

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

Group 7

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1 Abstract

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

2 Introduction

2.1 Background

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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.

```
C:\WINDOWS\system32\cmd. x + v
Activating conda environment: 5112Project...
Environment activated successfully!
Running dialogue system...
=== Task2: Dialogue System - EE5112 ===

🔥 Loading model: models/Llama-3.2-3B-Instruct-Q4_K_M.gguf
🔥 First load may take from several seconds to a few minutes (depends on disk/CPU/GPU)...
llama_context: n_ctx_per_seq (4096) < n_ctx_train (131072) -- the full capacity of the model will not be utilized
✅ Model loaded successfully! You can start chatting now.
✅ Dialogue System initialized successfully!

🤖 Dialogue System Ready!
Commands: 'exit' to quit, 'clear' to reset history, 'stats' for metrics
(Streaming enabled: tokens will stream in real time)
=====

👤 You: hello
🤖 Assistant: Hello! It's nice to meet you. Is there something I can help you with or would you like to chat?
🕒 Elapsed: 7.13s

👤 You: Who are you?
🤖 Assistant: I'm an artificial intelligence assistant, designed to provide helpful and informative responses. I don't have a personal identity or emotions, but my goal is to assist users like you with their questions and tasks.

I can help with a wide range of topics, from providing information on various subjects to offering suggestions and ideas for projects or problems. I'm constantly learning and improving, so please bear with me if I make any mistakes!

What can I help you with today?
🕒 Elapsed: 24.04s

👤 You: |
```

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 (`exitit"hello"` and `exitit"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.

```

Windows PowerShell
Working directory: D:\OneDrive\NUS\EE5112 Human Robot Interaction\Project1\Task2\GPU
Activating conda environment: 5112Project
LLAMA_CUBLAS set to 1 for GPU acceleration.
CUDA_VISIBLE_DEVICES set to 0
Running GPU dialogue system...

=====
🔥 Loading model from D:\OneDrive\NUS\EE5112 Human Robot Interaction\Project1\Task2\GPU\..\models\Llama-3.2-3B-Instruct-Q4_K_M.gguf
⚙️ GPU acceleration enabled
llama_context: n_ctx_per_seq (4096) < n_ctx_train (131072) -- the full capacity of the model will not be utilized
✅ Model ready in 1.14s
✅ Dialogue system initialised with GPU acceleration.

🗨️ Dialogue system ready (GPU mode)
Commands: 'exit' to quit, 'clear' to reset history, 'stats' for info
Streaming mode enabled: tokens will appear in real time.
=====

👤 You: hello
🤖 Assistant: Hello! I'm here to help with any questions or topics related to robotics and human-robot interaction. What's on your mind today?
🕒 Elapsed: 2.44s

👤 You: Who are you?
🤖 Assistant: I am an artificial intelligence assistant specializing in robotics and human-robot interaction. My purpose is to provide accurate, informative, and helpful responses on topics such as robot design, control systems, machine learning, and the social implications of robots in various domains.

I was trained on a vast amount of text data from academic journals, research papers, and online resources to ensure that my knowledge is up-to-date and grounded in scientific facts. I aim to provide clear, concise answers that are free from personal opinions or biases.

Some examples of topics I can assist with include:

* Robot kinematics and dynamics
* Control systems (PID, MPC, etc.)
* Machine learning for robotics
* Human-robot interaction (HRI) theories and applications
* Social robotics (e.g., social learning, embodiment)
* Industrial robots (e.g., manufacturing, logistics)

Feel free to ask me anything related to these areas or any other topic you're interested in!
🕒 Elapsed: 11.18s

```

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

4.4 Comparison of Different Pretrained Models

5 Task 3: LLM Performance Evaluation

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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

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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

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10.2 Future Work

[Placeholder for future work content]

11 References

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12 Appendix

12.1 Code Documentation

[Placeholder for code documentation]

12.2 Configuration Files

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12.3 User Manual

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