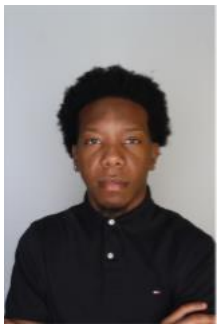
P10-T1 LLM Compression Final Report

Course: CS4850-03 | Semester: Fall 2025 | Professor Perry | Date 12/3/25

 Ryan Tran Developer/Documentation	 Aldi Susanto Developer/Documentation /Team Lead	 Thomas Graddy Developer/Documentation	 Pranav Kartha Developer/Documentation
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GitHub Repo Link:

https://github.com/RyanTren/AFB-LLM-Compression-Trade-off-Evaluator

Final Report Website Link:

https://afb-llm-compression-trade-off-evalu-lac.vercel.app/

Stats and Status	Project is under NDA
# of Lines of Code	15k+ Lines of code across our main, lora, knowledge_distilation, and quantization branches.
Number of Project Components/tools in project	10+: React + TypeScript + Vite, StreamLit, Python, Docker, HuggingFace, TensorFlow/PyTorch, pandas, numPy, Git, PuTTY + KSU VM
Estimate Hours	300
Actual	342
Status	95% complete for project (need to record final demo)

Table of Contents

Introduction

This project investigates how model compression techniques affect the balance between speed and accuracy for large language models (LLMs) on code-generation and debugging tasks. We build a baseline inference environment and implement several compression methods, including quantization, LoRA, and knowledge distillation. Using a suite of code-focused prompts, we evaluate each model's quality with HumanEval and CodeBLEU, along with latency, throughput, memory usage, and cost.

Based on these results, we developed a prototype system that dynamically routes queries between the full model and compressed variants. The router estimates query complexity and selects the smallest model that can maintain a target accuracy, which improves efficiency while limiting quality loss on difficult inputs. We compare this dynamic approach with static single-model deployments and analyze Pareto frontiers that relate model quality to performance.

The project concludes with a reporting dashboard (StreamLit + Python for LoRA and Quantization branch in our repo), training/inference/evaluation pipeline, and system documentation that support reproducibility and containerized deployment. Sponsor guidance informs benchmark selection, compression settings, and routing criteria, with the overall goal of enabling practical and scalable LLM inference for code-related workloads.

Challenges/Assumptions

1. VM Downtimes and System Instability

One of the most significant obstacles was the frequent downtime of our virtual machine. Our original VM experienced several crashes during critical stages of model training and data preprocessing. This instability forced us to repeat tasks, reconfigure environments, and maintain multiple backups of our data and code. The intermittent availability of the VM also slowed our development pace, as we had to wait for the system to recover before resuming work. As a result, we had to adjust our timeline and reduce the complexity of some experiments to maintain project feasibility.

2. Deprecated Dependencies and Software Conflicts

Because the VM environment used outdated system libraries, we encountered numerous dependency conflicts when installing modern machine learning frameworks. Several required packages were deprecated or incompatible with the default Python and system versions available on the VM. These conflicts required significant troubleshooting, including manually resolving version mismatches, testing alternative libraries, and modifying code to accommodate older dependencies. These limitations constrained the range of tools and models we could realistically use.

3. Limited VM Specifications

The hardware specifications of the VM and particularly RAM, CPU allocation, and lack of GPU acceleration restricted the types of models we could experiment with. Larger or more computationally intensive models either failed to run or took excessively long to train, making them impractical for our timeline. As a result, we had to use smaller models with fewer parameters, which affected both model performance and training efficiency. This constraint also forced us to shorten training epochs and batch sizes, which may have limited the final model's accuracy and generalization ability.

4. No Sudo Access

We also lacked sudo/root access on the VM, which prevented us from installing system-level packages, updating drivers, or optimizing the machine learning environment. Without administrative privileges, even simple tasks like upgrading Python, installing optimized versions of TensorFlow/PyTorch, or modifying kernel settings were not possible. This severely limited our ability to optimize performance and made us reliant on whatever versions were already installed on the system. In some cases, we had to find alternative implementations or rework parts of the pipeline to fit these constraints.

Requirements

Project Overview

The project aims to build a **Large Language Model (LLM) Compression Accelerator** for **Robins AFB**, focusing on optimizing LLM usage offline through compression techniques. It evaluates trade-offs between **model size, cost, and accuracy** for code-related tasks (debugging and cross-language translation). The solution includes a **dynamic query routing prototype** that selects between full and compressed models based on query complexity.

Key Objectives

- Implement and compare **compression methods**: quantization, pruning, and knowledge distillation.
- Measure performance using **BLEU/CodeBLEU**, **HumanEval**, latency, throughput, GPU hours, and memory usage.
- Develop a **dashboard** for visualizing trade-offs and exporting results.
- Ensure reproducibility via **Dockerized environments** and CI/CD workflows.

Scope

In-Scope:

- Containerized setup for LLaMA 3.3 (8B) for Quantization and DeepSeek-Coder V2 1B/CodeParrot Small Model for LoRA.
- Compression experiments and evaluation metrics.
- Dashboard with filtering, comparison, and export features.
- Prototype dynamic query router.

Out-of-Scope:

- Production deployment in Air Force systems.
- Proprietary datasets or advanced compression beyond the three chosen methods.

Success Criteria

- Compressed models retain **≥95% baseline CodeBLEU accuracy** while reducing latency/GPU usage by **≥2×**.
- Dashboard supports comparison of at least **three configurations**.
- Prototype routing system demonstrates dynamic allocation.

Design & Architecture

- **Environment:** GPU-enabled VM (4x Tesla A100s), Docker containers for LLM Training/Compression/Evaluation Scripts and StreamLit Dashboard.
- **System:** Modular architecture with Python (PyTorch/Transformers), compression tools, and full-stack dashboard (React/Angular or Streamlit/Dash).
- **Interfaces:** Dashboard for metrics visualization; export to PDF/CSV/JSON.

Functional Requirements

- Baseline LLM setup.
- Implement compression techniques.
- Dynamic query routing.
- Evaluation and reporting dashboard.
- Export functionality and milestone reporting.

Non-Functional Requirements

- **Security:** Open-source datasets only; containerized isolation.
- **Capacity:** Handle models up to 16B parameters; demonstrate 2× efficiency gains.
- **Usability:** Intuitive dashboard for non-ML experts.
- **Reproducibility:** Dockerized deployment and CI/CD pipelines.

Risks & Mitigations

- **Accuracy degradation:** Conservative compression thresholds.
- **Hardware constraints:** Use smaller models or optimization techniques.
- **Time constraints:** Scope routing system as prototype.

- **Generalizability:** Document assumptions clearly.
- **Operational integration:** Emphasize modular design for future adoption.

Analysis / design

Purpose

This SDD translates the requirements from the SRS into a concrete design for implementing the **LLM Compression Trade-Off Accelerator**. It defines architecture, components, interfaces, workflows, and quality attributes to ensure reproducibility, scalability, and maintainability.

System Overview

The system accelerates LLM inference for **code-related tasks** by:

- Establishing a baseline inference environment.
- Applying **compression techniques**: quantization, pruning, and knowledge distillation.
- Dynamically routing queries between baseline and compressed models.
- Presenting results in an interactive dashboard. Deployment uses **Docker** for containerization and supports GPU-enabled VMs or cloud environments.

Design Considerations

- **Assumptions:** Focus on code generation accuracy (evaluated via CodeBLEU), using DeepSeek V2 and LLaMA models; requires GPU-enabled VM; reproducibility via Docker and Conda.
- **Constraints:** Heavy resource requirements; goal is to reduce hardware needs while maintaining accuracy; SSH/FTP for VM communication; GitHub for version control.
- **Compression Methods:**
    - **Quantization:** Reduces precision for smaller size and faster inference.
    - **Pruning:** Removes redundant neurons for efficiency.
    - **Knowledge Distillation:** Transfers knowledge from large to smaller models.
- Each method has trade-offs in complexity, accuracy, and performance.

Architectural Strategies

- **Containerized Microservices:** Separate services for Model, Compression, Routing, Evaluation, Dashboard, and Results Store.
- **Stateless Compute & Versioned Artifacts:** All compute is stateless; artifacts and datasets are version-controlled for reproducibility.
- **Experiment Orchestration:** Controller manages runs, retries, and artifact persistence.
- **Routing Strategy:** Rule-based (prompt length, complexity) and learned classifier for dynamic model selection.
- **Observability:** Logging, metrics (latency, throughput, GPU hours), tracing, dashboards (Grafana), and alerts.
- **Failure Safety:** Fallback to baseline model, checkpointing, retries, and container isolation.

System Architecture

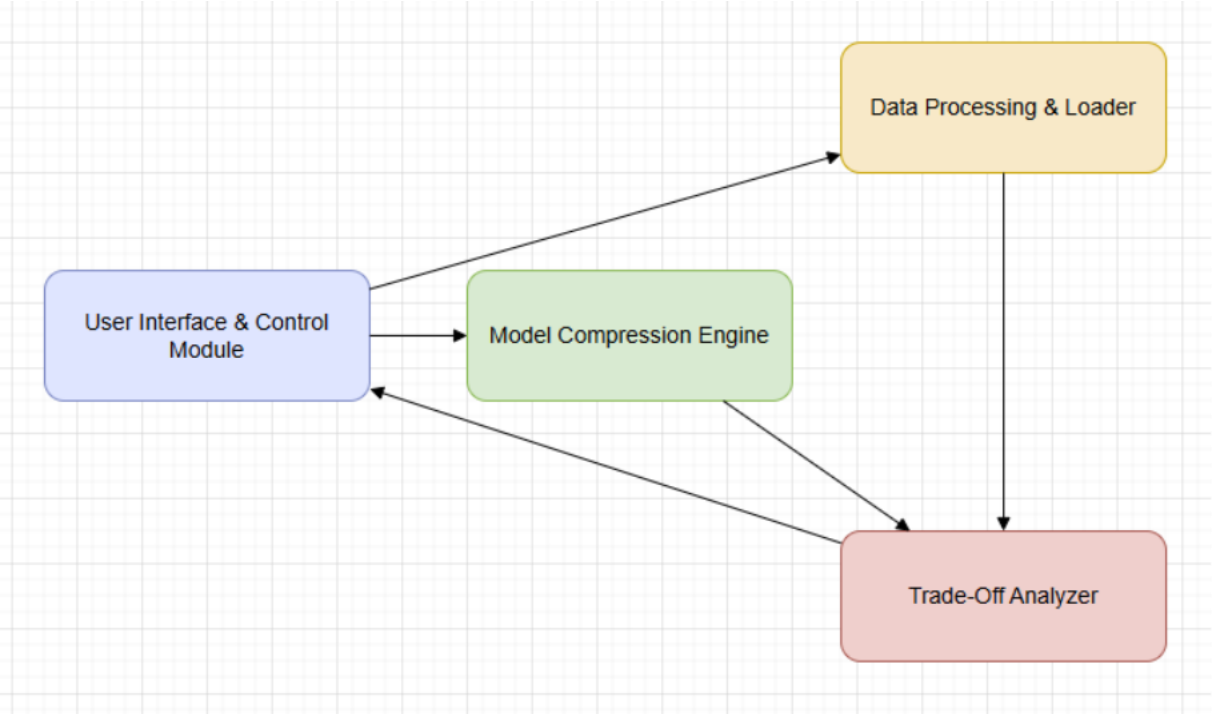
Four main subsystems:

1. **Model Compression Engine:** Applies quantization, pruning, and distillation.
2. **Data Processing & Loader:** Handles tokenization, batching, and dataset preparation.
3. **Trade-Off Analyzer:** Evaluates accuracy, latency, memory, and cost; generates reports.
4. **User Interface & Control Module:** CLI and optional web dashboard for configuration, monitoring, and exporting results.

Detailed Design

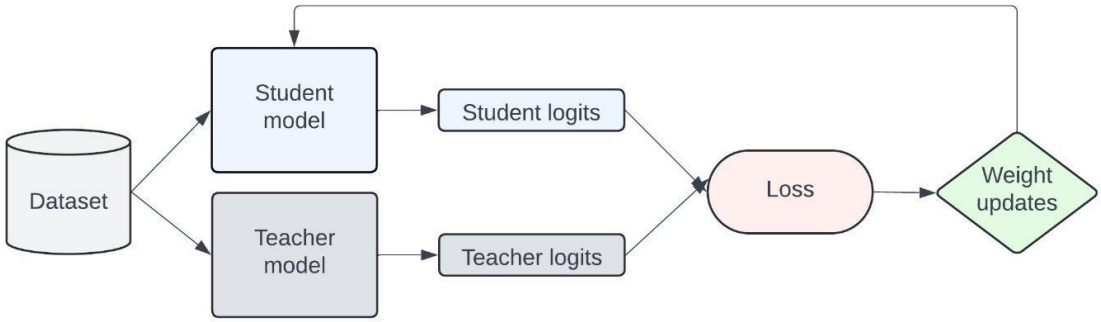
- **Interfaces:** Functions and endpoints for compression (`compress_model`), evaluation (`evaluate_tradeoff`), dataset loading, and reporting.
- **Resources:** GPU compute (CUDA/cuDNN), PyTorch, Hugging Face, Docker, GitHub for version control.
- **Constraints:** Must maintain functional correctness, support standard formats (.pt, .bin), and avoid deadlocks in parallel jobs.
- **Exports:** Reports in PDF, CSV, JSON; metrics and manifests for reproducibility.

Design Drawings

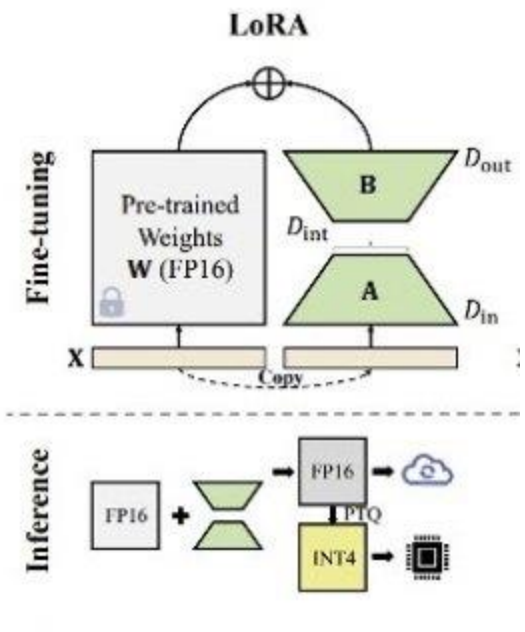


(Simple High Level Block Diagram for System Architecture)

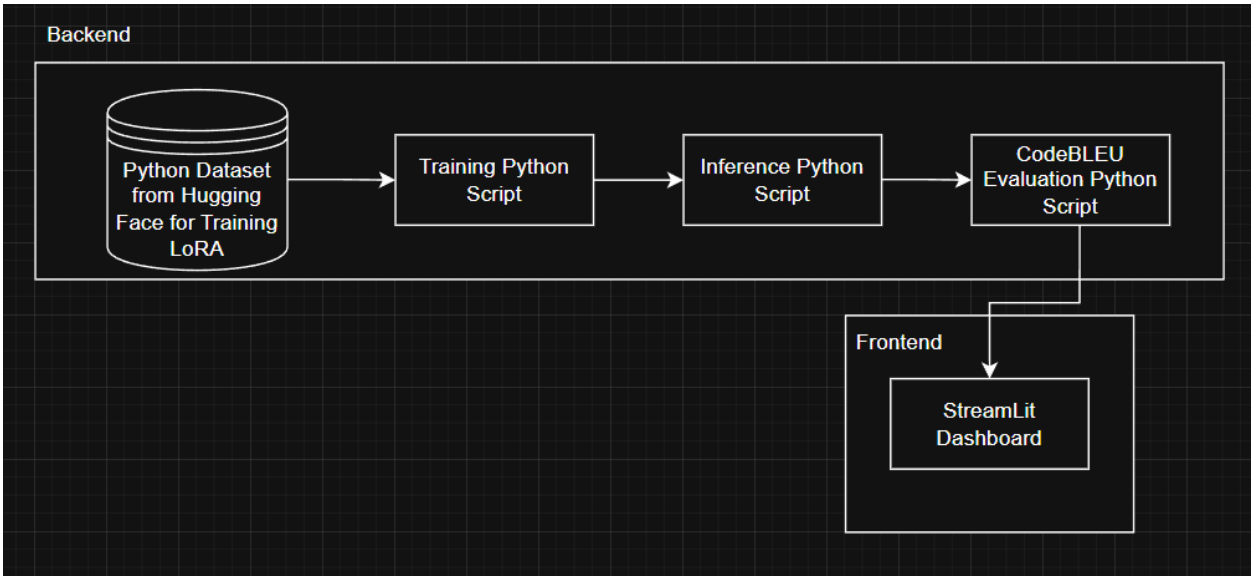
Knowledge Distillation -



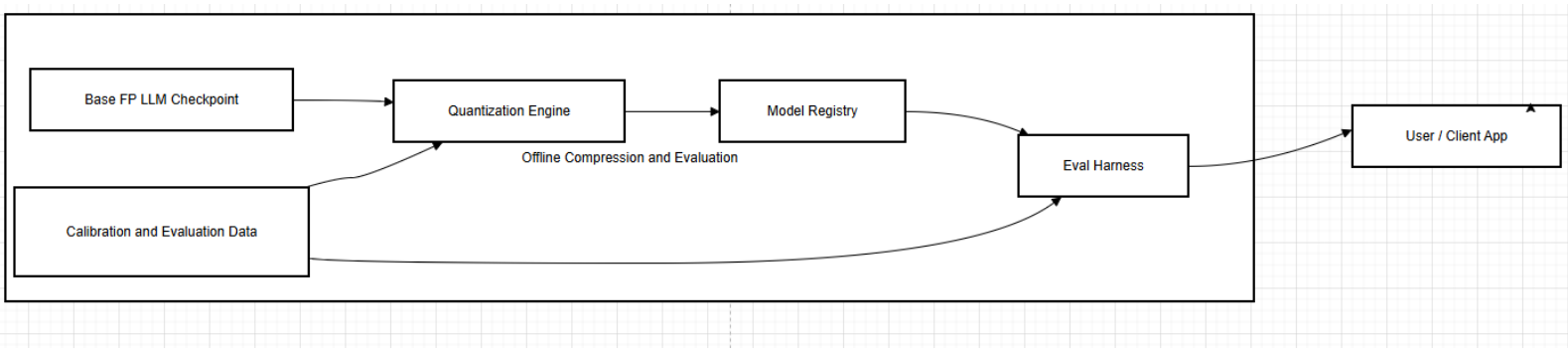
LoRA/PeFT -



LoRA/PeFT Development Design-



Quantization-



Development

Model Research and Selection

Three models were initially chosen for their coding capabilities:

- **DeepSeek-Coder-V2**: Excellent reasoning/debugging, open weights, multiple sizes (16B–236B).
- **Qwen2.5-Coder**: Strong multilingual debugging and translation, scalable sizes (7B–32B).
- **StarCoder2**: Cost-effective, permissively licensed, smaller sizes (3B–15B).

Due to hardware limitations (Tesla M40 GPUs, 11 GB VRAM), the team pivoted to smaller models like **GPT-2**, **CodeParrot-small (~100M)**, and **Llama 3.1-8B** for realistic compression experiments.

Hardware Constraints

The VM provided had:

- **4× NVIDIA Tesla M40 GPUs (11 GB VRAM each)**
- **Compute capability 5.2**
- **503 GB system memory**
- **220 GB disk storage**

These specs were insufficient for large models requiring Ampere/Hopper GPUs and advanced low-precision kernels. This led to adopting smaller models and parameter-efficient fine-tuning.

LoRA Training Environment

Implemented using:

- **Transformers** (model loading/tokenization)
- **PEFT** (LoRA layers)
- **Accelerate** (multi-GPU orchestration)
- **DeepSpeed** (ZeRO-Offload for memory optimization)
- **Torch/CUDA 13.0**

This setup allowed fine-tuning on legacy GPUs without loading full model weights.

Evaluation Metrics

- **Execution-Based**: Compile success rate, unit test pass@k, latency, GPU memory usage.
- **Quality-Based**: CodeBLEU, BLEU, exact match, APR metrics (plausible/correct/regression patch rates).

Execution-based metrics were prioritized for functional accuracy.

Datasets

- **Code Translation**: CodeXGLUE (Java ↔ C#)
- **Debugging/APR**: Defects4J, QuixBugs, MdEval
- **LoRA Training**: codeparrot-clean, python_code_instructions_18k_alpaca, codecomplex

Implementation Summary

- **Architecture**: Modular, containerized (Docker + CUDA 13.0 + PyTorch 2.1).
- **Compression**: Custom 4-bit GPTQ quantizer script for quantization.
- **LoRA/PEFT Pipeline**: Fine-tuning with low-rank adapters, FP16 precision, DeepSpeed ZeRO-3 offloading.
- **Outputs**: Adapter weights, metrics, generation samples stored under `/src/lora_out_<model_name>/`.

Risk Mitigation

- Accuracy degradation: Controlled via conservative thresholds.
- Hardware limits: Addressed with 4-bit quantization.
- Time constraints: Prototype-first approach.
- VM restrictions: Workarounds for read-only access.
- Deprecated functions: Adjustments for Python 3.11.9 and legacy GPUs.

Setup Instructions

- Connect to VM via **GlobalProtect VPN** and **PuTTY**.
- Clone repo with SSH keys.
- Build local environment using Python venv and install dependencies.
- Configure Hugging Face cache in `/tmp` due to limited permissions.
- Training and inference scripts: `train_lora.py`, `run_inference.py`.

Test (STR and STP)

Scope

Testing covers:

- Baseline vs. compressed model performance for code generation.
- Validation of **quantization**, **LoRA**, and **knowledge distillation** workflows.
- Dynamic query-routing behavior.
- Evaluation metrics: BLEU/CodeBLEU, latency, resource usage.
- Dashboard functionality for visualization and data integrity.
- End-to-end integration of scripts, routing logic, and metrics pipeline.

Out of Scope: UAT by sponsor, usability beyond basic dashboard checks, external system integration, training full-scale LLMs from scratch.

Testing Summary

- **In Scope:** Baseline/compressed LLM performance, compression pipelines, routing logic, metric evaluation, dashboard validation.
- **Out of Scope:** External integrations, new LLM architectures, non-code tasks.

Test Focus Areas

- **Release Content:** Working version of LLM Compression Framework integrating GPTQ and LoRA workflows for training, inference, and evaluation.

- **Regression Testing:** Ensures stability after changes in compression workflows, evaluation scripts, or routing logic.
- **Platform Testing:** Conducted on Ubuntu VM with NVIDIA Tesla P100 GPU, validating Python, PyTorch, Transformers, GPTQ, PEFT, and evaluation utilities.

Test Objectives

- **Progression:** Validate CodeBLEU similarity for compressed models (GPTQ, LoRA, self-distilled Llama).
- **Regression:** Confirm BLEU metric accuracy and system stability under compression.

Other Testing

- **Security:** Validate permissions, prevent external calls, and ensure no credential exposure.
- **Stress & Volume:** Assess system under heavy inference loads and large prompt batches.
- **Connectivity:** Confirm internal component communication and dataset/model access.
- **Disaster Recovery:** Verify restoration of LoRA checkpoints, GPTQ artifacts, datasets, and configs.
- **Unit Testing:** Validate individual modules (data utilities, LoRA helpers, quantization utilities, metrics).
- **Integration Testing:** Ensure workflows (LoRA, GPTQ) and evaluation tools work together seamlessly.

Test Strategy

- **Responsibilities:** Project team handles unit/integration; external party assists with security; business handles UAT.
- **Approach:** Separate testing for each compression method; Docker-based deployment.
- **Environment:** Ubuntu VM with GPU support; isolated VPC; controlled access and monitoring.

Entry/Exit Criteria

- **Entry:** Environment ready, access granted, stable code baseline, artifacts prepared.

- **Exit:** All tests executed, defects logged, results validated, environment stable.

Testing Metrics

Includes:

- Defect density, severity mix, reopen rate, escape rate.
- Test case pass rate, requirements coverage, automation coverage.
- Latency (p50/p90/p99), throughput, error rate.
- Cost per query, model quality (CodeBLEU, pass@k), routing effectiveness, footprint reduction.

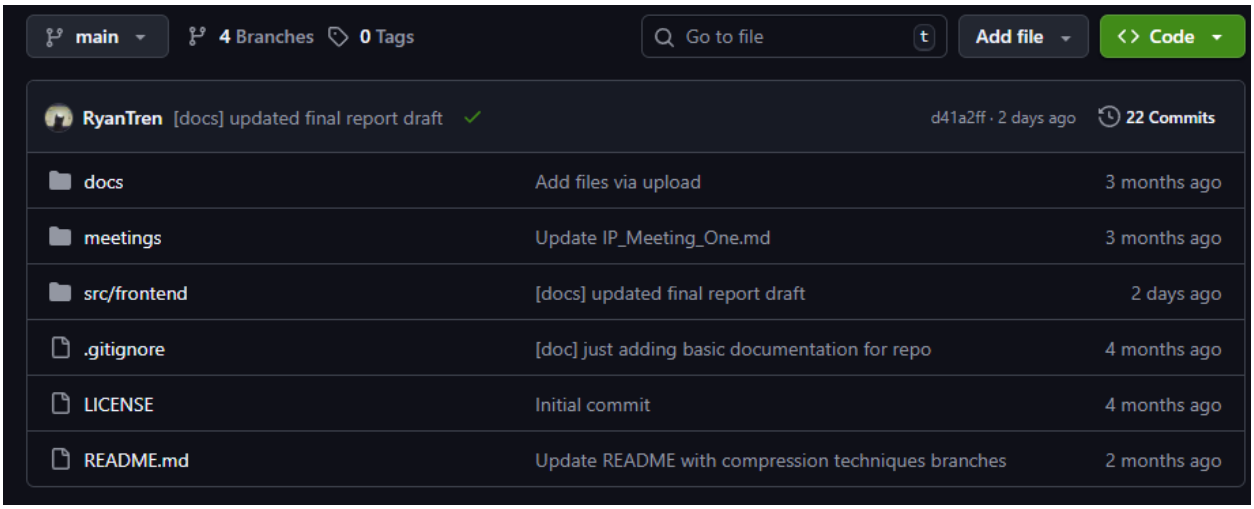
Software Test Results

Model	Compression	CodeBLEU	Status	Severity
Base Llama 3 8B	16 GB	0.67	Pass	Minor
GPTQ Llama	5.5 GB	0.33	Pass	Minor
CodeParrot LoRA	2 GB → 10–20 MB	0.31	Pass	Minor
DeepSeek LoRA	256 MB → 1 MB	0.59	Pass	Minor
Self-Distilled Llama3.2 1B	KL Loss: 6.688	N/A	WIP	Moderate

Version control

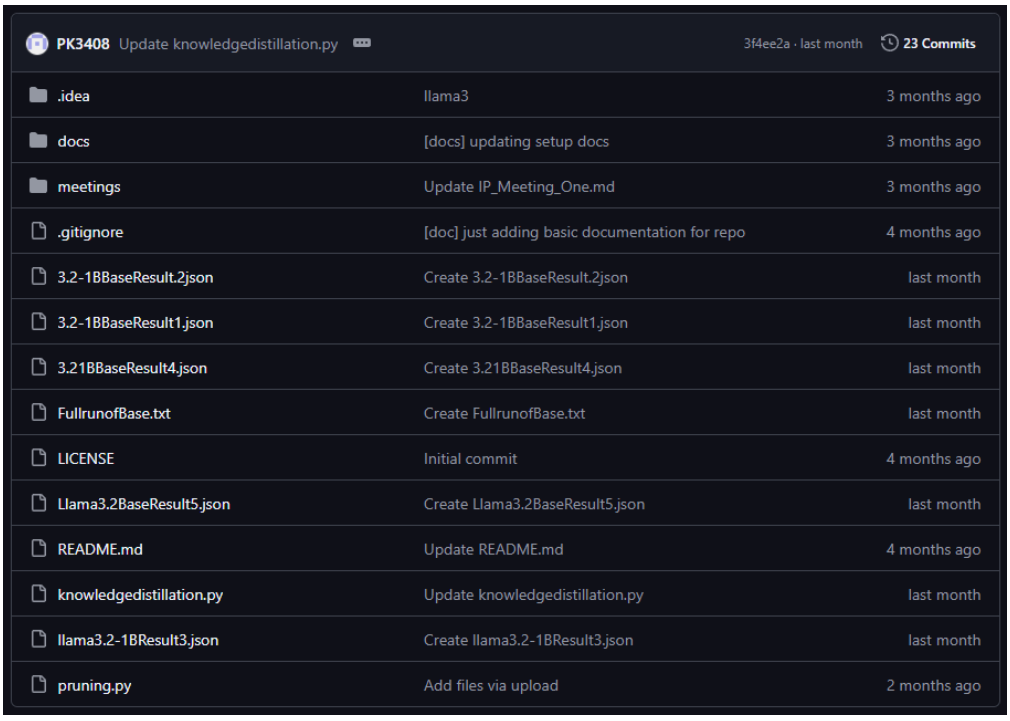
For version control, we chose GitHub as our platform and in our repository structure we have 4 branches. (Main, lora, quantization, and knowledge distillation)

- The main branch contains the context and documentation of our project as well as the final project website built with React + TypeScript + Vite.



- The other 3 branches have in-depth documented setups and logs of our development work between the three different compression methods we choose: LoRA, Quantization, & Knowledge Distillation.

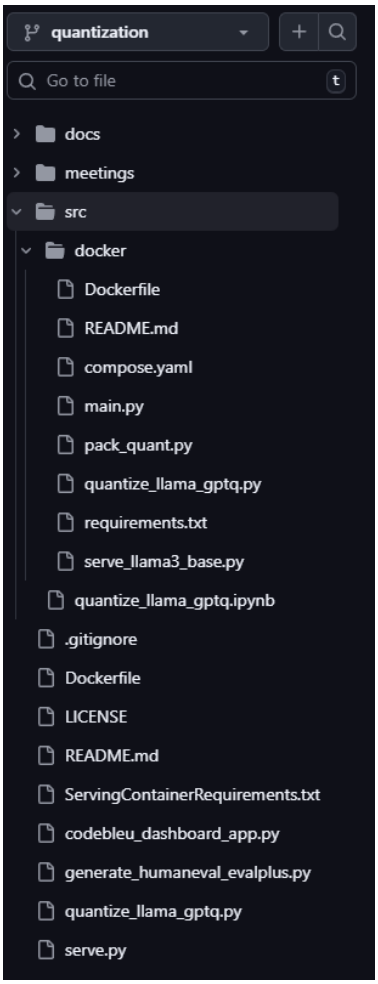
Knowledge Distillation:



LoRA:

Name	Last commit message
..	
data	[test]
lora_out_codeparrot_PROPER	adding files needed for inference
lora_out_codeparrot_small	adding files needed for inference
lora_out_deepseek_1b	[feat] added newly trained lora with deepseek coder 1b on new parameters
lora_out_deepseek_1b_v2	Update README.md
lora_out_deepseek_1b_v3	[feat] added a warmup and LR scheduler and dataset merging
models	[refractor and test] moving models into /model directory and changing...
results	[feat] added missing files from training and inference for deepseek
scripts	[upd] fix
.gitignore	Add LoRA configs and metrics for codeparrot and dryrun test
Dockerfile	[feat, fix, refractor] LoRA/PEFT FT implementation
README.md	Update README.md
accelerate_config.yaml	[feat, fix, refractor] LoRA/PEFT FT implementation
dashboard.py	[fix] weird scroolling
deepspeed_config.json	[feat, fix, refractor] LoRA/PEFT FT implementation
docker-compose.yml	[refractor] no sudo access in vm so docker can't read gpu images so r...
pyproject.toml	[refractor] working on LoRA LLM Compression apporach for this branch
requirements.txt	[fix] dependencies and dashboard fixing calling correct python scripts
why_QLoRA_won't_work.md	[fix] patched lora_config in train_lora.py

Quantization:



Conclusion

As a group, we all learned the importance of having a set and stone SDLC, communication, skill building with Streamlit, bash scripting, React/TypeScript, Python, Docker, etc. Being able to delegate and communicate project tasks and deadlines we're important to deliver quality work to present to Robins AFB Milestone Meetings on Teams.

We will all carry the skills acquired from this class and experience to our future endeavors whether that is a masters, PHD, internship, co-op, or full-time role. Thank you, Professor Perry, for your guidance and patience with not only our group but the other sections you had responsibility for.

Appendix – training verification (if mobile, web or desktop apps), project plan (optional), etc.

A. Docker

Docker is a containerization platform used for packaging applications and dependencies into isolated and reproducible environments (Merkel, 2014). Although VM constraints limited its use, understanding Docker helped us learn modern ML deployment practices.

Learning Resources

- Docker Documentation: https://docs.docker.com
- Bret Fisher's Docker Mastery (Udemy)

Citation

Merkel, D. (2014). *Docker: Lightweight Linux containers for consistent development and deployment*. Linux Journal, 239.

B. PyTorch

PyTorch is a deep learning framework supporting dynamic computation graphs, GPU acceleration, and seamless model development (Paszke et al., 2019). It served as the foundation for loading, training, and fine-tuning models.

Learning Resources

- PyTorch Docs: https://pytorch.org/docs/stable/
- Official PyTorch Tutorials

Citation

Paszke, A., et al. (2019). *PyTorch: An Imperative Style, High-Performance Deep Learning Library*. NeurIPS.

C. LLM Compression Techniques

1. Quantization

Quantization reduces weight precision (e.g., FP32 → INT8), reducing memory and inference time (Jacob et al., 2018).

Resource

- HuggingFace Quantization Guide: https://huggingface.co/docs/optimum/main/en/optimization/quantization

Citation

Jacob, B., et al. (2018). *Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference*. CVPR.

2. Knowledge Distillation

Knowledge distillation trains a small student model to mimic a larger teacher model, retaining most performance with fewer parameters (Hinton et al., 2015).

Resource

- Distillation overview: https://huggingface.co/docs/transformers/main/en/tasks/distillation

Citation

Hinton, G., Vinyals, O., & Dean, J. (2015). *Distilling the Knowledge in a Neural Network*. NIPS Deep Learning Workshop.

3. LoRA (Low-Rank Adaptation)

LoRA injects low-rank matrices into frozen layers, enabling lightweight fine-tuning and minimal storage overhead (Hu et al., 2021).

Resource

- PEFT LoRA Guide: https://huggingface.co/docs/peft/main/en/conceptual_guides/lora

Citation

Hu, E. J., et al. (2021). *LoRA: Low-Rank Adaptation of Large Language Models*. arXiv:2106.09685.

D. HuggingFace & Training Libraries

Transformers

The Transformers library provides pretrained LLM architectures for text classification, generation, and embeddings (Wolf et al., 2020).

Resource

- https://huggingface.co/docs/transformers

Citation

Wolf, T., et al. (2020). *Transformers: State-of-the-Art Natural Language Processing*. EMNLP.

Datasets

A framework for loading, preprocessing, and streaming large-scale datasets (Lhoest et al., 2021).

Resource

- https://huggingface.co/docs/datasets

Citation

Lhoest, Q., et al. (2021). *Datasets: A Community Library for NLP*. EMNLP.

Accelerate

Accelerate simplifies distributed training and device-agnostic execution.

Resource

- https://huggingface.co/docs/accelerate

Citation

HuggingFace. (2022). *Accelerate Library*. HuggingFace Documentation.

PEFT

Parameter-efficient fine-tuning framework supporting LoRA, adapters, and prefix tuning.

Resource

- https://huggingface.co/docs/peft

Citation

Mangrulkar, S., et al. (2022). *PEFT: Parameter-Efficient Fine-Tuning*. HuggingFace AI.

E. CUDA, cuDNN, and NVIDIA Libraries

These GPU toolkits accelerate deep learning workloads and enable PyTorch GPU support (NVIDIA, 2020).

Although unused for training due to VM constraints, they were required for dependency compatibility.

Resource

- NVIDIA CUDA: https://developer.nvidia.com/cuda-zone
- cuDNN: https://developer.nvidia.com/cudnn

Citation

NVIDIA. (2020). *CUDA Toolkit Documentation*. NVIDIA Corporation.

F. Data Science & Utility Libraries

NumPy

Core scientific computing package for tensor operations (Harris et al., 2020).

Pandas

Powerful data manipulation and analysis toolkit (McKinney, 2010).

Matplotlib

Visualization library for plotting training metrics and dataset distribution (Hunter, 2007).

Resources

- https://numpy.org

- https://pandas.pydata.org
- https://matplotlib.org

Citations

Harris, C. R., et al. (2020). *Array programming with NumPy*. Nature.
McKinney, W. (2010). *Data Structures for Statistical Computing in Python*. SciPy.
Hunter, J. D. (2007). *Matplotlib: A 2D Graphics Environment*. Computing in Science & Engineering.

G. HuggingFace Hub & Networking Libraries

HuggingFace Hub

Supports model download, versioning, and collaboration.

Requests / HTTPX / AIOHTTP

Used for dataset downloads and API communication (Reitz, 2012; Encode, 2021).

Resources

- https://huggingface.co/docs/huggingface_hub
- https://requests.readthedocs.io
- https://www.python-httpx.org
- https://docs.aiohttp.org

Citations

Reitz, K. (2012). *Requests: HTTP for Humans*.
Encode. (2021). *HTTPX Documentation*.

H. General Utility Libraries

- **PyYAML** for config files
- **Regex** for text preprocessing
- **Tokenizers** for fast BPE tokenization

- **Psutil** for VM resource monitoring

Resources

- https://pyyaml.org
- https://github.com/huggingface/tokenizers
- https://psutil.readthedocs.io

I. Streamlit

Streamlit provided a lightweight UI for demonstrating model predictions.

Resource

- https://docs.streamlit.io

Citation

Streamlit Inc. (2021). *Streamlit Documentation*.

J. Version Pinning & Environment Constraints

All packages were pinned to ensure compatibility with:

- Python 3.11.9
- No sudo access
- CPU-only environment
- VM memory limitations
- Outdated underlying OS libraries

This approach made the environment stable and reproducible under restricted system conditions.

References

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