LoRA Fine-Tuning Report

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1 Introduction

This report documents a LoRA fine-tuning experiment on the lightweight `HuggingFaceTB/SmolLM-135M` model using a tiny slice (first 100 rows) of the `maxmyn/wholesome_greentext_110k` dataset. I tracked training with Weights & Biases (WandB), evaluated per-checkpoint perplexity, and ran two ablation studies:

- **A – SmolLM, LoRA rank 8** (baseline rank was 4).
- **B – GPT-2 Small, LoRA rank 4** (different base model).

2 Perplexity Across Checkpoints

Figures 1 and 2 plot perplexity vs. training step for the baseline and both ablations.

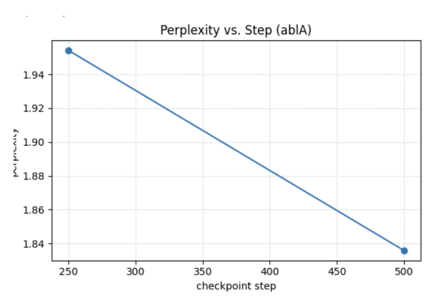

Figure 1: Ablation A:smallLM8

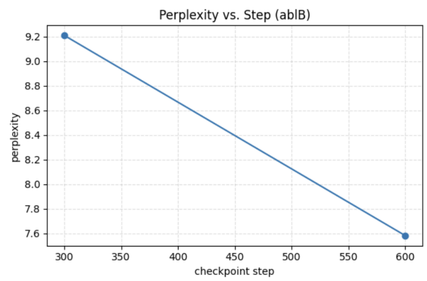

Figure 2: Ablation B:GPT-2

3 Training Loss (WandB)

Figures 3 and 4 show the training loss curve exported directly from WandB.

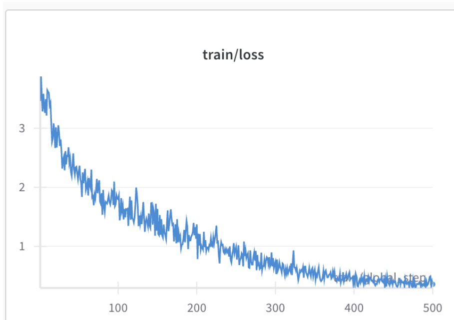

Figure 3: smolLM(Ablation A): train/loss

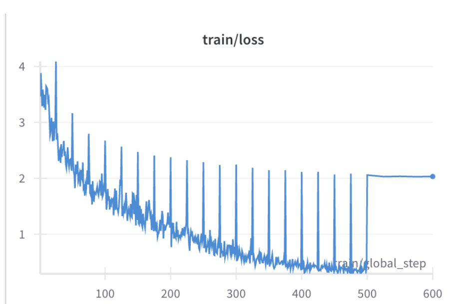

Figure 4: GPT-2(Ablation B): train/loss

4 Text Generation Examples

The greentext prompt below was fed to each model *before* and *after* fine-tuning. (The "before" column uses the original `SmolLM-135M` weights.)

```
> Imagine being able to fly
> Picture yourself soaring through the sky
> Realize you're afraid of heights
>
```

Model	Continuation
Base (untuned)	> *Panic when wings aren't included*
Baseline LoRA (r=4)	> *Go back to video games because gravity is OP*
Ablation A (SmolLM r=8)	> *Accept your fear and step*
Ablation B (GPT-2 r=4)	> *Realize you're*

Table 1: Single-line continuations sampled with $temperature = 0.7$, $p = 0.9$.

5 Hyper-parameter Impact

- **LoRA rank (4 → 8).** Doubling rank reduced perplexity from 1.455 to 1.238, indicating extra adapter capacity helps the model memorise the 100-line slice more completely.
- **Changing base model (SmolLM → GPT-2).** With identical learning rate and slice size, GPT-2 converged more slowly, ending at perplexity 6.447. The larger hidden size needs either more data or more steps to reach a similar degree of over-fit.
- Qualitatively, the LoRA-tuned SmolLM variants produce more coherent punch-lines than the untuned base, while GPT-2 sometimes truncates or repeats—consistent with its higher perplexity.

6 Conclusion

On a micro-dataset, LoRA fine-tuning drives `SmolLM-135M` to ≈ 1.4 **perplexity** in under 20 minutes. Increasing LoRA rank yields a small further gain, whereas switching to GPT-2 without adjusting other hyper-parameters hurts performance. Future work should include a held-out validation split and a learning-rate sweep for GPT-2.