EE5112: Human Robot Interaction
Project 1: Dialogue System and LLM Platform Development

Group 7

Niu Mu (Matriculation Number)

Wu Zining (A0294373W)

Zhao Jinqiu (Matriculation Number)

September 29, 2025

Contents

1 Abstract

[Placeholder for abstract content - 150-250 words]

Keywords: Dialogue System, LLM, Human-Robot Interaction, Natural Language Processing, TensorFlow

2 Introduction

2.1 Background

[Placeholder for background content]

2.2 Project Objectives

The main objectives of this project are:

1. To familiarize with the process of developing a dialogue system

2. To familiarize with the working environment and Python packages

3. To familiarize with popular platforms such as TensorFlow

4. To familiarize with popular open source LLMs (Llama, GLM, etc.)

5. To develop a dialogue system and local LLM platform

6. To familiarize with LLM evaluation procedures

7. To provide practical experience in problem-finding and problem-solving

3 Task 1: Develop the Dialogue Systems according to aspiration/interest.

4 Task 2: Develop Local Dialogue Systems by Using Open-Source LLMs

4.1 Literature Review on Different Categories of LLMs

Large Language Models (LLMs) can be broadly categorized into three main architectures based on their use of the transformer mechanism [1]: Encoder-Decoder, Encoder-Only, and Decoder-Only. Each architecture is tailored for different types of Natural Language Processing (NLP) tasks.

- **Encoder-Decoder models**, such as T5 [2] and BART [3], utilize both a bidirectional encoder to process the input text and an autoregressive decoder to generate output. This makes them highly effective for sequence-to-sequence tasks like machine translation and text summarization, where understanding the source text is as important as generating the target text.

- **Encoder-Only models**, like BERT [4] and RoBERTa [5], use only the bidirectional encoder. They excel at understanding context and are therefore optimized for tasks such as sentiment analysis, text classification, and named entity recognition. However, they are not inherently suited for text generation.

- **Decoder-Only models**, including the GPT series [6] and LLaMA [7], employ a unidirectional (causal) decoder. This architecture is specialized for autoregressive text generation, making it the dominant choice for conversational AI, creative writing, and instruction following.

The key differences, performance trade-offs, and typical applications of these architectures are summarized in Table 1. Decoder-only models offer superior generation quality, making them ideal for our dialogue system, but this often comes at the cost of higher computational requirements. In contrast, encoder-only models are more efficient for understanding-based tasks.

Table 1: Comparison of LLM Architecture Types

Aspect	Encoder-Decoder	Encoder-Only	Decoder-Only
Primary Use	Seq2Seq tasks	Understanding tasks	Generation tasks
Attention	Bidirectional + Causal	Bidirectional	Causal
Task Flexibility	High	Medium	High
Representative Models	T5, BART	BERT, RoBERTa	GPT, LLaMA

Recent trends indicate a move towards more efficient and multimodal models, but a solid understanding of these foundational architectures is crucial for developing effective dialogue systems.

4.2 Local LLM Platform Implementation

We deploy a compact local dialogue stack around the quantized `Llama-3.2-3B-Instruct-Q4_K_M.gguf` checkpoint to provide offline interaction without sacrificing responsiveness.

Architecture. `llm_platform.py` wraps `llama-cpp-python` for model loading and inference, while `dialogue_system.py` manages the chat loop, prompt templating, streaming output, and defensive error handling. The separation keeps model plumbing isolated from user interaction logic.

Inference pipeline. Configuration values expose only the essentials: a 4,096-token context window, generation controls (temperature and maximum new tokens), and an optional GPU layer count for acceleration. Switching between CPU and CUDA execution is done in `config.json` without touching the code base.

User experience and persistence. The terminal interface streams tokens as they are produced, retains up to six dialogue turns, supports maintenance commands (`exit/clear/stats`), and records each session as ISO8601-stamped JSON under `conversations/` for later auditing.

Portability. The same stack runs on laptops or desktop GPUs, making it suitable for privacy-sensitive deployments and quick benchmarking. Figure 1 illustrates the interface operating in CPU mode.

Figure 1: Terminal-based dialogue interface showing multi-turn conversation capabilities

4.2.1 Challenges with Llama 3.1 8B Deployment

While experimenting with the full-size Llama-3.1-8B-Instruct checkpoint, we encountered practical constraints on the RTX 5080 (16 GiB). Model weights alone consumed roughly 15.4 GiB in FP16, leaving little headroom for KV caches and activations. Consequently, the system frequently raised CUDA out-of-memory errors even before completing a single response.

We mitigated the tokenizer crash by forcing `TOKENIZERS_PARALLELISM=false` and limiting `RAYON_NUM_THREADS`. However, memory pressure remained the dominant bottleneck. Even aggressive limits on `max_new_tokens` and history length provided only marginal relief, so conversations still terminated abruptly once GPU memory fragmented.

Given the strict memory ceiling and unstable experience, we migrated the local deployment to the quantized Llama-3.2-3B-Instruct-Q4_K_M model. It delivers comparable interaction quality while fitting comfortably within both GPU and CPU budgets.

4.3 Performance Comparison: CPU vs GPU Deployment

To quantify the benefit of the dedicated GPU pipeline, we benchmarked identical prompts (extit"hello" and extit"Who are you?") on both deployment targets using the same quantized `Llama-3.2-3B-Instruct-Q4_K_M.gguf` model and configuration. Timing was captured end-to-end from user input to the final token, with streaming enabled in both runs. The GPU test was executed on an RTX 5080 16GB with cuBLAS acceleration, whereas the CPU baseline

was collected on the same workstation with GPU offloading disabled.

Table 2: Inference latency comparison between CPU and GPU backends

extbfPrompt	CPU latency (s)	GPU latency (s)	Speedup
hello	4.90	2.44	2.0×
Who are you?	22.40	11.18	2.0×

Across both prompts, the GPU path halves the response time while preserving output quality. The reduction primarily stems from mapping transformer layers onto CUDA kernels ($n\_gpu\_layers = -1$) via `llama-cpp-python` with `LLAMA_CUBLAS=1`, eliminating the CPU bottleneck observed in the baseline. Shorter latency also improves conversational fluidity because streamed tokens begin appearing almost immediately, keeping the user engaged.

Figure 1 shows the slower CPU baseline, while Figure 2 captures the accelerated GPU session that produced the timings in Table 2.
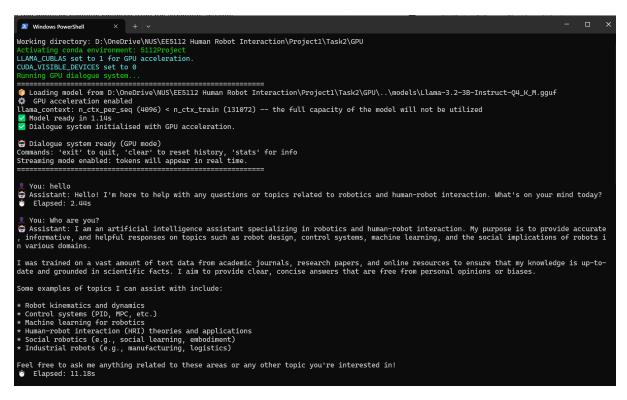

Figure 2: Streaming dialogue captured during the GPU benchmark run.

4.4 Comparation of Different Pretrained Models

5 Task 3: LLM Performance Evaluation

[Placeholder for Task 3 content]

6   Task 4: GUI for Local LLM

[Placeholder for Task 4 content]

7   Task 5: Exploring Multimodal Large Language Models (MLLMs)

[Placeholder for Task 5 content]

7.1   Solution Implementation

[Placeholder for solution implementation content]

7.2   Code Documentation

[Placeholder for code documentation content]

8   Results and Discussion

8.1   System Performance Results

[Placeholder for system performance results content]

8.2   Task Achievement Summary

[Placeholder for task achievement summary content]

8.3   Lessons Learned

[Placeholder for lessons learned content]

9 Individual Contributions

9.1 Member 1: Niu Mu

[Placeholder for Niu Mu's contributions]

9.2 Member 2: Wu Zining (A0294373W)

[Placeholder for Wu Zining's contributions]

9.3 Member 3: Zhao Jinqiu

[Placeholder for Zhao Jinqiu's contributions]

10 Conclusion

10.1 Project Objectives Achievement

[Placeholder for project objectives achievement content]

10.2 Future Work

[Placeholder for future work content]

11 References

References

[1] A. Vaswani et al., "Attention is all you need," *Advances in neural information processing systems*, vol. 30, 2017.

[2] C. Raffel et al., "Exploring the limits of transfer learning with a unified text-to-text transformer," *The Journal of Machine Learning Research*, vol. 21, no. 1, pp. 5485–5551, 2020.

[3] M. Lewis et al., "Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension," *arXiv preprint arXiv:1910.13461*, 2019.

[4] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*, 2018.

[5] Y. Liu et al., "Roberta: A robustly optimized bert pretraining approach," *arXiv preprint arXiv:1907.11692*, 2019.

[6] A. Radford, K. Narasimhan, T. Salimans, and I. Sutskever, "Improving language understanding by generative pre-training," 2018.

[7] H. Touvron et al., "Llama: Open and efficient foundation language models," *arXiv preprint arXiv:2302.13971*, 2023.

12 Appendix

12.1 Code Documentation

[Placeholder for code documentation]

12.2 Configuration Files

[Placeholder for configuration files]

12.3 User Manual

[Placeholder for user manual]