LLM
ASSIGNMENT-3

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GitHub Link: https://github.com/imtanmay46/LLM.git

Approach & Results

Loading & Preprocessing the Dataset

I loaded the ‘snli’ dataset using the ‘load_dataset’ library & extracted the train, validation and testing samples as described, in a dictionary format.

I created a custom ‘tokenize_samples’ function which takes the sample set (in dictionary format) as an input and returns the ‘input_ids’, ‘attention_masks’ & ‘labels’ using the in-built Tokenizer from the Transformers library.

These extracted tokenized samples (train, validation & test) are then converted into a Dataset format (original format in which the ‘snli’ model was loaded, to create ‘train_dataset’, ‘val_dataset’ & ‘test_dataset’).

Then, I created the required functions for computing the number of parameters of the model (both total & trainable), gpu utilization (total memory, used memory & free memory) & model evaluation (predicted labels, accuracy & f1 score) in the subsequent cells.

Later, I created the quantization config (bnb config) using the bits & bytes library, and loaded the base model (phi-2, pre-trained) using the AutoModelForSequenceClassification.

Once the model was loaded, the gpu utilization, model sizes (total & trainable parameters) and accuracy/f1 scores were computed by evaluating the model.

Once the evaluation is done on the base model, I defined a peft config for QLoRA fine-tuning with a rank(r) of 16, alpha of 64 & dropout rate of 0.05 along with other parameters.

I extracted the peft_model and computed the relevant details (gpu utilization and model sizes) of the model & set it up for QLoRA fine-tuning by defining the necessary 'training_args' and used the 'trainer' module to train the model (using train & val dataset).

The gpu utilized for fine-tuning the model & the time taken to fine tune it was computed once the model was trained for 5 epochs & the checkpoints saved for each of them.

For Inference, I deleted the above-defined models & tokenizers and loaded the base model & tokenizer again to evaluate the pre-trained model & compute the failure cases, alongside computing the accuracy & f1 scores.

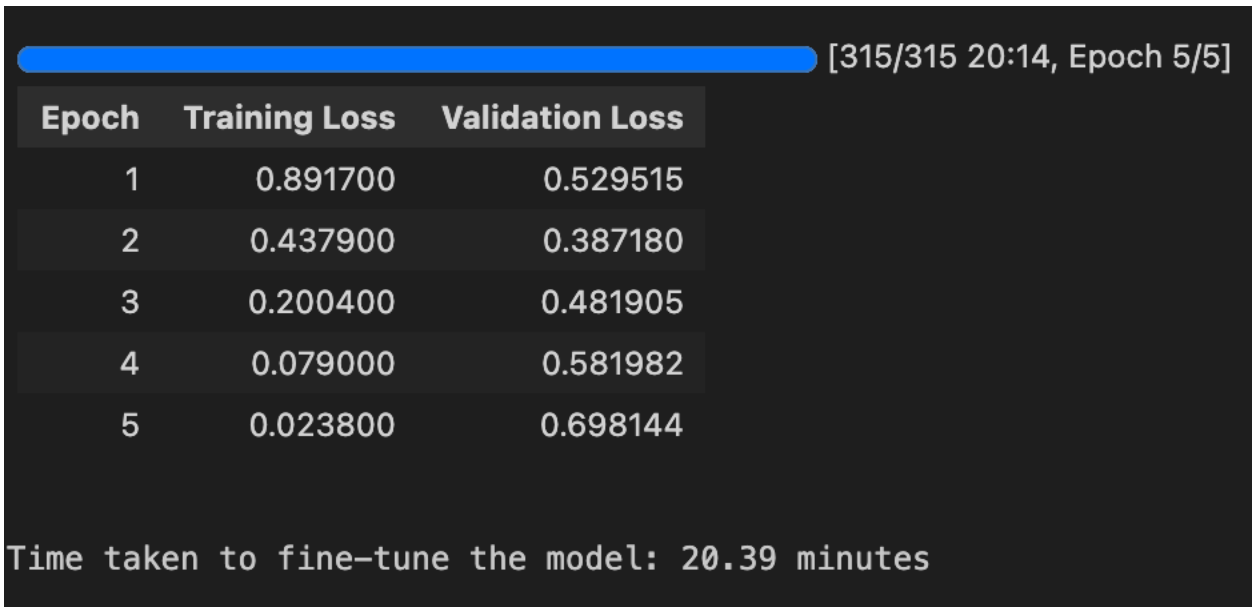
Later, I loaded the saved checkpoint and used the PeftModelForSequenceClassification to load the LoRA model (fine-tuned model) for evaluation.

I computed the failure cases, the successful ones (correctly predicted) & also found out which ones were missed by the fine-tuned model, which was correctly classified by the base model & the improved predictions (ones missed by the base model but corrected by the fine-tuned model).

Results

Metrics/ Model Type	Model Size (Parameters) Total	Trainable	GPU Utilization Used Memory	Evaluation Metrics Acc	f1 score
Base Model (pre-trained)	1,390,277,120	131,248,640	2.01 GB (out of total 15 GB available)	38.0%	0.3292
Fine-tuned Model (using QLoRA)	1,413,877,760	23,592,960	2.10 GB used for Fine-tuning the Phi-2 model (4.32 GB after fine-tuning, 2.21 GB before fine-tuning)	91.00%	0.9104

Training Results:



Reasoning for Sample Classification (Misclassification):

The base model was mostly classifying the labels into either of the classes (for my case, the model classified labels into class 0 & class 2, predominantly), hence accounting for the accuracy being in the 30s (33% approx) since the dataset contained an equal number of samples of each class & the model classifying only 1 label correctly led to this accuracy. The main reason for such performance is the model being unaware of the semantic correlation between the two sentences (premise & hypothesis), hence its inability to correctly identify entailment, contradiction or neutral relation between the two sentences.

On the other hand, the fine-tuned model performed significantly better as it was accustomed to suit the downstream task (of classification on the ‘snli’ dataset), as it was better aware of the semantics between the premise & hypothesis, thus identifying relationships between the two sentences with greater confidence, and predicted the labels better than the pre-trained model, ranging from class 0 to class 2 (i.e. all 3 classes instead of only 1 or 2 class), hence performing better than the base-model.

Although there was a significant improvement in the performance of the fine-tuned model over the pre-trained one, yet, it faltered in a few cases pertaining to the neutral relationships between premise & hypothesis (it’s easier to find an entailment or contradiction due to the vast vocabulary the model learned over the fine-tuning period, and it is slightly difficult for the fine-tuned model to identify neutral relations between the sentences), and ones having indirect/implicit linkage between the premise and the hypothesis (highly correlated words which often lead to entailment) or the ones who have low correlation where the model fails to categorize it into neutral (no entailment, but also no contradiction) & contradiction.