**Tweet Emotion Detection - Full Project Summary**

**Overview**

This project focuses on **Tweet Emotion Detection**, where models were trained to classify tweets into multiple emotion categories, such as *joy, sadness, anger, optimism*, and more. The project evolved through four phases, each improving upon the previous approaches, ultimately leading to an efficient, high-performing model for sentiment classification.

**Evolution of the Project**

**Phase 1: Custom MLP Model (HW5)**

* Implemented a **Multi-Layer Perceptron (MLP)** model.
* Designed a **custom Hugging Face-compatible architecture** with a configuration class.
* Model performance was **limited**, struggling with emotions like trust and surprise.
* Showed **decent accuracy** for common emotions like **anger and disgust**, but lacked generalization.

**Phase 2: Transformer-Based Fine-Tuning (HW6)**

* Introduced **pre-trained transformer models**: **RoBERTa, ALBERT, and DistilBERT**.
* Full fine-tuning was performed on tweet sentiment data.
* **RoBERTa emerged as the best model**, significantly outperforming the custom MLP in all emotion categories.
* Despite the accuracy improvement, **full fine-tuning was computationally expensive**.

**Phase 3: PEFT-Based Fine-Tuning (HW7)**

* Shifted to **Parameter-Efficient Fine-Tuning (PEFT)** using **LoRA and BitsAndBytes quantization**.
* Introduced larger models: **E5-Mistral-7B, Google Gemma-2-2B, and Meta LLaMA-3.2-1B**.
* **E5-Mistral-7B emerged as the best**, particularly excelling in **optimism, sadness, and anger detection**.
* **PEFT significantly reduced training costs**, making large-scale models more feasible.

**Phase 4: Prompt-Based Fine-Tuning with PEFT (HW8)**

* Introduced **prompt-based learning**, further optimizing model efficiency.
* Models used: **Qwen2.5-0.5B, Meta LLaMA-3.2-1B-Instruct, and Meta LLaMA-3.1-8B-Instruct**.
* **Meta LLaMA-3.2-1B-Instruct (Experiment 2) performed the best**, excelling in **optimism, anger, and disgust classification**.
* **Prompt-based tuning helped guide models to understand emotions better** without requiring full fine-tuning.

**Best Findings & Key Takeaways**

* **Best Performing Model**: **Meta LLaMA-3.2-1B-Instruct (HW8, Experiment 2)** had the best balance of **accuracy, efficiency, and memory optimization**.
* **Most Computationally Expensive**: **HW6 full fine-tuning (RoBERTa)**, despite its accuracy, required extensive resources.
* **Best Efficiency vs. Performance Tradeoff**: **HW7's PEFT-based fine-tuning (E5-Mistral-7B)** showed that **large models can be fine-tuned efficiently** without training the entire network.
* **Prompt Engineering Matters**: HW8’s **prompt-based learning approach enhanced model adaptability** and reduced training data dependency.

**Conclusion**

This project evolved from **basic MLP models to advanced PEFT fine-tuning with prompt learning**, demonstrating the power of **efficient transformer fine-tuning** for emotion detection. The final model, **Meta LLaMA-3.2-1B-Instruct (PEFT + Prompt-Based Tuning)**, emerged as the best-performing approach, providing **high accuracy with minimal computational cost**. Future work could explore **further prompt optimization and ensemble learning** for even better results.