TensLoRA + Heterogeneous Allocation of Rank and Learning Rate

ECE 273 FINAL REPORT

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Project Scope Adjustment

ORIGINAL TOPIC

~~Tensor Enhanced Semantic Adapter for Agentic Tool Retrieval~~

NEW TOPIC

TensLoRA +

Heterogeneous Allocation of Rank and Learning Rate

TensLora

TensLoRA introduces a tensor based LoRA that reduces redundant correlations across layers and projections, offering better allocation of trainable parameters.

$$W = W_0 + \Delta W$$

$$\Delta W = \sout{A \times B} \rightarrow \text{Tensor Decomposition}$$

Reason for Change

- Inference performance remained low, even after trying smaller models, smaller domain specific datasets, and retriever training.
- GPU resources were limited and full pipeline training was too slow.
- A focused study on TensLoRA behavior provided clearer scientific value.

Motivation 1: Heterogeneous Learning Rate

> *"Using the same learning rate for A and B does not allow efficient feature learning."* - LoRA+

LoRA+ Approach

$$\eta_B = \lambda \eta_A \,,\ (with\ \lambda > 1)$$

TensLoRA+

$$\eta_C = \lambda \eta_F \,,\ (with\ \lambda > 1)$$

> **Note:** Core *C* corresponds to *B* (due to zero-initialization), while Factors *F* correspond to *A*.

Hypothesis

Since TensLoRA separates the update into a Core tensor and multiple Factor matrices, applying heterogeneous learning rates may improve optimization efficiency for each component.

→ **Therefore, we propose using a Heterogeneous Learning Rate.**

Motivation 2: Heterogeneous Rank

TensLoRA Insights

1. **Rank is Critical:** Rank significantly impacts model performance and parameter efficiency.
2. **Dimensional Variance:** Different dimensions within the tensor hold varying degrees of importance.

GAP

TensLoRA does not experimentally explore how rank should vary across modes, despite explicitly acknowledging mode specific differences.

→ Therefore, we apply Heterogeneous Rank

assigning different ranks to different tensor modes based on metrics describing complexity, and contribution.

Three Phase Experimental Design

Phase 1: Baseline

Approaches:

- Standard LoRA
- CP LoRA
- Tucker LoRA

Metrics Tracked:

- **SVD_Entropy:**
  Information spread.
- **SVD_Top1_Energy:**
  Contribution magnitude.

Phase 2: Learning Rate

We apply different λ values to ηC

Phase 3: Rank

Rank allocation based on Phase 1 metrics

High Top1 Energy / Low Entropy:

↓ Reduce Rank

Low Top1 Energy / High Entropy:

↑ Increase Rank

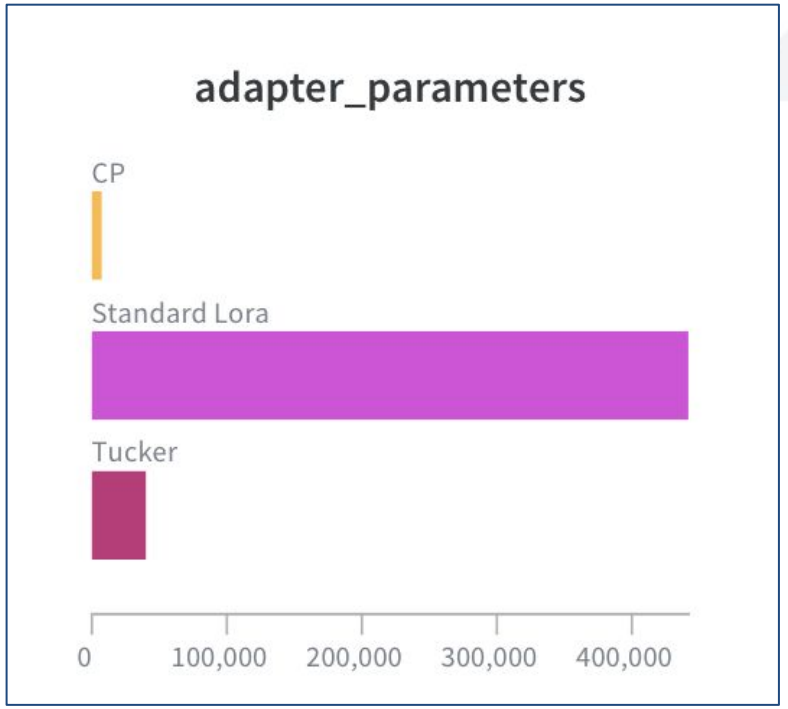
"Information is concentrated, suggests that more rank is required to avoid information loss."

Phase 1 Results: Baseline Comparison

Settings

- **Model:** RoBERTa
- **Dataset:** CoLa
- **Main Approach:** Tucker
- **Rank:** 8

Approach	Params	MCC
Standard Lora	442368	0.58
CP	6872	0.52
Tucker	39640	0.52



ANALYSIS

- *CP gives same MCC as Tucker despite smallest parameter budget.*
- *Perhaps because CoLA is a low capacity task, so aggressive compression does not hurt performance.*

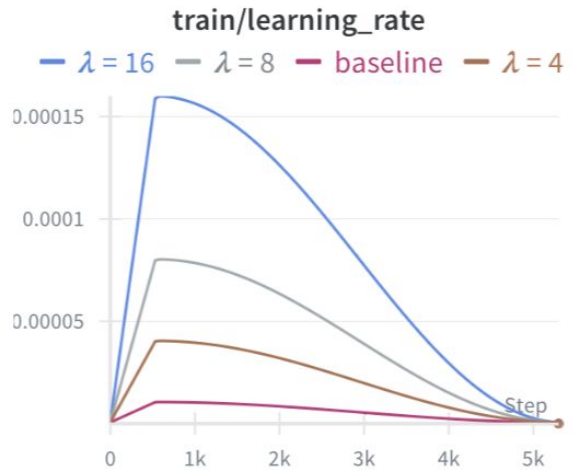
Phase 1 Results: Metric Analysis

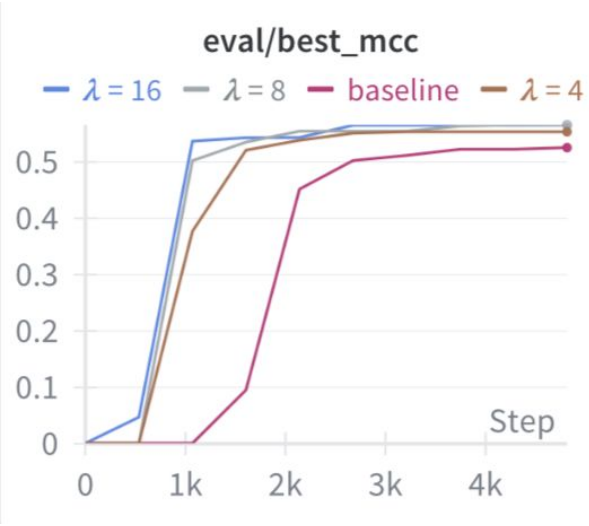
Metric	Input	Layers	Heads	HeadDim	QKV
SVD Entropy	0.6817	1.6908	2.0049	1.999	0.8918
SVD Energy (Top 1)	0.8284	0.4656	0.213	0.2321	0.6188

METRIC INTERPRETATION

- *Green: High Entropy & Low Energy → Information Density → Increase Rank*
- *Yellow: Low Entropy & High Energy → Spectral Redundancy → Decrease Rank*

Phase 2 Results: Heterogeneous Learning Rate



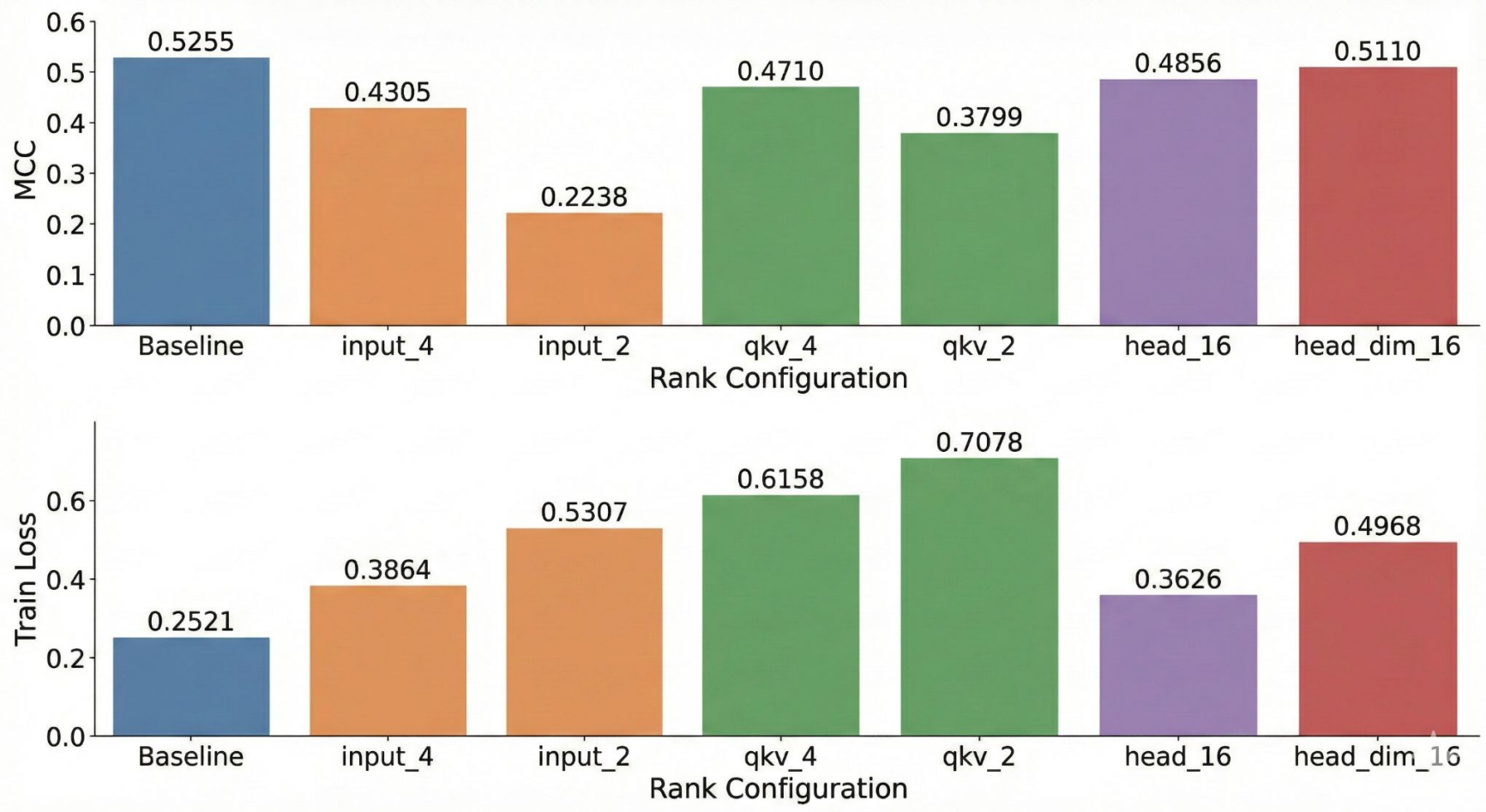


Experiment	Accuracy	MCC
Baseline	0.8063	0.5255
λ=4	0.8092	0.5536
λ=8	0.8159	0.5656
λ=16	0.8187	0.5658

LR ANALYSIS

- *Larger λ gives faster convergence and higher MCC.*
- *These results confirm the TensLora+'s heterogeneous LR hypothesis.*

Phase 3: Heterogeneous Rank



- *Input, qkv: collapse when rank is sharply reduced, indicating that extreme compression removes essential information these modes must preserve.*
- *Head, head_dim: degrade when rank is doubled, meaning extra capacity adds noise or leads to overfitting rather than improving representation quality.*

Limitation & Future Directions

- Theoretical Rigor
  - Mathematical Proof for Heterogeneous LR
  - Justification for Rank Selection Metrics
- Experimental Optimization
  - Extensive Hyperparameter Tuning
  - Complex Rank Combinations

Reference

Marmoret, Axel, et al. "TensLoRA: Tensor Alternatives for Low-Rank Adaptation." *arXiv preprint arXiv:2509.19391* (2025).

Hayou, Soufiane, Nikhil Ghosh, and Bin Yu. "Lora+: Efficient low rank adaptation of large models." *arXiv preprint arXiv:2402.12354* (2024).

Thank you