

Project Title: Math Adventures – AI-Powered Adaptive Learning Prototype

Introduction

This project aims to design a simple adaptive learning system that helps children aged 5 to 10 practice basic mathematical operations such as addition, subtraction, multiplication, and division. The system dynamically adjusts the difficulty of math problems based on the learner's performance, ensuring an optimal balance between challenge and skill.

System Architecture and Flow

The system consists of four main components. The user interface collects the student's name, displays math puzzles, and shows results. The puzzle generator creates math problems dynamically based on the current difficulty level. The performance tracker records whether each answer is correct and measures the time taken to respond. The adaptive engine analyzes recent performance and decides the difficulty of the next puzzle.

The flow of the system starts with the learner selecting a difficulty level. A math puzzle is generated and displayed. The learner submits an answer, after which correctness and response time are recorded. The adaptive engine then evaluates performance and adjusts the difficulty before generating the next puzzle. At the end of the session, a performance summary is displayed.

Adaptive Logic Used

The system uses rule-based adaptive logic. A rolling window of the last three answers is evaluated to determine learner performance. If the learner achieves high accuracy, the difficulty is increased. If the learner struggles, the difficulty is reduced. If performance is stable, the difficulty remains unchanged. This approach prevents sudden or unstable difficulty changes.

Key Metrics Tracked

The system tracks answer correctness to calculate accuracy and response time to assess learner confidence and speed. Recent accuracy, calculated using the last three responses, is the primary metric used to control difficulty adaptation.

How Metrics Influence Difficulty

High accuracy over recent questions leads to an increase in difficulty. Low accuracy results in a decrease in difficulty. Moderate accuracy maintains the current level. Response time provides additional insight into learner comfort, though difficulty decisions are mainly driven by correctness.

Reason for Choosing This Approach

Rule-based adaptation was chosen because it is simple, explainable, and does not require training data. It allows clear visibility into how difficulty decisions are made, which is important in educational systems. This approach is ideal for a prototype and aligns well with the assignment's focus on adaptive logic rather than model complexity.

Conclusion

This adaptive learning prototype demonstrates how AI-inspired logic can personalize learning experiences. By dynamically adjusting difficulty based on learner performance, the system helps maintain engagement and supports effective skill development in basic mathematics.