Part 1: Short Answer Questions (30 points)

1. Problem Definition (6 points)

Define a hypothetical AI problem:

Predicting individualized learning pathways and identifying optimal intervention strategies for Special Needs Learners (SNLs) struggling with foundational literacy skills in Kenyan primary schools.

Objectives:

1. To improve literacy skill acquisition for SNLs by **20%** within one academic year.
2. To reduce the time teachers, spend on creating individualized learning plans for SNLs by **30%**.
3. To increase learner engagement and reduce frustration for SNLs by providing personalized and adaptive content.

Stakeholders:

1. Special Needs Education (SNE) Teachers
2. Learners with Special Needs and their Parents/Guardians

Key Performance Indicator (KPI):

Average improvement in standardized literacy assessment scores for SNLs after using the AI tutor for a defined period (e.g., 6 months).

2. Data Collection & Preprocessing (8 points)

Data Sources:

Anonymized learner performance data: Includes assessment scores (diagnostic, formative, summative), progress tracking from existing learning systems (if any), and interaction logs with digital learning tools.

Curriculum content and SNE-specific learning materials: Digitized textbooks, exercises, teaching aids, and expert-annotated content aligned with the Kenyan SNE curriculum.

Potential Bias:

Selection Bias: If data is primarily collected from urban schools or schools with better existing technological infrastructure, the AI model may not generalize well to SNLs in rural or underserved areas with different learning environments or types of special needs.

Preprocessing Steps:

Handling Missing Data: Impute missing assessment scores or interaction logs using statistical methods (e.g., mean imputation for numerical data) or remove incomplete records if data volume allows.

Normalization/Scaling: Scale numerical data (e.g., assessment scores, time spent on tasks) to a common range (e.g., 0-1) to prevent features with larger values from dominating model training.

Categorical Encoding: Convert categorical features (e.g., type of special need, content topic, type of error made) into numerical representations using one-hot encoding or label encoding.

3. Model Development (8 points)

Choose a model and justify your choice:

Model: Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) units**.**

Justification: LSTMs are excellent for sequence data, which is crucial for tracking a learner's progress over time. They can capture long-term dependencies in learning patterns (e.g., how understanding of one concept impacts another over weeks/months) and adapt to individual learning trajectories, which is essential for personalized learning in SNE.

Data Split:

Training Set (70%): Used to train the model, allowing it to learn patterns from the vast majority of the data.

Validation Set (15%): Used during model development to tune hyperparameters and prevent overfitting. The model's performance on this set guides adjustments.

Test Set (15%): A completely unseen dataset used *only once* at the end to evaluate the final model's generalization ability to new, real-world data. This ensures an unbiased assessment of performance.

Hyperparameters to tune and why:

Learning Rate: Determines the step size at each iteration while moving toward a minimum of a loss function. Tuning it prevents the model from converging too slowly or overshooting the optimal solution.

Number of LSTM Layers/Units: Controls the model's complexity and capacity to learn intricate patterns. Tuning helps balance model performance with computational resources, especially for deployment on potentially limited hardware in Kenya.

4. Evaluation & Deployment (8 points)

Evaluation Metrics and Relevance:

- **Root Mean Squared Error (RMSE):** Relevant for predicting continuous values (e.g., future assessment scores or skill mastery levels). Lower RMSE indicates more accurate predictions of learning outcomes.
- **Precision and Recall (for classification tasks within the tutor, e.g., identifying specific learning difficulties):**

Precision: Measures how many of the identified learning difficulties are actually correct (minimizes false positives – avoids misdiagnosing a non-existent issue).

Recall: Measures how many of the actual learning difficulties were correctly identified (minimizes false negatives – avoids missing a real issue). Both are critical to ensure the tutor accurately identifies and addresses specific SNL challenges without overburdening the learner or teacher.

Concept Drift and Monitoring:

Concept Drift: Occurs when the relationship between input data and the target variable changes over time. In this context, it could mean that SNLs' learning patterns evolve, the curriculum changes, or teaching methodologies shift, making the existing AI model's predictions less accurate.

Monitoring post-deployment:

Performance Monitoring: Continuously track the model's performance on new incoming data (e.g., regularly check RMSE on new assessment data, or precision/recall for new difficulty identifications). Significant drops indicate potential drift.

Feedback Loop: Implement a system for SNE teachers and specialists to provide direct feedback on the AI tutor's recommendations and identified learning pathways. Discrepancies between AI recommendations and expert opinion could signal drift.

Technical Challenge during Deployment:

Limited and Inconsistent Internet Connectivity:
Deploying the AI tutor in rural Kenyan schools often means dealing with unreliable or non-existent internet access. This impacts real-time data synchronization for model updates, cloud-based inference, and the delivery of rich, interactive content. Solutions require prioritizing offline capabilities, edge computing (running models directly on devices), and efficient data compression for periodic syncing.

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