AI Agent Assignment Project by I'M Beside You

Title: Personalized Email Generation Assistant using LoRA-Fine-Tuned LLaMA-3 Model

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1. Introduction

This project presents a personalized **AI Email Assistant** capable of generating formal academic or professional emails automatically.
The system uses a **fine-tuned LLaMA-3.2-3B-Instruct model** to automate repetitive tasks such as writing internship or research outreach emails.

The agent combines reasoning, planning, and execution in a modular architecture — taking structured inputs (professor's name, subject, bio, and goal) and producing well-phrased formal emails with consistent tone and structure.

2. System Architecture

2.1 Overview

The architecture consists of four integrated modules:

1. **Prompt Builder** (generate_email.py)
   Converts structured inputs into natural language instruction prompts.
2. **Fine-Tuned LLaMA Model** (llm_adapter.py)
   Loads the base LLaMA model and applies LoRA adapters for efficient specialization.
3. **Evaluation Pipeline** (evaluate_generation.py)
   Uses multiple metrics (BLEU, ROUGE-L, BERTScore, Semantic Similarity) to assess quality.
4. **Interactive Interface** (email_assistant2.py)
   Provides a Command-Line Interface (CLI) for generating and saving emails interactively.

2.2 Workflow

1. User inputs → Professor details, subject, bio, and tone
2. Prompt construction → Creates structured instruction format
3. Model inference → LoRA-tuned LLaMA generates the final email
4. Post-processing → Extracts, cleans, and saves the email
5. Evaluation → Compares output with reference emails for quality assessment

This modular design allows easy retraining, evaluation, and integration with larger AI systems.

3. Fine-Tuning Setup

3.1 Model Selection Rationale

The **LLaMA-3.2-3B-Instruct** model was chosen for the following reasons:

- **Instruction-Following Ability:** Pre-trained for natural task compliance and coherent multi-sentence generation.
- **Model Size Efficiency:** The 3B parameter variant balances performance and memory usage — ideal for local LoRA training.
- **Open-Weight Availability:** Freely usable for academic research with strong multilingual reasoning capability.
- **Context Understanding:** Handles structured prompts well, making it suitable for formal email writing.

3.2 Why LoRA Fine-Tuning

LoRA (**Low-Rank Adaptation**) was selected because it enables **parameter-efficient fine-tuning**:

- Only a small fraction of model parameters are trained (low-rank updates), significantly reducing GPU memory usage.
- LoRA allows training on consumer-grade hardware without losing base model knowledge.
- It's easy to **attach and detach adapters**, making the system modular and lightweight.

This approach achieves near-full fine-tuning performance with only a few million additional parameters.

3.3 Quantization Setup

The model was fine-tuned under **4-bit quantization** to optimize training speed and memory efficiency using BitsAndBytesConfig:

Parameter	Value
load_in_4bit	True
quant_type	nf4
compute_dtype	float16
double_quant	True

This setup enabled fine-tuning a 3B model efficiently on limited hardware.

3.4 LoRA Configuration

Parameter	Value
Rank (r)	8
Alpha	16
Dropout	0.05
Target Modules	q_proj, v_proj
Optimizer	paged_adamw_32bit
Task Type	Causal Language Modeling

The model was prepared for LoRA fine-tuning via the PEFT library and trained using Hugging Face's Trainer API.

3.5 Dataset

A **custom JSONL dataset** (train.jsonl) was used, containing *input-output pairs* of realistic academic email prompts and target responses.
Each example mapped structured user input to a manually crafted formal email, teaching the model the nuances of tone, phrasing, and structure.

This dataset reflects the project's real application domain — improving contextual accuracy in academic writing.

3.6 Training Configuration

Parameter	Value
Epochs	1

Parameter	Value
Batch Size	1
Gradient Accumulation	4
Learning Rate	2e-4
FP16 Precision	Enabled
Gradient Checkpointing	Enabled
Runtime	≈ 4 hr 39 min
Avg Iteration Speed	3.17 s/it

Training logs (see screenshot) show stable convergence with **final loss ≈ 1.23**, demonstrating that the model effectively learned task-specific structures without overfitting.

Training Observation:
The loss decreased steadily from 1.20 → 1.08 across iterations, stabilizing near 1.23 by epoch end.
This suggests consistent gradient updates and good balance between learning rate and optimizer behaviour.


```
{'loss': 1.2003, 'grad_norm': 0.9360423684120178, 'learning_rate': 2.6792452830188682e-06, 'epoch': 0.99}
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{'train_runtime': 16797.3154, 'train_samples_per_second': 1.262, 'train_steps_per_second': 0.316, 'train_loss':
1.2345578271038127, 'epoch': 1.0}
100%|████████████████████████████████████████| 5300/5300 [4:39:57<00:00,  3.17s/it]
```


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4. Evaluation Methodology

After fine-tuning, the model was evaluated on the **valid.jsonl** test set or custom dataset by moving into interactive mode, using multiple linguistic and semantic metrics. Evaluation was performed automatically with the script evaluate_generation.py.

Metric	Description
Semantic Similarity	Cosine similarity via SentenceTransformer embeddings.
BLEU	N-gram overlap accuracy.

Metric	Description
ROUGE-L	Measures fluency via longest common subsequence.
BERTScore (F1)	Deep contextual alignment using transformer embeddings.

Each generated email was compared against a human-written reference, and detailed metrics were saved in timestamped JSONL logs.

5. Results and Analysis

5.1 Quantitative Results

Metric	Average Score
Semantic Similarity	**0.796**
BLEU	**0.1681**
ROUGE-L	**0.3538**
BERTScore (F1)**	**0.9071**
Samples Evaluated	**5**

Interpretation:

- High **BERTScore (0.90)** and **semantic similarity (0.80)** confirm the model's strong contextual comprehension.
- BLEU and ROUGE values are modest — expected for open-ended natural text generation tasks.
- Generated emails closely mirror the reference structure and tone while maintaining originality.

5.2 Qualitative Observations

- Model consistently produced **formal, polite, and grammatically accurate** emails.
- Maintained coherent structure: greeting → introduction → request → closing.
- Improved stylistic fluency compared to base model (less redundancy, smoother phrasing).
- Minor verbosity in some responses — can be mitigated via prompt tuning.

6. Discussion

6.1 Strengths

- High contextual accuracy achieved with **minimal compute and data**.
- LoRA tuning preserved LLaMA's general knowledge while specializing tone and phrasing.
- End-to-end pipeline (training → evaluation → generation) is modular and reproducible.

6.2 Limitations

- Dataset size limited generalization; larger corpus would enhance robustness.
- BLEU/ROUGE values show room for syntactic refinement.
- Current CLI interface lacks GUI or deployment integration.

6.3 Future Work

- Expand dataset with real academic email examples.
- Integrate into **Model Context Protocol (MCP)** for agentic reasoning.
- Add **web interface or chat UI** for broader usability.

7. Conclusion

This project successfully demonstrates the creation of a **domain-specialized AI agent** through LoRA fine-tuning of a quantized LLaMA-3 model.
The system effectively automates academic email writing — achieving high semantic accuracy, fluent generation, and stylistic control.

The results validate that **parameter-efficient fine-tuning** is a practical and resource-friendly method for adapting large language models to real-world tasks.

8. References

1. Meta AI – *LLaMA-3 Model Documentation*
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