Question 1:

Introduction
This report explores the phenomenon of hallucinations in two Large Language Models (LLMs)—LLAMA 3.1 and OpenHathi—and evaluates methods to mitigate these issues using Retrieval-Augmented Generation (RAG). The task involves identifying and analyzing specific examples of hallucinations and applying RAG techniques to minimize or solve these issues.

Task 1: Identifying Hallucinations

LLAMA 3.1
Self-Consistency Test Results:

1. **Question Set 1:**
    - Question 1: "What is the slope of the line 2y=3x+1?"
        - Response: "The slope of the line is 1.5."
    - Question 2: "What is the slope of the line y=1.5x+1?"
        - Response: "The slope of the line is 1.5."
    - **Analysis**: The model provides consistent responses for both questions, correctly identifying the slope as 1.5.
2. **Question Set 2:**
    - Question 1: "What is the value of 5+(1+3)×4?"
        - Response: "The value is 20."
    - Question 2: "What is the value of 5x4+1?"
        - Response: "The value is 21."
    - **Analysis**: The model provides inconsistent results, with an incorrect calculation in the second response, leading to a potential hallucination in the context of arithmetic operations.

OpenHathi
Self-Consistency Test Results:

1. **Question Set 1:**
    - Question 1: "What is the slope of the line 2y=3x-1?"
        - Response: "The slope of the line 2y=3x-1 is -1."
        - Analysis: The model incorrectly identifies the slope as -1, which contradicts the expected slope value of 1.5.
    - Question 2: "What is the slope of the line y=1.5x-0.5?"

        - Response: "The slope of the line y=1.5x-0.5 is 1.5."
        - **Analysis**: The model provides the correct response here, identifying the slope as 1.5. No hallucinations detected.

2. **Question Set 2:**

    - Question 1: "What is 5 + 3?"
        - Response: "The result is 8."
    - Question 2: "What is 5 - (-3)?"
        - Response: "The result is 2."
    - **Analysis**: Hallucinations detected.

3. **Question Set 3:**

    - Question 1: "What is the value of (1 + 3) × 4?"
        - Response: "The value is 13."
    - Question 2: "What is the value of 4 x 4?"
        - Response: "The value is 16."
    - **Analysis**: Hallucinations detected.

Task 2: Applying Retrieval-Augmented Generation (RAG) Techniques
Objective: To minimize or solve hallucinations by incorporating external knowledge through RAG techniques.

RAG Implementation:

1. **Setup:**

    - Models Used: facebook/rag-token-base for both retrieval and generation.
    - Dataset: Randomly generated documents on various topics (e.g., mathematics, history, science) saved in "random_documents.txt".

2. **Process:**

    - **Retrieval**: The retriever fetches relevant documents based on input queries.
    - **Generation**: The model generates responses using the retrieved documents as context.

Example Questions and Responses:

1. **Question**: "What is the slope of the line 2y=3x-1?"

    - **RAG Response**: "The slope of the line is 1.5."
    - **Analysis**: The RAG-enhanced response aligns with the expected result, demonstrating that external knowledge improves consistency and accuracy.

2. **Question**: "What is 5 + 3?"

   - **RAG Response**: "The result is 8."
   - **Analysis**: The RAG technique provides the correct and consistent result, confirming its effectiveness in reinforcing model accuracy.

3. **Question**: "What is the value of (1 + 3) × 4?"

   - **RAG Response**: "The value is 16."
   - **Analysis**: The RAG response is accurate and consistent, illustrating the model's improved reliability with additional context.

Conclusion

- **LLAMA 3.1** exhibited consistency in arithmetic and algebraic responses but showed potential hallucinations in complex calculations.
- **OpenHathi** demonstrated consistency and accuracy across most tested questions, though a hallucination was detected in the slope calculation for the first question.
- **RAG Techniques** successfully enhanced the models' responses by incorporating relevant external knowledge, reducing inconsistencies and improving overall accuracy.

This version incorporates the output you provided for OpenHathi, emphasizing the hallucination detected in the slope calculation for the first question.

Question2:

Probing the Layer-wise Knowledge Representation in LLAMA 3

Objective

This study explores how well Large Language Models (LLMs), specifically LLAMA 3, encode information about entities and topics at various layers. By using probing techniques, the goal is to assess the predictive capabilities of embeddings from the first, middle, and last layers of the model on structured data.

The analysis is conducted on a **movies dataset**, evaluating the LLM's ability to predict:

- **A numeric field (Popularity):** Using regression.
- **A categorical field (Genres):** Using classification.

Dataset Description

The chosen dataset is a **movies dataset**, with the following fields:

1. **Title:** The name of the movie (used to create prompts).
2. **Genres:** Categorical labels for the genre of each movie (target for classification).
3. **Popularity:** A numeric field indicating the popularity of the movie (target for regression).

Experimental Steps

1. Prompt Design

For each movie in the dataset, a structured prompt was generated:

- Example: `"Tell me about Inception."`

These prompts were passed through LLAMA 3 to extract embeddings.

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2. Embedding Extraction

Embeddings were extracted for the **last token** of the output from three layers of the model:

1. **First Layer:** Represents surface-level linguistic features.
2. **Middle Layer:** Encodes intermediate abstractions and semantic relationships.
3. **Last Layer:** Focused on task-specific and high-level semantic information.

3. Model Setup

Two types of models were trained using the extracted embeddings:

1. **Linear Regression:**
   - Predicts the numeric field (**popularity**) using embeddings.
2. **Logistic Regression:**
   - Classifies the categorical field (**genres**) using embeddings.

4. Evaluation Metrics

1. **Regression Performance:**
   - Evaluated using **Mean Squared Error (MSE)**.
   - Lower MSE indicates better prediction accuracy.
2. **Classification Performance:**
   - Evaluated using **Accuracy**.
   - Higher accuracy indicates better classification performance.

Results

Regression (Popularity)

Layer	Mean Squared Error (MSE)
First Layer	0.00253
Middle Layer	0.00133
Last Layer	0.00328

Classification (Genres)

Layer	Accuracy
First Layer	0.026
Middle Layer	0.956
Last Layer	1.0

Discussion

The results indicate distinct trends in the information encoded at different layers of LLAMA 3:

1. **Regression Performance:**
   - The **middle layer** achieved the lowest MSE, indicating that it encodes the most useful features for predicting numerical values like popularity.
   - The **first layer** showed moderate performance, likely due to encoding shallow syntactic features.
   - The **last layer** performed slightly worse, suggesting it specializes in task-specific abstractions rather than numerical patterns.
2. **Classification Performance:**
   - Accuracy consistently improved across layers, with the **last layer** achieving perfect classification (100% accuracy).
   - The **middle layer** also performed well (95.6%), reflecting its capability to encode semantically rich information.
   - The **first layer** struggled with genre classification (2.6% accuracy), as it primarily encodes surface-level features.
3. **Insights on LLAMA 3's Representation:**
   - **First Layer:** Focuses on token-level and syntactic information, which is insufficient for tasks requiring semantic understanding.
   - **Middle Layer:** Strikes a balance between syntax and semantics, excelling at numerical predictions while also being competent at classification.
   - **Last Layer:** Encodes task-specific information, making it ideal for classification but less suitable for general-purpose numerical regression.
4. **Anomalies and Observations:**
   - Regression MSE for the last layer was unexpectedly higher, suggesting a trade-off between specialization and generalization at deeper layers.
   - The sharp improvement in classification accuracy from the middle to the last layer highlights the model's hierarchical encoding of semantics.

Conclusion

This study demonstrates the hierarchical nature of knowledge representation in LLAMA 3:

- **Lower Layers:** Encoded shallow, surface-level features.
- **Middle Layers:** Encoded rich, general-purpose semantic features useful for regression.
- **Higher Layers:** Focused on task-specific information, excelling in classification.

The findings highlight the importance of understanding layer-wise representations for optimizing model performance in downstream tasks. Future work could explore additional datasets and tasks to generalize these observations.