctness, response time).
4. The adaptive engine analyzes performance to adjust the next difficulty level.
5. Session summary is shown at the end.

## 3. Adaptive Logic (Hybrid System)

The adaptive decision is made using two complementary approaches:

- **Rule-Based Logic:** Uses accuracy and average response time over a sliding window of recent attempts. Promotes the user if accuracy  $\geq 80\%$  and response time is below threshold; demotes if accuracy  $\leq 50\%$  or response time exceeds threshold.
- **ML-Based Logic:** A Decision Tree model trained on simulated learning data predicts one of  $\{-1, 0, +1\}$  actions (Demote, Stay, Promote) using features such as accuracy, average time, correct streak, and current level.
- **Fallback Mechanism:** If the ML model is unavailable or fails, the system automatically falls back to the rule-based decision.

## 4. Metrics Tracked

- Accuracy (% of correct answers in the recent window)
  - Average response time per question
  - Correct answer streak
  - Difficulty transition history
- These metrics drive the adaptive adjustments and are logged for performance visualization and analytics.

## 5. Design Reasoning

The hybrid approach balances simplicity and scalability. The rule-based logic ensures reliability without requiring large datasets, while the ML model enables data-driven personalization as real learner data becomes available. This combination provides robust, interpretable, and extensible adaptation for diverse learning behaviors.

## 6. Summary

This adaptive learning system demonstrates how AI and rule-based logic can work together to create personalized learning experiences. The hybrid architecture ensures adaptability even with limited data, while maintaining clarity and modularity suitable for educational AI applications.