

Group Project LLM

- r=2,4,8,16, epoch=10
- seed=42
- evaluation:
 - accuracy, f1, precision, recall
 - efficiency (time, trainable parameters, trainable parameters ratio, convergence)

```
In [36]: import warnings
warnings.filterwarnings("default", module="__main__")
warnings.filterwarnings("ignore", module=".*")
```

Base Model: DistilBERT

```
In [2]: # ===== BASELINE DISTILBERT =====

import os, time, random
import numpy as np
import torch

from datasets import load_dataset
from transformers import (
    DistilBertTokenizerFast,
    DistilBertForSequenceClassification,
    DataCollatorWithPadding,
    TrainingArguments,
    Trainer,
    set_seed
)
import evaluate

SEED = 42
DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
DATASET = "stanfordnlp/sst2"
TEXT_COL = "sentence"
LABEL_COL = "label"
NUM_EPOCHS = 10
BATCH_SIZE = 16
LR = 2e-5

'''
for IMDB dataset:
DATASET = "imdb"
TEXT_COL = "text"
LABEL_COL = "label"
'''

def set_all_seeds(seed=42):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
    set_seed(seed)

set_all_seeds(SEED)

# ----- Load dataset and split (8:1:1) -----
raw = load_dataset(DATASET)
train_full = raw["train"]

train_temp = train_full.train_test_split(test_size=0.2, seed=SEED)
train_ds = train_temp["train"]
temp = train_temp["test"]

val_test = temp.train_test_split(test_size=0.5, seed=SEED)
```

```

val_ds = val_test["train"]
test_ds = val_test["test"]

# ----- Tokenization -----
tokenizer = DistilBertTokenizerFast.from_pretrained("distilbert-base-uncased")
def preprocess(x):
    return tokenizer(x[TEXT_COL], truncation=True, max_length=128)

train_ds = train_ds.map(preprocess, batched=True)
val_ds = val_ds.map(preprocess, batched=True)
test_ds = test_ds.map(preprocess, batched=True)

train_ds = train_ds.rename_column(LABEL_COL, "labels")
val_ds = val_ds.rename_column(LABEL_COL, "labels")
test_ds = test_ds.rename_column(LABEL_COL, "labels")

cols = ["input_ids", "attention_mask", "labels"]
train_ds.set_format(type="torch", columns=cols)
val_ds.set_format(type="torch", columns=cols)
test_ds.set_format(type="torch", columns=cols)

collator = DataCollatorWithPadding(tokenizer)

# ----- Metrics -----
acc = evaluate.load("accuracy")
f1 = evaluate.load("f1")
prec = evaluate.load("precision")
rec = evaluate.load("recall")

def compute_metrics(eval_pred):
    logits, labels = eval_pred
    preds = np.argmax(logits, axis=-1)
    return {
        "accuracy": acc.compute(predictions=preds, references=labels)["accuracy"],
        "f1": f1.compute(predictions=preds, references=labels, average="binary")["f1"],
        "precision": prec.compute(predictions=preds, references=labels, average="binary")["precision"],
        "recall": rec.compute(predictions=preds, references=labels, average="binary")["recall"],
    }

# ----- Model -----
model = DistilBertForSequenceClassification.from_pretrained(
    "distilbert-base-uncased", num_labels=2
).to(DEVICE)

total_params = sum(p.numel() for p in model.parameters())
trainable_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
ratio = trainable_params / total_params

print(f"Baseline: total={total_params}, trainable={trainable_params}, ratio={ratio:.4%}")

# ----- Train -----
args = TrainingArguments(
    output_dir="./baseline_distilbert",
    num_train_epochs=10,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    learning_rate=2e-5,
    eval_strategy="epoch",
    save_strategy="epoch",
    logging_strategy="epoch",
    load_best_model_at_end=True,
    metric_for_best_model="f1",
    greater_is_better=True,
    seed=SEED,
    report_to="none",
)

trainer = Trainer(
    model=model,
    args=args,
    train_dataset=train_ds,

```

```

eval_dataset=val_ds,
data_collator=collator,
tokenizer=tokenizer,
compute_metrics=compute_metrics,
)

start = time.time()
trainer.train()
end = time.time()

print(f"Baseline training time: {end-start:.2f}s")
print("Eval:", trainer.evaluate(test_ds))
print("Convergence history:", trainer.state.log_history)

```

Some weights of DistilBertForSequenceClassification were not initialized from the model checkpoint at distilbert-base-uncased and are newly initialized: ['classifier.bias', 'classifier.weight', 'pre_classifier.bias', 'pre_classifier.weight']

You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

/tmp/ipykernel_2836370/2350084452.py:110: FutureWarning: `tokenizer` is deprecated and will be removed in version 5.0.0 for `Trainer.__init__`. Use `processing_class` instead.

```
trainer = Trainer(
```

Baseline: total=66955010, trainable=66955010, ratio=100.0000%

/hpc/group/yizhanglab/yh151/miniconda3/envs/my-conda-env/lib/python3.9/site-packages/torch/nn/parallel/_functions.py:71: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

```
warnings.warn(
```

[16840/16840 27:00, Epoch 10/10]

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	0.238700	0.175075	0.941203	0.945409	0.943848	0.946976
2	0.125100	0.178515	0.944024	0.947704	0.952062	0.943386
3	0.088600	0.206909	0.944172	0.948521	0.940538	0.956642
4	0.061500	0.221665	0.944469	0.948385	0.947862	0.948909
5	0.047500	0.239832	0.947587	0.950979	0.956425	0.945595
6	0.033500	0.305291	0.945805	0.949759	0.946762	0.952775
7	0.027500	0.310512	0.946102	0.949966	0.948266	0.951671
8	0.018200	0.368410	0.946102	0.949924	0.949008	0.950842
9	0.012600	0.406172	0.946845	0.950580	0.950317	0.950842
10	0.010900	0.424868	0.946993	0.950670	0.951327	0.950014


```

Eval: {'eval_loss': 0.23587322235107422, 'eval_accuracy': 0.9452115812917594, 'eval_f1': 0.9513513513513514,
'eval_precision': 0.9504741833508957, 'eval_recall': 0.952230139878596, 'eval_runtime': 8.7337, 'eval_samples_per_second': 771.149, 'eval_steps_per_second': 24.159, 'epoch': 10.0}
Convergence history: [{'loss': 0.2387, 'grad_norm': 10.51264762878418, 'learning_rate': 1.800118764845606e-05, 'epoch': 1.0, 'step': 1684}, {'eval_loss': 0.17507508397102356, 'eval_accuracy': 0.9412026726057906, 'eval_f1': 0.9454094292803971, 'eval_precision': 0.9438480594549958, 'eval_recall': 0.9469759734879868, 'eval_runtime': 9.6709, 'eval_samples_per_second': 696.421, 'eval_steps_per_second': 21.818, 'epoch': 1.0, 'step': 1684}, {'loss': 0.1251, 'grad_norm': 5.240935325622559, 'learning_rate': 1.6001187648456057e-05, 'epoch': 2.0, 'step': 3368}, {'eval_loss': 0.1785149723291397, 'eval_accuracy': 0.9440237564959169, 'eval_f1': 0.9477042585656817, 'eval_precision': 0.9520624303232998, 'eval_recall': 0.9433858050262358, 'eval_runtime': 9.4749, 'eval_samples_per_second': 710.827, 'eval_steps_per_second': 22.269, 'epoch': 2.0, 'step': 3368}, {'loss': 0.0886, 'grad_norm': 11.543757438659668, 'learning_rate': 1.4001187648456058e-05, 'epoch': 3.0, 'step': 5052}, {'eval_loss': 0.2069089114665985, 'eval_accuracy': 0.9441722345953972, 'eval_f1': 0.9485213581599123, 'eval_precision': 0.9405376052131414, 'eval_recall': 0.9566418116542391, 'eval_runtime': 9.5145, 'eval_samples_per_second': 707.863, 'eval_steps_per_second': 22.177, 'epoch': 3.0, 'step': 5052}, {'loss': 0.0615, 'grad_norm': 0.22485654056072235, 'learning_rate': 1.2001187648456058e-05, 'epoch': 4.0, 'step': 6736}, {'eval_loss': 0.22166526317596436, 'eval_accuracy': 0.9444691907943579, 'eval_f1': 0.948385316036434, 'eval_precision': 0.9478620689655173, 'eval_recall': 0.9489091411212373, 'eval_runtime': 9.9979, 'eval_samples_per_second': 673.64, 'eval_steps_per_second': 21.104, 'epoch': 4.0, 'step': 6736}, {'loss': 0.0475, 'grad_norm': 0.09435376524925232, 'learning_rate': 1.0001187648456059e-05, 'epoch': 5.0, 'step': 8420}, {'eval_loss': 0.2398320436477661, 'eval_accuracy': 0.9475872308834447, 'eval_f1': 0.950979030690182, 'eval_precision': 0.9564245810055866, 'eval_recall': 0.9455951394642363, 'eval_runtime': 9.6024, 'eval_samples_per_second': 701.39, 'eval_steps_per_second': 21.974, 'epoch': 5.0, 'step': 8420}, {'loss': 0.0335, 'grad_norm': 0.45556309819221497, 'learning_rate': 8.001187648456058e-06, 'epoch': 6.0, 'step': 10104}, {'eval_loss': 0.3052908778190613, 'eval_accuracy': 0.9458054936896808, 'eval_f1': 0.9497591190640055, 'eval_precision': 0.9467618002195389, 'eval_recall': 0.9527754763877382, 'eval_runtime': 9.7726, 'eval_samples_per_second': 689.169, 'eval_steps_per_second': 21.591, 'epoch': 6.0, 'step': 10104}, {'loss': 0.0275, 'grad_norm': 8.011517524719238, 'learning_rate': 6.001187648456057e-06, 'epoch': 7.0, 'step': 11788}, {'eval_loss': 0.3105123043060303, 'eval_accuracy': 0.9461024498886415, 'eval_f1': 0.9499655410062027, 'eval_precision': 0.9482663731425427, 'eval_recall': 0.9516708091687379, 'eval_runtime': 9.3925, 'eval_samples_per_second': 717.063, 'eval_steps_per_second': 22.465, 'epoch': 7.0, 'step': 11788}, {'loss': 0.0182, 'grad_norm': 6.816328525543213, 'learning_rate': 4.001187648456058e-06, 'epoch': 8.0, 'step': 13472}, {'eval_loss': 0.36840957403182983, 'eval_accuracy': 0.9461024498886415, 'eval_f1': 0.9499241274658573, 'eval_precision': 0.9490077177508269, 'eval_recall': 0.9508423087544877, 'eval_runtime': 9.4225, 'eval_samples_per_second': 714.781, 'eval_steps_per_second': 22.393, 'epoch': 8.0, 'step': 13472}, {'loss': 0.0126, 'grad_norm': 2.9003257751464844, 'learning_rate': 2.001187648456057e-06, 'epoch': 9.0, 'step': 15156}, {'eval_loss': 0.4061717391014099, 'eval_accuracy': 0.9468448403860431, 'eval_f1': 0.9505797901711761, 'eval_precision': 0.9503174165056583, 'eval_recall': 0.9508423087544877, 'eval_runtime': 9.7566, 'eval_samples_per_second': 690.301, 'eval_steps_per_second': 21.626, 'epoch': 9.0, 'step': 15156}, {'loss': 0.0109, 'grad_norm': 0.011784575879573822, 'learning_rate': 1.1876484560570071e-09, 'epoch': 10.0, 'step': 16840}, {'eval_loss': 0.4248684048652649, 'eval_accuracy': 0.9469933184855234, 'eval_f1': 0.9506701671963521, 'eval_precision': 0.9513274336283186, 'eval_recall': 0.9500138083402375, 'eval_runtime': 9.4631, 'eval_samples_per_second': 711.713, 'eval_steps_per_second': 22.297, 'epoch': 10.0, 'step': 16840}, {'train_runtime': 1624.274, 'train_samples_per_second': 331.711, 'train_steps_per_second': 10.368, 'total_flos': 5586612026141100.0, 'train_loss': 0.06640054981385728, 'epoch': 10.0, 'step': 16840}, {'eval_loss': 0.23587322235107422, 'eval_accuracy': 0.9452115812917594, 'eval_f1': 0.9513513513513514, 'eval_precision': 0.9504741833508957, 'eval_recall': 0.952230139878596, 'eval_runtime': 8.7337, 'eval_samples_per_second': 771.149, 'eval_steps_per_second': 24.159, 'epoch': 10.0, 'step': 16840}]

```

```

In [10]: import pandas as pd
# ----- Final Evaluation -----
final_metrics = trainer.evaluate(test_ds)

# ----- Save metrics -----
os.makedirs("./baseline_distilbert", exist_ok=True)
with open("./baseline_distilbert/final_metrics.json", "w") as f:
    json.dump(final_metrics, f, indent=4)

print("Saved final metrics to baseline_distilbert/final_metrics.json")

# ----- Save model -----
trainer.save_model("./baseline_distilbert/final_model")
print("Saved model to baseline_distilbert/final_model")

# ----- Convergence history -----
log_history = trainer.state.log_history
df_logs = pd.DataFrame(trainer.state.log_history)
# Separate clean tables
df_train = df_logs[df_logs["loss"].notnull()].reset_index(drop=True)
df_eval = df_logs[df_logs["eval_loss"].notnull()].reset_index(drop=True)

df_train.to_csv("./baseline_distilbert/train_log.csv", index=False)
df_eval.to_csv("./baseline_distilbert/eval_log.csv", index=False)

```

```
/hpc/group/yizhanglab/yh151/miniconda3/envs/my-conda-env/lib/python3.9/site-packages/torch/nn/parallel/_functions.py:71: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.
```

```
warnings.warn(
```

```
Saved final metrics to baseline_distilbert/final_metrics.json
```

```
Saved model to baseline_distilbert/final_model
```

```
In [28]: import matplotlib.pyplot as plt
```

```
df_eval_clean = df_eval.groupby("epoch").last().reset_index()
```

```
plt.figure(figsize=(8,5))
```

```
plt.plot(df_train["epoch"], df_train["loss"], label="Train Loss")
```

```
plt.plot(df_eval_clean["epoch"], df_eval_clean["eval_loss"], label="Eval Loss")
```

```
plt.xlabel("Epoch")
```

```
plt.ylabel("Loss")
```

```
plt.title("Convergence: Train vs Eval Loss")
```

```
plt.legend()
```

```
plt.grid()
```

```
plt.savefig("./baseline_distilbert/loss_curve.png", dpi=300)
```

```
plt.show()
```

```
plt.figure(figsize=(8,5))
```

```
plt.plot(df_eval_clean["epoch"], df_eval_clean["eval_accuracy"], label="Eval Accuracy")
```

```
plt.plot(df_eval_clean["epoch"], df_eval_clean["eval_f1"], label="Eval F1")
```

```
plt.xlabel("Epoch")
```

```
plt.ylabel("Metric")
```

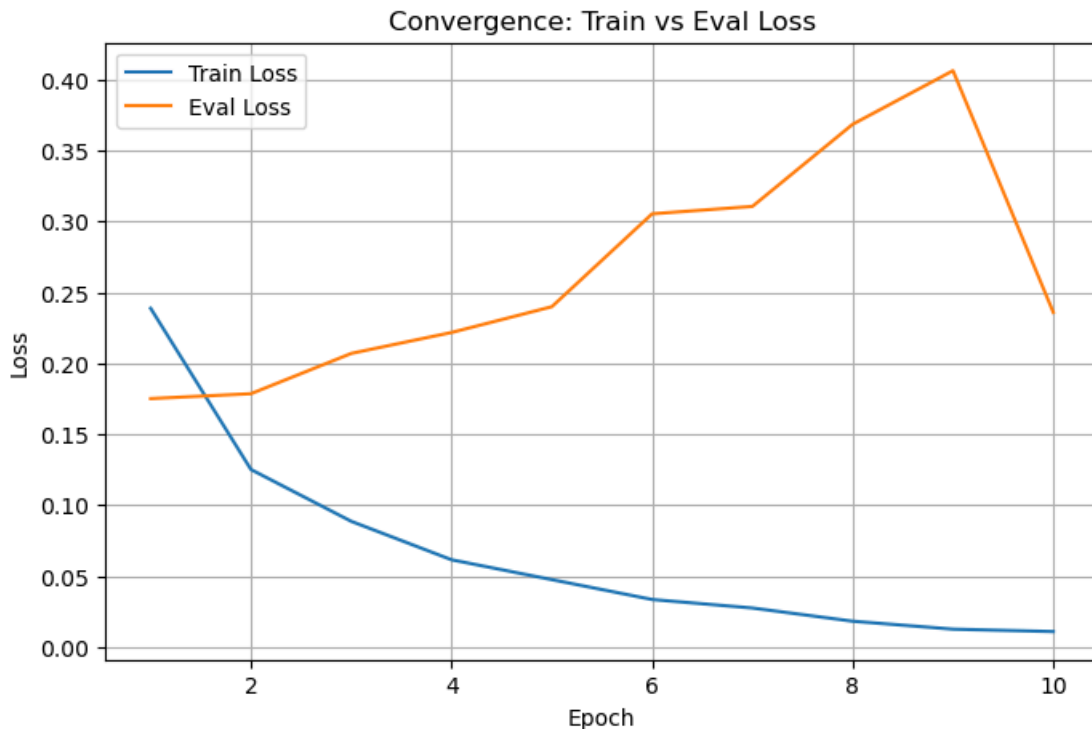
```
plt.title("Evaluation: Accuracy & F1")
```

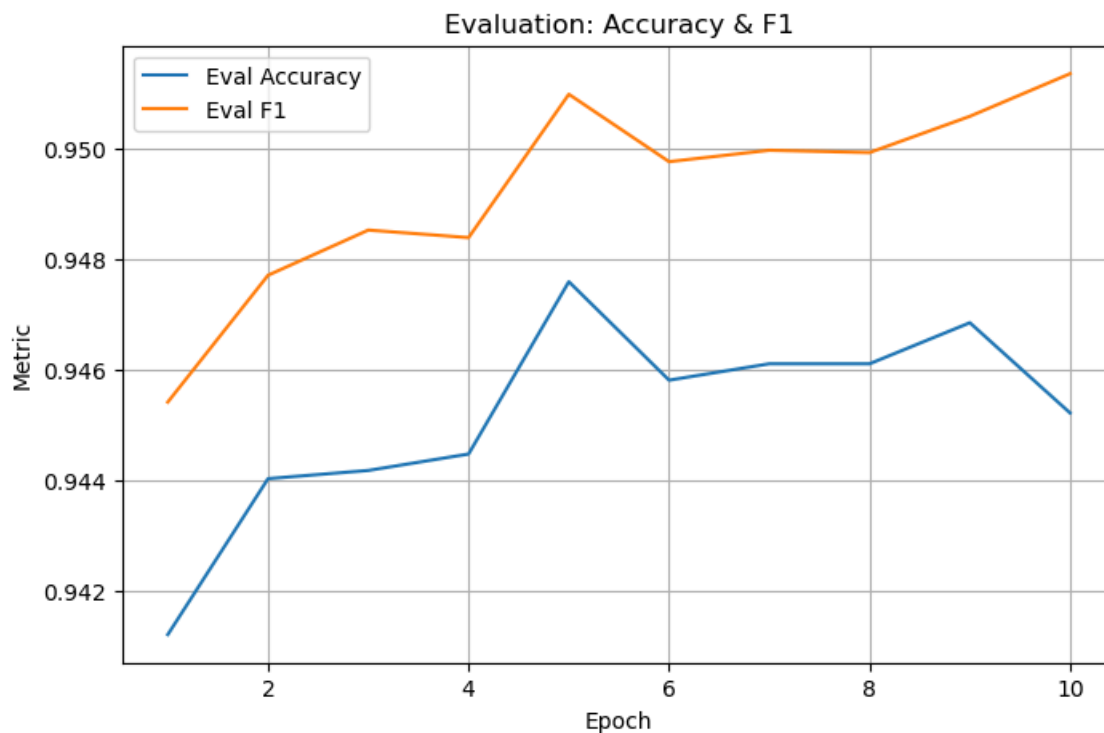
```
plt.legend()
```

```
plt.grid()
```

```
plt.savefig("./baseline_distilbert/metric_curve.png", dpi=300)
```

```
plt.show()
```





Sparse LoRA

```
In [39]: # ===== SPARSE LoRA MODEL =====

from typing import Dict, Any, List, Optional
import math
from peft import LoraConfig, get_peft_model

# ----- Sparse LoRA config -----
RANKS: List[int] = [2, 4, 8, 16]
L1_LAMBDA = 1e-5 # sparsity strength for LoRA weights

def count_trainable_params(model: torch.nn.Module) -> int:
    return sum(p.numel() for p in model.parameters() if p.requires_grad)

def count_total_params(model: torch.nn.Module) -> int:
    return sum(p.numel() for p in model.parameters())

def compute_lora_sparsity(model: torch.nn.Module, threshold: float = 1e-3) -> float:
    """
    Approximate sparsity: fraction of LoRA parameters with |w| < threshold.
    """
    total = 0
    near_zero = 0
    for name, param in model.named_parameters():
        if "lora_" in name and param.requires_grad:
            data = param.detach().abs()
            total += data.numel()
            near_zero += (data < threshold).sum().item()
    return near_zero / total if total > 0 else math.nan

class SparseLoraTrainer(Trainer):
    """
    Trainer with L1 penalty only on LoRA parameters.
    """
    def __init__(self, l1_lambda: float = 0.0, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self.l1_lambda = l1_lambda
```

```

def compute_loss(
    self,
    model,
    inputs,
    return_outputs: bool = False,
    num_items_in_batch: Optional[int] = None,
):
    outputs = model(**inputs)
    loss = outputs.loss

    if self.l1_lambda > 0:
        l1_reg = 0.0
        for name, param in model.named_parameters():
            if "lora_" in name and param.requires_grad:
                l1_reg = l1_reg + param.abs().sum()
        loss = loss + self.l1_lambda * l1_reg

    return (loss, outputs) if return_outputs else loss

```

```

results_per_rank: List[Dict[str, Any]] = []

```

```

for r in RANKS:
    print("\n" + "=" * 80)
    print(f"Training Sparse LoRA DistilBERT with rank = {r}, epochs = {NUM_EPOCHS}")
    print("=" * 80)

    set_all_seeds(SEED)

    # Base DistilBERT for this rank
    base_model = DistilBertForSequenceClassification.from_pretrained(
        "distilbert-base-uncased",
        num_labels=2,
    )

    # LoRA config: attention projections in DistilBERT
    lora_config = LoraConfig(
        r=r,
        lora_alpha=2 * r,
        lora_dropout=0.1,
        bias="none",
        task_type="SEQ_CLS",      # sequence classification
        target_modules=["q_lin", "k_lin", "v_lin", "out_lin"],
    )

    lora_model = get_peft_model(base_model, lora_config)
    lora_model.to(DEVICE)

    total_params = count_total_params(lora_model)
    trainable_params = count_trainable_params(lora_model)
    param_ratio = trainable_params / total_params

    print(f"[Rank {r}] total params: {total_params:,}")
    print(f"[Rank {r}] trainable params: {trainable_params:,}")
    print(f"[Rank {r}] trainable params ratio (trainable / total): {param_ratio:.4%}")

    output_dir = f"./sparse_lora_rank{r}"
    os.makedirs(output_dir, exist_ok=True)

    training_args_lora = TrainingArguments(
        output_dir=output_dir,
        num_train_epochs=NUM_EPOCHS,
        per_device_train_batch_size=BATCH_SIZE,
        per_device_eval_batch_size=BATCH_SIZE,
        learning_rate=LR,
        weight_decay=0.01,
        eval_strategy="epoch",
        save_strategy="epoch",
        logging_strategy="epoch",
        load_best_model_at_end=True,
        metric_for_best_model="f1",
        greater_is_better=True,
    )

```



```

        seed=SEED,
        report_to="none",
    )

    trainer = SparseLoraTrainer(
        ll_lambda=L1_LAMBDA,
        model=lora_model,
        args=training_args_lora,
        train_dataset=train_ds,
        eval_dataset=val_ds,
        tokenizer=tokenizer,
        data_collator=collator,
        compute_metrics=compute_metrics,
    )

    start_time = time.time()
    trainer.train()
    end_time = time.time()
    train_time = end_time - start_time
    print(f"[Rank {r}] Training time: {train_time:.2f} seconds")

    # --- final evals ---
    val_metrics = trainer.evaluate(eval_dataset=val_ds)
    test_metrics = trainer.evaluate(eval_dataset=test_ds)
    lora_sparsity = compute_lora_sparsity(lora_model, threshold=1e-3)

    print(f"[Rank {r}] Validation metrics: {val_metrics}")
    print(f"[Rank {r}] Test metrics: {test_metrics}")
    print(f"[Rank {r}] LoRA sparsity (<1e-3): {lora_sparsity:.2%}")

    # =====
    # SAVE METRICS / MODEL / LOG
    # =====
    # 1) save metrics
    metrics_payload = {
        "rank": r,
        "train_time_sec": train_time,
        "total_params": int(total_params),
        "trainable_params": int(trainable_params),
        "param_ratio": float(param_ratio),
        "lora_sparsity_<1e-3": float(lora_sparsity),
        "val_metrics": val_metrics,
        "test_metrics": test_metrics,
    }
    with open(os.path.join(output_dir, "final_metrics.json"), "w") as f:
        json.dump(metrics_payload, f, indent=4)

    # 2) save final model (best checkpoint)
    final_model_dir = os.path.join(output_dir, "final_model")
    trainer.save_model(final_model_dir) # saves model + config
    tokenizer.save_pretrained(final_model_dir) # save tokenizer too
    print(f"[Rank {r}] Saved model to {final_model_dir}")

    # 3) save convergence history
    log_history = trainer.state.log_history
    with open(os.path.join(output_dir, "log_history.json"), "w") as f:
        json.dump(log_history, f, indent=4)
    print(f"[Rank {r}] Saved log history to log_history.json")

    # --- store in-memory summary for printing ---
    results_per_rank.append(
        {
            "rank": r,
            "total_params": total_params,
            "trainable_params": trainable_params,
            "param_ratio": param_ratio,
            "train_time_sec": train_time,
            "val_metrics": val_metrics,
            "test_metrics": test_metrics,
            "lora_sparsity(<1e-3)": lora_sparsity,
        }
    )

```

```

print("\n\n=== Summary over ranks (Sparse LoRA) ===")
for res in results_per_rank:
    r = res["rank"]
    print(f"\nRank {r}:")
    print(f"  Params: {res['trainable_params']:,} / {res['total_params']:,} "
          f"f"({res['param_ratio']:.2%})")
    print(f"  Train time: {res['train_time_sec']:.2f} s")
    print(f"  Val F1: {res['val_metrics'].get('eval_f1', float('nan')):.4f}, "
          f"Acc: {res['val_metrics'].get('eval_accuracy', float('nan')):.4f}")
    print(f"  Test F1: {res['test_metrics'].get('eval_f1', float('nan')):.4f}, "
          f"Acc: {res['test_metrics'].get('eval_accuracy', float('nan')):.4f}")
    print(f"  LoRA sparsity (<1e-3): {res['lora_sparsity(<1e-3)']:.2%}")

```

=====
Training Sparse LoRA DistilBERT with rank = 2, epochs = 10
=====

Some weights of DistilBertForSequenceClassification were not initialized from the model checkpoint at distilbert-base-uncased and are newly initialized: ['classifier.bias', 'classifier.weight', 'pre_classifier.bias', 'pre_classifier.weight']

You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

[Rank 2] total params: 67,620,868

[Rank 2] trainable params: 665,858

[Rank 2] trainable params ratio (trainable / total): 0.9847%

[16840/16840 33:19, Epoch 10/10]

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	0.393900	0.296121	0.876466	0.882320	0.904320	0.861364
2	0.316000	0.280038	0.885375	0.892867	0.897350	0.888429
3	0.302800	0.270784	0.891314	0.898951	0.898703	0.899199
4	0.292400	0.262972	0.894432	0.900989	0.908708	0.893400
5	0.285900	0.261988	0.896659	0.904422	0.899481	0.909417
6	0.281500	0.254590	0.897847	0.904205	0.911823	0.896714
7	0.277900	0.252679	0.899183	0.904995	0.917187	0.893123
8	0.275900	0.251038	0.899926	0.906957	0.906707	0.907208
9	0.272700	0.250182	0.900371	0.907231	0.908361	0.906103
10	0.271600	0.249398	0.900371	0.906793	0.912241	0.901408

[Rank 2] Training time: 2000.22 seconds

[211/211 00:21]

[Rank 2] Validation metrics: {'eval_loss': 0.25018182396888733, 'eval_accuracy': 0.9003711952487008, 'eval_f1': 0.9072307479607356, 'eval_precision': 0.9083610188261351, 'eval_recall': 0.9061032863849765, 'eval_runtime': 11.2932, 'eval_samples_per_second': 596.375, 'eval_steps_per_second': 18.684, 'epoch': 10.0}

[Rank 2] Test metrics: {'eval_loss': 0.26539742946624756, 'eval_accuracy': 0.8914625092798812, 'eval_f1': 0.9028313172936329, 'eval_precision': 0.9094804499196572, 'eval_recall': 0.8962787015043547, 'eval_runtime': 10.8577, 'eval_samples_per_second': 620.299, 'eval_steps_per_second': 19.433, 'epoch': 10.0}

[Rank 2] LoRA sparsity (<1e-3): 15.55%

[Rank 2] Saved model to ./sparse_lora_rank2/final_model

[Rank 2] Saved log history to log_history.json

=====
Training Sparse LoRA DistilBERT with rank = 4, epochs = 10
=====

Some weights of DistilBertForSequenceClassification were not initialized from the model checkpoint at distilbert-base-uncased and are newly initialized: ['classifier.bias', 'classifier.weight', 'pre_classifier.bias', 'pre_classifier.weight']

You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

[Rank 4] total params: 67,694,596

[Rank 4] trainable params: 739,586

[Rank 4] trainable params ratio (trainable / total): 1.0925%

[16840/16840 34:11, Epoch 10/10]

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	0.386300	0.294177	0.879733	0.885915	0.903995	0.868545
2	0.312500	0.276367	0.890275	0.897801	0.899169	0.896437
3	0.298700	0.267596	0.894878	0.902399	0.900908	0.903894
4	0.287600	0.258988	0.899926	0.905761	0.917304	0.894504
5	0.280500	0.258202	0.902004	0.909564	0.902638	0.916598
6	0.275400	0.249693	0.904083	0.910103	0.917251	0.903065
7	0.271600	0.247551	0.905865	0.911477	0.921774	0.901408
8	0.268800	0.245857	0.906756	0.913451	0.911692	0.915217
9	0.265800	0.244966	0.906607	0.913062	0.913946	0.912179
10	0.265100	0.244083	0.907053	0.913152	0.917480	0.908865

[Rank 4] Training time: 2051.59 seconds

[211/211 00:22]

[Rank 4] Validation metrics: {'eval_loss': 0.245857372879982, 'eval_accuracy': 0.9067557535263548, 'eval_f1': 0.9134509371554576, 'eval_precision': 0.9116918844566713, 'eval_recall': 0.9152167909417288, 'eval_runtime': 11.4603, 'eval_samples_per_second': 587.683, 'eval_steps_per_second': 18.411, 'epoch': 10.0}

[Rank 4] Test metrics: {'eval_loss': 0.2627865672111511, 'eval_accuracy': 0.895025983667409, 'eval_f1': 0.9063948100092678, 'eval_precision': 0.9094048884165781, 'eval_recall': 0.9034045922406968, 'eval_runtime': 11.9928, 'eval_samples_per_second': 561.588, 'eval_steps_per_second': 17.594, 'epoch': 10.0}

[Rank 4] LoRA sparsity (<1e-3): 21.52%

[Rank 4] Saved model to ./sparse_lora_rank4/final_model

[Rank 4] Saved log history to log_history.json

=====
Training Sparse LoRA DistilBERT with rank = 8, epochs = 10
=====

Some weights of DistilBertForSequenceClassification were not initialized from the model checkpoint at distilbert-base-uncased and are newly initialized: ['classifier.bias', 'classifier.weight', 'pre_classifier.bias', 'pre_classifier.weight']

You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

[Rank 8] total params: 67,842,052

[Rank 8] trainable params: 887,042

[Rank 8] trainable params ratio (trainable / total): 1.3075%

[16840/16840 33:55, Epoch 10/10]

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	0.386200	0.295880	0.884781	0.891134	0.905617	0.877106
2	0.313800	0.277604	0.894878	0.902237	0.902237	0.902237
3	0.299300	0.268710	0.897847	0.905546	0.900355	0.910798
4	0.287800	0.259213	0.904826	0.910362	0.922096	0.898923
5	0.280200	0.259396	0.904380	0.912094	0.901754	0.922673
6	0.273700	0.249641	0.908389	0.914222	0.920493	0.908036
7	0.269600	0.247296	0.911359	0.916468	0.928815	0.904446
8	0.266700	0.245347	0.910171	0.916632	0.914741	0.918531
9	0.263500	0.244415	0.911210	0.917220	0.919512	0.914941
10	0.262700	0.243555	0.912101	0.917823	0.922690	0.913007

[Rank 8] Training time: 2036.44 seconds

[211/211 00:22]


```
[Rank 16] Validation metrics: {'eval_loss': 0.25151702761650085, 'eval_accuracy': 0.9170007423904974, 'eval_f1': 0.9223934471747883, 'eval_precision': 0.9274148520379676, 'eval_recall': 0.9174261253797293, 'eval_runtime': 11.2259, 'eval_samples_per_second': 599.952, 'eval_steps_per_second': 18.796, 'epoch': 10.0}
[Rank 16] Test metrics: {'eval_loss': 0.2650555968284607, 'eval_accuracy': 0.9097253155159614, 'eval_f1': 0.9195128408790045, 'eval_precision': 0.9224435590969455, 'eval_recall': 0.9166006861968857, 'eval_runtime': 10.8663, 'eval_samples_per_second': 619.804, 'eval_steps_per_second': 19.418, 'epoch': 10.0}
[Rank 16] LoRA sparsity (<1e-3): 35.68%
[Rank 16] Saved model to ./sparse_lora_rank16/final_model
[Rank 16] Saved log history to log_history.json
```

=== Summary over ranks (Sparse LoRA) ===

Rank 2:

```
Params: 665,858 / 67,620,868 (0.98%)
Train time: 2000.22 s
Val F1: 0.9072, Acc: 0.9004
Test F1: 0.9028, Acc: 0.8915
LoRA sparsity (<1e-3): 15.55%
```

Rank 4:

```
Params: 739,586 / 67,694,596 (1.09%)
Train time: 2051.59 s
Val F1: 0.9135, Acc: 0.9068
Test F1: 0.9064, Acc: 0.8950
LoRA sparsity (<1e-3): 21.52%
```

Rank 8:

```
Params: 887,042 / 67,842,052 (1.31%)
Train time: 2036.44 s
Val F1: 0.9178, Acc: 0.9121
Test F1: 0.9122, Acc: 0.9017
LoRA sparsity (<1e-3): 27.88%
```

Rank 16:

```
Params: 1,181,954 / 68,136,964 (1.73%)
Train time: 2026.30 s
Val F1: 0.9224, Acc: 0.9170
Test F1: 0.9195, Acc: 0.9097
LoRA sparsity (<1e-3): 35.68%
```

IMDB Dataset

Have commented out in the corresponding section

Just to replace the loaded dataset accordingly:

- DATASET = "imdb"
- TEXT_COL = "text"
- LABEL_COL = "label"

In []: