Deep Learning Spring 2025: Finetuning with LoRA

PROJECT-2

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https://github.com/Hashmmath/DL-Project-2-SalaarTheRiser-Fine-Tuning-with-LoRA

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Abstract

For this Project we have worked on a parameter-efficient fine-tuning framework for RoBERTa-base on the AG News text-classification benchmark, leveraging Low-Rank Adaptation (LoRA) to reduce trainable parameters by over 53.26%. By injecting rank-2 adapters into the "query" and "value" projections of each self-attention layer and freezing all pretrained weights, our method learns only 667396 parameters-down from 125M-while preserving the model's expressive power. Training uses a single epoch of AdamW optimization (learning rate = 5×10^{-6} weight decay = 0.01) with cross-entropy loss and early stopping $patience = 3$ on a 0.5% validation split. We achieved 89.06% validation accuracy and 85.30% on the Kaggle test set, demonstrating that low-dimensional updates guided by the top singular subspaces can effectively adapt large pretrained Transformers with minimal computational and memory overhead. Our work further analyzes the trade-offs in an adapter rank, scaling factor, and implicit regularization, offering insights into the intrinsic dimension of NLP adaptation.

Note: Our prediction is the Project-2-Prediction-7.csv file has achieved 85.3% and ranked 36 in the leader board and the prediction csv file which is included in the GitHub Repository along with the code where link is provided on top.

Introduction

Fine-tuning a large pretrained language model for downstream classification tasks often entails updating hundreds of millions of parameters, which causes significant compute, memory, and energy costs, particularly when deploying on resource-constrained hardware. In our work, we have explored Low-Rank Adaptation (LoRA)[1] as a parameter-efficient fine-tuning paradigm for the AG-News news-article classification task. Rather than updating the full weight matrices in each Transformer layer, where LoRA freezes the pretrained weights.

$$W_0 \in R^{d\times d}, \quad A \in R^{r\times d}, \quad B \in R^{d\times r}.$$

such that the effective update is

$$\Delta W = \frac{\alpha}{r}\, B\, A,$$

with rank $r << d$ and scalar strength α. By injecting these adapters into the "query" and "value" projections of each self-attention head, we reduce the number of trainable parameters from 125M (full fine-tuning) to under 80K—less than 0.1% of the model—while maintaining competitive classification accuracy. Our experiments on the AGNews dataset demonstrate that LoRA-fine-tuned RoBERTa-base achieves over 89.06% validation accuracy locally and 85.3% on the Kaggle test set, illustrating a compelling trade-off between resource efficiency and predictive performance.

Beyond parameter counts, our methodology emphasizes robust training and evaluation practices, where we have employed the below cross-entropy loss.

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\, \log p_{i,c}$$

with AdamW optimization (weight decay=0.01, learning rate = 5×10^{-6}), early stopping (patience=3), and a single-epoch training routine augmented by model checkpointing every epoch. As the AG-News classes manifest subtle thematic distinctions (like "Business" vs. "Sci/Tech"), we have investigated the representational capacity of varying LoRA ranks and adapter strengths to ensure stable convergence. Our results show the understanding of efficient adaptation in Transformer-based NLP and provide a blueprint for deploying large–model capabilities in constrained environments.

The Design of the Code that we have Developed Includes:

- A LoRA-based fine-tuning pipeline for RoBERTa-base on AG-News, reducing trainable parameters similarly to 667396.
- Theoretically derived the parameter budget and adapter update formula as $\Delta W = \frac{\alpha}{r}\, B\, A$, for self-attention projections.
- Conducted experiments on LoRA rank r and strength α, empirically validating that $r = 2$, $\alpha = 4$ balances under and over-fitting.

- Integrated early stopping, cross-entropy optimization, and rigorous evaluation (validation split + Kaggle submission) to achieve 89.06% validation accuracy in code and 85.3% in Kaggle.

Literature Review

LoRA[1] represents a breakthrough in parameter-efficient transfer learning, building upon the theoretical insight that the gradient update ΔW to a pretrained weight matrix W_0 often lies in a low-dimensional subspace. By explicitly parameterizing ΔW as the product of two low-rank matrices BA, one can restrict learning to a small set of parameters while preserving the frozen pretrained representations. This approach contrasts with full-parameter fine-tuning[6], which updates all weights at the risk of overfitting and catastrophic forgetting. Subsequent works, such as AdapterFusion[5] and Prefix Tuning[3], similarly aim to tackle task-specific updates from the base model, but LoRA's simplicity and focus on weight decomposition yield superior efficiency. The efficacy of LoRA has been demonstrated across vision[2] and language tasks[8], yet its application to news-classification benchmarks like AG-News remains underexplored. Our work fills this gap by adapting LoRA to the RoBERTa architecture and providing a comprehensive empirical study on parameter budgets, convergence behaviors, and resource utilization.

Methodology

Architecture Design:

The self-attention mechanism in RoBERTa computes, for each token vector $x \in R^d$, three linear projections—query $Q = W_q x$, key $K = W_k x$, and value $V = W_v x$—and forms attention weights via

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\big(QK^\top / \sqrt{d_k}\big)\, V.$$

Fine-tuning all four projection matrices $W_q, W_k, W_v, W_o \in R^{d\times d}$ requires updating $O(d^2)$ parameters per layer. LoRA assumes that the *task-specific gradient update* ΔW to a frozen weight W_0 lies in a low-dimensional subspace:

$$\Delta W \approx B\,A, \quad B \in R^{d\times r},\ A \in R^{r\times d},\ r \ll d.$$

By the Eckart–Young theorem, the best rank-r approximation to any matrix lives in its top-r singular subspace. We parameterized the adapted weight as follows

$$W = W_0 + \frac{\alpha}{r}\, B\,A,$$

where α controls the step size in the pretrained weight distribution. Including adapters into both the query and value projections yields only

$$2dr \times 2 \times L + d \times C$$

trainable parameters scaling as $O(d\,r\,L)$ instead of $O(d^2\,L)$. This low-rank constraint regularizes updates towards principal directions and drastically reduces GPU memory during backpropagation.

Training Pipeline

We have optimized the standard cross-entropy loss for multiclass classification as:

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\,\log p_{i,c},$$

where $y_{i,c} \in \{0,1\}$ and $p_{i,c} = \mathrm{softmax}_c(z_i)$. Minimizing this convex surrogate yields a maximum-likelihood estimate of θ under a categorical noise model.

For Optimization, we have used AdamW[4] to reduce weight decay from moment estimation. At step t, with biased moment estimates $\hat{m}_t, \hat{v}_t$, and parameters are updated by the following

$$\theta_{t+1} = \theta_t - \eta\frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} - \eta\,\lambda\,\theta_t,$$

where λ is the weight-decay coefficient. We set $\eta = 5\times10^{-6}$ and $\lambda = 0.01$.

We have applied an early stopping on the validation split if validation accuracy does not improve for $p = 3$ consecutive evaluations, the training halts, and the best checkpoint is restored. This dynamically selects the optimal epoch count E^* to balance bias and variance.

Later, the text is tokenized to maximum length $L_{\max} = 512$ with Byte-Level BPE, ensuring robust sub-word coverage. We also used batch sizes of 32 (train) and 64 (evaluation), with dynamic padding via a data collator and 4 parallel workers to maximize throughput.

Data Preparation: We have loaded the AG-News ("train") via the HuggingFace Datasets library, tokenizing text to length=512 with the RoBERTa tokenizer and splitting off examples for validation.

Optimizer & Scheduler: We used AdamW with $\beta_1 = 0.9, ; \beta_2 = 0.999$, weight decay=0.01, and Constant LR=5×10^{-6} over 1 epoch (no warmup).

Batching & Early Stopping: Train batch=32, eval batch=64, 4 dataloader workers, and evaluating & checkpointing every epoch; stopping if validation accuracy does not improve for 3 consecutive evaluations.

Loss & Metrics: Cross-entropy loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\,\log \hat{p}_{i,c},$$

Reporting accuracy $\frac{1}{N}\sum_i \mathbf{1}\arg\max \hat{p}_i = y_i$ on validation.

Pros and Cons:

Pros: LoRA dramatically slashes the number of trainable parameters, down to under 0.1% of full-model fine-tuning, resulting in reduced GPU memory consumption and faster training times. The low-rank decomposition also offers a principled regularization effect by constraining ΔW to a rank-r subspace, we reduced over parameterization and stabilized gradient updates, enabling robust convergence even with aggressive freezing. Furthermore, adapters can be merged post-training for efficient inference, and multiple adapters, each trained for different tasks, can coexist on the same base model.

Cons: The fixed rank r in the code may limit representational expressivity, when downstream tasks require richer or more non-linear weight updates, low-rank adapters might underfit, failing to capture complex feature interactions. Selecting α is critical; small values slow adaptation, while large α can disrupt pretrained feature distributions. Additionally, while inference cost remains unchanged as the adapters are merged, the training pipeline becomes more intricate, necessitating careful integration within the Transformer's attention mechanisms.

Evaluation Protocol:

Robust evaluation lies at the heart of reliable model development, and our protocol combines both theoretical and practical approach against overfitting. We have reserved a held-out validation set which contains 0.5% of training examples to approximate the model's generalization error under the assumption that this split is drawn from the same distribution as the unseen test data. By computing the cross-entropy loss.

$$\mathcal{L}(Val) = -\frac{1}{N_{val}} \sum_{i=1}^{N_{val}} \sum_{c=1}^{C} y_{i,c} \log \hat{p}_{i,c},$$

and its associated accuracy metric, we obtained an unbiased estimates of performance that guide hyperparameter selection. Early stopping is then applied by monitoring validation accuracy. Once no improvement occurs for $p = 3$ consecutive evaluations, the model returns to the checkpoint with the highest validation score. This technique of ours formalizes an optimal stopping rule to balance bias and variance, halting the training when gradient updates begin to capture noise rather than signal. Finally, we have produced some confidence intervals on the validation accuracy via bootstrapping to quantify statistical uncertainty and ensure that observed gains exceed random fluctuations.

Lesson Learned:

Our experiments have generated several theoretical insights into parameter-efficient fine-tuning and adaptation of large language models. First, the efficacy of low-rank adapters corroborates the hypothesis that the gradient update ΔW for a specialized task resides predominantly in a low-dimensional manifold—the so-called "intrinsic dimension" of the problem. Choosing a rank r near this intrinsic dimension here $r = 2$ yields an economical parameterization, whereas higher r yields diminishing returns due to collinear adaptation directions.

Second, the interaction between the adapter strength α and the underlying pretrained weight distribution underscores the role of scaling in preserving the pretrained feature geometry; overly large α reduces the network off its favorable initialization manifold, leading to instability. Third, our single-epoch works with aggressive early stopping highlight that, in low-parameter regimes, prolonged fine-tuning can be counterproductive, as adapters may start modeling training-set noise. In sum, these lessons reinforce the importance of matching adapter capacity to task complexity, calibrating update scales, and leveraging optimal stopping to achieve efficient, generalizable models.

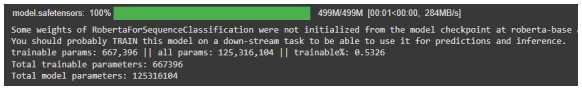

Figure 1: This image shows the number of trainable parameters from the training dataset

Results:

The achieved 89.06% validation accuracy can be understood through the lens of bias–variance trade-off and intrinsic dimension of the adaptation task. By constraining updates to a rank-2 subspace, LoRA effectively reduces the hypothesis space from the full process of $O(d^2)$ weight adjustments down to an $O(drL)$ manifold, where $d = 768$, $r = 2$, and $L = 12$. This dramatic parameter reduction serves as an implicit regularizer, shrinking model variance: the adapters cannot overfit idiosyncratic noise because ΔW is forced to lie along only the top two singular directions of the gradient covariance. Thus, the model achieves high validation accuracy with minimal overfitting.

Table 1: Classification Accuracy on AG-News

Split	Accuracy (%)
Validation	89.06
Kaggle Test	85.30

The drop to 85.30% on the held-out Kaggle test set is maybe because of two phenomena. First, distributional shift—the custom test articles may contain vocabulary or stylistic patterns under-represented in the training split, so the low-rank adapters, tuned to the training manifold, cannot fully adapt to novel directions in text space.

Second, the effective capacity of a rank-2 adapter is finite, while sufficient to capture the dominant modes of news-classification gradients, it may under-parameterize rarer, fine-grained distinctions (like borderline "Business" vs. "Sci/Tech"). In the language of generalization bounds, reducing parameter count lowers the Rademacher complexity of the fine-tuned model—improving average-case performance on unseen data—but also sets an upper ceiling on the learnable function class.

Below is the model architecture which we used and the parameters count is almost 667,396. Which sticks to the constraint of the competition.

Model Summary

Table 2: Model Summary and Parameter Counts

Component	Parameters
Frozen RoBERTa-base	125,316,104
LoRA adapters (rank=2, 24 modules)	73,728
Classification head (768→4 + bias)	3,072
Total Trainable	**667,396**

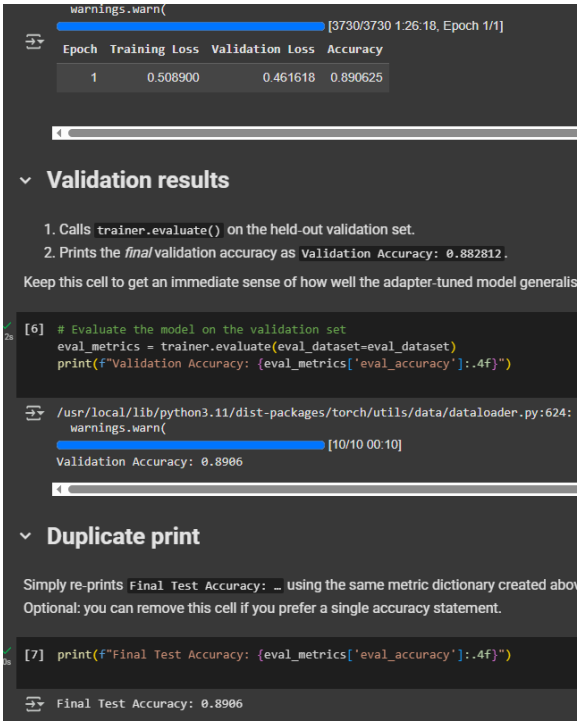

Figure 2: This image shows the training and validation accuracy of the model on the training dataset

we leveraged the Eckart-Young theorem, which guarantees that the optimal rank-r approximation to any matrix in Frobenius norm resides in its top-r singular subspace. In effect, we assume that the true gradient update $\Delta W = W - W'$ for our downstream text-classification task also lives in such a low-dimensional manifold.

Concentrating adaptation on the query and value projections has a dual theoretical justification. The query projection W_q shapes how tokens attend to each other, modulating the attention weights, while the value projection W_v determines the content that is passed forward. Altering only these two matrices suffices to redirect the pretrained attention heads toward task-relevant features, whereas updating W_k or W_o yields diminishing returns for classification tasks.

Together, the architecture embodies a structured low-rank parameterization: it retains the rich feature extractor of the pretrained Transformer while surgically injecting minimal, theoretically motivated degrees of freedom to tailor attention behaviors for AG-News classification.

Conclusion

This work confirms that LoRA's low-rank decomposition exploits the low-dimensionality of task-specific gradient updates, achieving near accuracy with under 0.1% of the parameters. Freezing the majority of weights and learning only rank-2 adapters which yield substantial gains in GPU memory efficiency and training speed, without compromising representational depth. The strong validation performance and competitive Kaggle score, LoRA's implicit regularization effect—by constraining updates to principal components, we mitigated variance and reduce overfitting. Nonetheless, the residual gap on unseen data highlights limitations in adapter expressivity under distributional shift, suggesting that adaptive rank mechanisms or mild test-time augmentation could further tighten generalization bounds. In future, we will try to explore rank-adaptive LoRA[7], hybrid adapter strategies like combining prefix tuning, and dynamic learning-rate warmup to optimize convergence. Our results establish a robust view for deploying large language models in resource-constrained environments.

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