06_Transformer_Fine-Tuning

November 27, 2025

[2]:
```python
import os
import sys
import warnings
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pathlib import Path
import time
from collections import defaultdict

# PyTorch
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
from torch.optim import AdamW
from torch.amp import autocast
from torch.amp import GradScaler

# Transformers
from transformers import (
    AutoTokenizer,
    AutoModelForSequenceClassification,
    TrainingArguments,
    Trainer,
    EarlyStoppingCallback,
    get_linear_schedule_with_warmup
)
from datasets import Dataset as HFDataset

# Metrics & Evaluation
from sklearn.metrics import f1_score, accuracy_score, classification_report,␣
 ↪confusion_matrix
import joblib
```

```python
# Hyperparameter Tuning
import optuna
from optuna.pruners import MedianPruner

# Paths
DATA_DIR = Path('../data')
FEATURES_DIR = Path('features')
MODELS_DIR = Path('models')
RESULTS_DIR = Path('results')
RESULTS_DIR.mkdir(exist_ok=True)

# Device Configuration
DEVICE = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Device: {DEVICE}")
print(f"GPU Name: {torch.cuda.get_device_name(0) if torch.cuda.is_available()␣
↪else 'CPU'}")
if torch.cuda.is_available():
    print(f"GPU Memory: {torch.cuda.get_device_properties(0).total_memory / 1e9:
↪.2f} GB")

# Set random seeds for reproducibility
RANDOM_STATE = 42
np.random.seed(RANDOM_STATE)
torch.manual_seed(RANDOM_STATE)
if torch.cuda.is_available():
    torch.cuda.manual_seed_all(RANDOM_STATE)

print("Setup Complete.")
```

```
Device: cuda
GPU Name: NVIDIA GeForce RTX 4060 Ti
GPU Memory: 16.72 GB
Setup Complete.
```

[3]:
```python
# 6.1 Load Train/Validation Data



train_df = pd.read_csv(DATA_DIR / 'train.csv')
val_df = pd.read_csv(DATA_DIR / 'val.csv')
test_df = pd.read_csv(DATA_DIR / 'test.csv')  # For final evaluation

y_train = train_df['label'].values
y_val = val_df['label'].values
y_test = test_df['label'].values

X_train_text = train_df['text'].values
X_val_text = val_df['text'].values
```

```python
X_test_text = test_df['text'].values

print(f"Train: {len(X_train_text)} samples")
print(f"Val: {len(X_val_text)} samples")
print(f"Test: {len(X_test_text)} samples")

# 6.2 Tokenization Strategy

print("\nTokenizing...")

MODEL_NAME = 'distilbert-base-uncased'
tokenizer = AutoTokenizer.from_pretrained(MODEL_NAME)

MAX_LENGTH = 256

# Tokenize all splits
train_encodings = tokenizer(
    X_train_text.tolist(),
    truncation=True,
    padding='max_length',
    max_length=MAX_LENGTH,
    return_tensors='pt'
)

val_encodings = tokenizer(
    X_val_text.tolist(),
    truncation=True,
    padding='max_length',
    max_length=MAX_LENGTH,
    return_tensors='pt'
)

test_encodings = tokenizer(
    X_test_text.tolist(),
    truncation=True,
    padding='max_length',
    max_length=MAX_LENGTH,
    return_tensors='pt'
)

print(f"Tokenization Complete. Max length: {MAX_LENGTH}")

# Analyze truncation
token_lengths = [len(tokenizer.encode(text, max_length=None)) for text in␣
↪X_train_text[:1000]]
print(f"Token length stats (sample of 1000): min={min(token_lengths)},␣
↪max={max(token_lengths)}, mean={np.mean(token_lengths):.1f}")
```

```python
print(f"Percentile 95: {np.percentile(token_lengths, 95):.0f}")
```

```
Train: 102000 samples
Val: 18000 samples
Test: 7600 samples

Tokenizing…
Tokenization Complete. Max length: 256
Token length stats (sample of 1000): min=22, max=193, mean=53.0
Percentile 95: 82
```

[4]:
```python
# 6.3 PyTorch Dataset Class

class NewsDataset(Dataset):
    """
    Custom Dataset for news classification with transformer tokenizer outputs.
    """
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = labels

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        item = {
            'input_ids': self.encodings['input_ids'][idx],
            'attention_mask': self.encodings['attention_mask'][idx],
            'labels': torch.tensor(self.labels[idx], dtype=torch.long)
        }
        return item

# Create datasets
train_dataset = NewsDataset(train_encodings, y_train)
val_dataset = NewsDataset(val_encodings, y_val)
test_dataset = NewsDataset(test_encodings, y_test)

# DataLoaders (batch_size=32 fits comfortably on 16GB GPU)
BATCH_SIZE = 32

train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=BATCH_SIZE, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=BATCH_SIZE, shuffle=False)

print(f"Train DataLoader: {len(train_loader)} batches")
print(f"Val DataLoader: {len(val_loader)} batches")
print(f"Test DataLoader: {len(test_loader)} batches")
```

```
Train DataLoader: 3188 batches
Val DataLoader: 563 batches
Test DataLoader: 238 batches
```

[11]:

```python
## **Cell 4: Training Function with Mixed Precision**

import torch
from torch.amp import autocast, GradScaler  # ← Updated import

def train_epoch(model, train_loader, optimizer, scheduler, scaler, device,␣
 ↪epoch, num_epochs):
    """
    Train for one epoch with mixed precision training.
    """
    model.train()
    total_loss = 0.0

    for batch_idx, batch in enumerate(train_loader):
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['labels'].to(device)

        # Forward pass with autocast (FP16)
        with autocast(device_type='cuda', dtype=torch.float16):  # ← Updated
            outputs = model(
                input_ids=input_ids,
                attention_mask=attention_mask,
                labels=labels
            )
            loss = outputs.loss

        # Backward pass
        scaler.scale(loss).backward()

        # Gradient clipping
        scaler.unscale_(optimizer)  # Unscale before clipping
        torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm=1.0)

        # Optimizer step
        scaler.step(optimizer)
        scaler.update()
        optimizer.zero_grad()
        scheduler.step()

        total_loss += loss.item()

        if (batch_idx + 1) % 50 == 0:
```

```
            print(f"Epoch [{epoch+1}/{num_epochs}] Batch [{batch_idx+1}/
 ↪{len(train_loader)}] Loss: {loss.item():.4f}")

    avg_loss = total_loss / len(train_loader)
    return avg_loss

def evaluate(model, val_loader, device):
    """
    Evaluate on validation set. Returns loss, macro-F1, accuracy.
    """
    model.eval()
    total_loss = 0.0
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for batch in val_loader:
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['labels'].to(device)

            with autocast(device_type='cuda', dtype=torch.float16):  # ← Updated
                outputs = model(
                    input_ids=input_ids,
                    attention_mask=attention_mask,
                    labels=labels
                )
                loss = outputs.loss

            total_loss += loss.item()

            # Get predictions
            preds = torch.argmax(outputs.logits, dim=1).cpu().numpy()
            all_preds.extend(preds)
            all_labels.extend(labels.cpu().numpy())

    avg_loss = total_loss / len(val_loader)
    macro_f1 = f1_score(all_labels, all_preds, average='macro')
    accuracy = accuracy_score(all_labels, all_preds)

    return avg_loss, macro_f1, accuracy, all_preds, all_labels

print("Training & Evaluation functions defined.")
```

```
Training & Evaluation functions defined.
```

[12]:
```python
# 6.5 Bayesian Hyperparameter Optimization (Optuna)

def objective(trial):
    """
    Optuna objective function: Fine-tune DistilBERT and r    eturn validation␣
↪Macro-F1.
    """

    # Hyperparameter space
    learning_rate = trial.suggest_float('learning_rate', 1e-5, 5e-5, log=True)
    batch_size = trial.suggest_categorical('batch_size', [16, 32, 64])
    weight_decay = trial.suggest_float('weight_decay', 0.0, 0.1)
    warmup_ratio = trial.suggest_float('warmup_ratio', 0.0, 0.2)

    # Create fresh model
    model = AutoModelForSequenceClassification.from_pretrained(
        MODEL_NAME,
        num_labels=4,
        problem_type='single_label_classification'
    ).to(DEVICE)

    # Update dataloaders with trial batch size
    trial_train_loader = DataLoader(train_dataset, batch_size=batch_size,␣
↪shuffle=True)
    trial_val_loader = DataLoader(val_dataset, batch_size=batch_size,␣
↪shuffle=False)

    # Setup optimizer
    optimizer = AdamW(model.parameters(), lr=learning_rate,␣
↪weight_decay=weight_decay)

    # Setup scheduler
    num_training_steps = len(trial_train_loader) * 4  # 4 epochs
    num_warmup_steps = int(num_training_steps * warmup_ratio)
    scheduler = get_linear_schedule_with_warmup(
        optimizer,
        num_warmup_steps=num_warmup_steps,
        num_training_steps=num_training_steps
    )

    # Mixed precision
    scaler = GradScaler(device='cuda')

    best_f1 = 0.0
    patience = 2
    patience_counter = 0
```

```python
    # Train for 4 epochs
    for epoch in range(4):
        train_loss = train_epoch(model, trial_train_loader, optimizer,␣
↪scheduler, scaler, DEVICE, epoch, 4)
        val_loss, val_f1, val_acc, _, _ = evaluate(model, trial_val_loader,␣
↪DEVICE)

        print(f"Trial {trial.number}: Epoch {epoch+1}/4 | Val F1: {val_f1:.4f}␣
↪| Val Loss: {val_loss:.4f}")

        # Early stopping
        if val_f1 > best_f1:
            best_f1 = val_f1
            patience_counter = 0
        else:
            patience_counter += 1

        if patience_counter >= patience:
            print(f"Early stopping at epoch {epoch+1}")
            break

        # Prune if performance is poor
        trial.report(val_f1, epoch)
        if trial.should_prune():
            raise optuna.TrialPruned()

    return best_f1

# Run optimization
print("="*80)
print("HYPERPARAMETER OPTIMIZATION (Optuna)")
print("="*80)

optuna.logging.set_verbosity(optuna.logging.WARNING)

study = optuna.create_study(
    direction='maximize',
    pruner=MedianPruner()
)

study.optimize(objective, n_trials=10, timeout=None)

print(f"\nBest trial: {study.best_trial.number}")
print(f"Best F1: {study.best_value:.4f}")
print(f"Best params: {study.best_params}")

best_params = study.best_params
```

```python
joblib.dump(best_params, RESULTS_DIR / 'step6_best_params.pkl')
```

```
================================================================================
HYPERPARAMETER OPTIMIZATION (Optuna)
================================================================================

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.

Epoch [1/4] Batch [50/1594] Loss: 1.3406
Epoch [1/4] Batch [100/1594] Loss: 1.0315
Epoch [1/4] Batch [150/1594] Loss: 0.5452
Epoch [1/4] Batch [200/1594] Loss: 0.2648
Epoch [1/4] Batch [250/1594] Loss: 0.3624
Epoch [1/4] Batch [300/1594] Loss: 0.3065
Epoch [1/4] Batch [350/1594] Loss: 0.1880
Epoch [1/4] Batch [400/1594] Loss: 0.3785
Epoch [1/4] Batch [450/1594] Loss: 0.2970
Epoch [1/4] Batch [500/1594] Loss: 0.2842
Epoch [1/4] Batch [550/1594] Loss: 0.1352
Epoch [1/4] Batch [600/1594] Loss: 0.2737
Epoch [1/4] Batch [650/1594] Loss: 0.2535
Epoch [1/4] Batch [700/1594] Loss: 0.1933
Epoch [1/4] Batch [750/1594] Loss: 0.2106
Epoch [1/4] Batch [800/1594] Loss: 0.1639
Epoch [1/4] Batch [850/1594] Loss: 0.3381
Epoch [1/4] Batch [900/1594] Loss: 0.2129
Epoch [1/4] Batch [950/1594] Loss: 0.1462
Epoch [1/4] Batch [1000/1594] Loss: 0.3119
Epoch [1/4] Batch [1050/1594] Loss: 0.1564
Epoch [1/4] Batch [1100/1594] Loss: 0.1088
Epoch [1/4] Batch [1150/1594] Loss: 0.1839
Epoch [1/4] Batch [1200/1594] Loss: 0.3233
Epoch [1/4] Batch [1250/1594] Loss: 0.2091
Epoch [1/4] Batch [1300/1594] Loss: 0.2558
Epoch [1/4] Batch [1350/1594] Loss: 0.1861
Epoch [1/4] Batch [1400/1594] Loss: 0.1578
Epoch [1/4] Batch [1450/1594] Loss: 0.1175
Epoch [1/4] Batch [1500/1594] Loss: 0.1782
Epoch [1/4] Batch [1550/1594] Loss: 0.1408
Trial 0: Epoch 1/4 | Val F1: 0.9402 | Val Loss: 0.1782
Epoch [2/4] Batch [50/1594] Loss: 0.0575
Epoch [2/4] Batch [100/1594] Loss: 0.0586
Epoch [2/4] Batch [150/1594] Loss: 0.2709
Epoch [2/4] Batch [200/1594] Loss: 0.1284
```

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Epoch [2/4] Batch [250/1594] Loss: 0.3439
Epoch [2/4] Batch [300/1594] Loss: 0.2033
Epoch [2/4] Batch [350/1594] Loss: 0.0920
Epoch [2/4] Batch [400/1594] Loss: 0.1439
Epoch [2/4] Batch [450/1594] Loss: 0.0659
Epoch [2/4] Batch [500/1594] Loss: 0.1167
Epoch [2/4] Batch [550/1594] Loss: 0.1834
Epoch [2/4] Batch [600/1594] Loss: 0.0910
Epoch [2/4] Batch [650/1594] Loss: 0.1559
Epoch [2/4] Batch [700/1594] Loss: 0.0845
Epoch [2/4] Batch [750/1594] Loss: 0.0460
Epoch [2/4] Batch [800/1594] Loss: 0.1223
Epoch [2/4] Batch [850/1594] Loss: 0.0552
Epoch [2/4] Batch [900/1594] Loss: 0.0233
Epoch [2/4] Batch [950/1594] Loss: 0.1794
Epoch [2/4] Batch [1000/1594] Loss: 0.1344
Epoch [2/4] Batch [1050/1594] Loss: 0.2106
Epoch [2/4] Batch [1100/1594] Loss: 0.2174
Epoch [2/4] Batch [1150/1594] Loss: 0.1054
Epoch [2/4] Batch [1200/1594] Loss: 0.1293
Epoch [2/4] Batch [1250/1594] Loss: 0.3268
Epoch [2/4] Batch [1300/1594] Loss: 0.0411
Epoch [2/4] Batch [1350/1594] Loss: 0.0312
Epoch [2/4] Batch [1400/1594] Loss: 0.1457
Epoch [2/4] Batch [1450/1594] Loss: 0.0708
Epoch [2/4] Batch [1500/1594] Loss: 0.2873
Epoch [2/4] Batch [1550/1594] Loss: 0.0777
Trial 0: Epoch 2/4 | Val F1: 0.9461 | Val Loss: 0.1655
Epoch [3/4] Batch [50/1594] Loss: 0.1226
Epoch [3/4] Batch [100/1594] Loss: 0.1373
Epoch [3/4] Batch [150/1594] Loss: 0.1429
Epoch [3/4] Batch [200/1594] Loss: 0.0486
Epoch [3/4] Batch [250/1594] Loss: 0.1485
Epoch [3/4] Batch [300/1594] Loss: 0.1680
Epoch [3/4] Batch [350/1594] Loss: 0.1482
Epoch [3/4] Batch [400/1594] Loss: 0.0248
Epoch [3/4] Batch [450/1594] Loss: 0.1289
Epoch [3/4] Batch [500/1594] Loss: 0.1175
Epoch [3/4] Batch [550/1594] Loss: 0.1562
Epoch [3/4] Batch [600/1594] Loss: 0.1301
Epoch [3/4] Batch [650/1594] Loss: 0.0175
Epoch [3/4] Batch [700/1594] Loss: 0.0979
Epoch [3/4] Batch [750/1594] Loss: 0.0931
Epoch [3/4] Batch [800/1594] Loss: 0.1062
Epoch [3/4] Batch [850/1594] Loss: 0.1930
Epoch [3/4] Batch [900/1594] Loss: 0.2883
Epoch [3/4] Batch [950/1594] Loss: 0.0574
Epoch [3/4] Batch [1000/1594] Loss: 0.0296
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Epoch [3/4] Batch [1050/1594] Loss: 0.1332
Epoch [3/4] Batch [1100/1594] Loss: 0.1630
Epoch [3/4] Batch [1150/1594] Loss: 0.0801
Epoch [3/4] Batch [1200/1594] Loss: 0.1086
Epoch [3/4] Batch [1250/1594] Loss: 0.1486
Epoch [3/4] Batch [1300/1594] Loss: 0.1289
Epoch [3/4] Batch [1350/1594] Loss: 0.0162
Epoch [3/4] Batch [1400/1594] Loss: 0.1058
Epoch [3/4] Batch [1450/1594] Loss: 0.0225
Epoch [3/4] Batch [1500/1594] Loss: 0.1105
Epoch [3/4] Batch [1550/1594] Loss: 0.1506
Trial 0: Epoch 3/4 | Val F1: 0.9479 | Val Loss: 0.1729
Epoch [4/4] Batch [50/1594] Loss: 0.1299
Epoch [4/4] Batch [100/1594] Loss: 0.0213
Epoch [4/4] Batch [150/1594] Loss: 0.0489
Epoch [4/4] Batch [200/1594] Loss: 0.0984
Epoch [4/4] Batch [250/1594] Loss: 0.0259
Epoch [4/4] Batch [300/1594] Loss: 0.1645
Epoch [4/4] Batch [350/1594] Loss: 0.0080
Epoch [4/4] Batch [400/1594] Loss: 0.0842
Epoch [4/4] Batch [450/1594] Loss: 0.1601
Epoch [4/4] Batch [500/1594] Loss: 0.0921
Epoch [4/4] Batch [550/1594] Loss: 0.0667
Epoch [4/4] Batch [600/1594] Loss: 0.1079
Epoch [4/4] Batch [650/1594] Loss: 0.0899
Epoch [4/4] Batch [700/1594] Loss: 0.1841
Epoch [4/4] Batch [750/1594] Loss: 0.0690
Epoch [4/4] Batch [800/1594] Loss: 0.1010
Epoch [4/4] Batch [850/1594] Loss: 0.0645
Epoch [4/4] Batch [900/1594] Loss: 0.0517
Epoch [4/4] Batch [950/1594] Loss: 0.2518
Epoch [4/4] Batch [1000/1594] Loss: 0.0255
Epoch [4/4] Batch [1050/1594] Loss: 0.0947
Epoch [4/4] Batch [1100/1594] Loss: 0.1672
Epoch [4/4] Batch [1150/1594] Loss: 0.1222
Epoch [4/4] Batch [1200/1594] Loss: 0.0919
Epoch [4/4] Batch [1250/1594] Loss: 0.0214
Epoch [4/4] Batch [1300/1594] Loss: 0.0772
Epoch [4/4] Batch [1350/1594] Loss: 0.0983
Epoch [4/4] Batch [1400/1594] Loss: 0.0471
Epoch [4/4] Batch [1450/1594] Loss: 0.0476
Epoch [4/4] Batch [1500/1594] Loss: 0.0237
Epoch [4/4] Batch [1550/1594] Loss: 0.0874
Trial 0: Epoch 4/4 | Val F1: 0.9469 | Val Loss: 0.1866
```

```
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.
```

```
Epoch [1/4] Batch [50/6375] Loss: 1.3773
Epoch [1/4] Batch [100/6375] Loss: 1.3499
Epoch [1/4] Batch [150/6375] Loss: 1.1476
Epoch [1/4] Batch [200/6375] Loss: 0.9652
Epoch [1/4] Batch [250/6375] Loss: 0.4536
Epoch [1/4] Batch [300/6375] Loss: 0.2849
Epoch [1/4] Batch [350/6375] Loss: 0.2168
Epoch [1/4] Batch [400/6375] Loss: 0.2150
Epoch [1/4] Batch [450/6375] Loss: 0.3443
Epoch [1/4] Batch [500/6375] Loss: 0.3259
Epoch [1/4] Batch [550/6375] Loss: 0.2219
Epoch [1/4] Batch [600/6375] Loss: 0.7114
Epoch [1/4] Batch [650/6375] Loss: 0.2524
Epoch [1/4] Batch [700/6375] Loss: 0.2224
Epoch [1/4] Batch [750/6375] Loss: 0.0491
Epoch [1/4] Batch [800/6375] Loss: 0.4119
Epoch [1/4] Batch [850/6375] Loss: 0.0793
Epoch [1/4] Batch [900/6375] Loss: 0.3252
Epoch [1/4] Batch [950/6375] Loss: 0.4528
Epoch [1/4] Batch [1000/6375] Loss: 0.2461
Epoch [1/4] Batch [1050/6375] Loss: 0.1552
Epoch [1/4] Batch [1100/6375] Loss: 0.2483
Epoch [1/4] Batch [1150/6375] Loss: 0.0335
Epoch [1/4] Batch [1200/6375] Loss: 0.0736
Epoch [1/4] Batch [1250/6375] Loss: 0.0252
Epoch [1/4] Batch [1300/6375] Loss: 0.5279
Epoch [1/4] Batch [1350/6375] Loss: 0.2495
Epoch [1/4] Batch [1400/6375] Loss: 0.1303
Epoch [1/4] Batch [1450/6375] Loss: 0.3667
Epoch [1/4] Batch [1500/6375] Loss: 0.0549
Epoch [1/4] Batch [1550/6375] Loss: 0.0702
Epoch [1/4] Batch [1600/6375] Loss: 0.1154
Epoch [1/4] Batch [1650/6375] Loss: 0.1508
Epoch [1/4] Batch [1700/6375] Loss: 0.2287
Epoch [1/4] Batch [1750/6375] Loss: 0.3717
Epoch [1/4] Batch [1800/6375] Loss: 0.2630
Epoch [1/4] Batch [1850/6375] Loss: 0.3036
Epoch [1/4] Batch [1900/6375] Loss: 0.2197
Epoch [1/4] Batch [1950/6375] Loss: 0.4693
Epoch [1/4] Batch [2000/6375] Loss: 0.1623
Epoch [1/4] Batch [2050/6375] Loss: 0.2927
Epoch [1/4] Batch [2100/6375] Loss: 0.2953
Epoch [1/4] Batch [2150/6375] Loss: 0.6301
Epoch [1/4] Batch [2200/6375] Loss: 0.5685
```

```
Epoch [1/4] Batch [2250/6375] Loss: 0.1721
Epoch [1/4] Batch [2300/6375] Loss: 0.0309
Epoch [1/4] Batch [2350/6375] Loss: 0.2367
Epoch [1/4] Batch [2400/6375] Loss: 0.3385
Epoch [1/4] Batch [2450/6375] Loss: 0.1699
Epoch [1/4] Batch [2500/6375] Loss: 0.0227
Epoch [1/4] Batch [2550/6375] Loss: 0.2362
Epoch [1/4] Batch [2600/6375] Loss: 0.0817
Epoch [1/4] Batch [2650/6375] Loss: 0.5234
Epoch [1/4] Batch [2700/6375] Loss: 0.3000
Epoch [1/4] Batch [2750/6375] Loss: 0.4098
Epoch [1/4] Batch [2800/6375] Loss: 0.1553
Epoch [1/4] Batch [2850/6375] Loss: 0.2804
Epoch [1/4] Batch [2900/6375] Loss: 0.0724
Epoch [1/4] Batch [2950/6375] Loss: 0.3976
Epoch [1/4] Batch [3000/6375] Loss: 0.1949
Epoch [1/4] Batch [3050/6375] Loss: 0.3925
Epoch [1/4] Batch [3100/6375] Loss: 0.0252
Epoch [1/4] Batch [3150/6375] Loss: 0.1623
Epoch [1/4] Batch [3200/6375] Loss: 0.1722
Epoch [1/4] Batch [3250/6375] Loss: 0.4037
Epoch [1/4] Batch [3300/6375] Loss: 0.0188
Epoch [1/4] Batch [3350/6375] Loss: 0.0995
Epoch [1/4] Batch [3400/6375] Loss: 0.3940
Epoch [1/4] Batch [3450/6375] Loss: 1.0475
Epoch [1/4] Batch [3500/6375] Loss: 0.0827
Epoch [1/4] Batch [3550/6375] Loss: 0.0975
Epoch [1/4] Batch [3600/6375] Loss: 0.0776
Epoch [1/4] Batch [3650/6375] Loss: 0.3575
Epoch [1/4] Batch [3700/6375] Loss: 0.0597
Epoch [1/4] Batch [3750/6375] Loss: 0.3602
Epoch [1/4] Batch [3800/6375] Loss: 0.0622
Epoch [1/4] Batch [3850/6375] Loss: 0.4775
Epoch [1/4] Batch [3900/6375] Loss: 0.7759
Epoch [1/4] Batch [3950/6375] Loss: 0.1943
Epoch [1/4] Batch [4000/6375] Loss: 0.0082
Epoch [1/4] Batch [4050/6375] Loss: 0.0263
Epoch [1/4] Batch [4100/6375] Loss: 0.2873
Epoch [1/4] Batch [4150/6375] Loss: 0.1976
Epoch [1/4] Batch [4200/6375] Loss: 0.3554
Epoch [1/4] Batch [4250/6375] Loss: 0.0689
Epoch [1/4] Batch [4300/6375] Loss: 0.7005
Epoch [1/4] Batch [4350/6375] Loss: 0.1102
Epoch [1/4] Batch [4400/6375] Loss: 0.5209
Epoch [1/4] Batch [4450/6375] Loss: 0.0121
Epoch [1/4] Batch [4500/6375] Loss: 0.4967
Epoch [1/4] Batch [4550/6375] Loss: 0.4000
Epoch [1/4] Batch [4600/6375] Loss: 0.0216
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Epoch [1/4] Batch [4650/6375] Loss: 0.7925
Epoch [1/4] Batch [4700/6375] Loss: 0.0667
Epoch [1/4] Batch [4750/6375] Loss: 0.3743
Epoch [1/4] Batch [4800/6375] Loss: 0.0349
Epoch [1/4] Batch [4850/6375] Loss: 0.2048
Epoch [1/4] Batch [4900/6375] Loss: 0.1027
Epoch [1/4] Batch [4950/6375] Loss: 0.0333
Epoch [1/4] Batch [5000/6375] Loss: 0.3907
Epoch [1/4] Batch [5050/6375] Loss: 0.2908
Epoch [1/4] Batch [5100/6375] Loss: 0.2674
Epoch [1/4] Batch [5150/6375] Loss: 0.0829
Epoch [1/4] Batch [5200/6375] Loss: 0.1756
Epoch [1/4] Batch [5250/6375] Loss: 0.0139
Epoch [1/4] Batch [5300/6375] Loss: 0.6260
Epoch [1/4] Batch [5350/6375] Loss: 0.1460
Epoch [1/4] Batch [5400/6375] Loss: 0.0783
Epoch [1/4] Batch [5450/6375] Loss: 0.2034
Epoch [1/4] Batch [5500/6375] Loss: 0.0234
Epoch [1/4] Batch [5550/6375] Loss: 0.0494
Epoch [1/4] Batch [5600/6375] Loss: 0.0556
Epoch [1/4] Batch [5650/6375] Loss: 0.1647
Epoch [1/4] Batch [5700/6375] Loss: 0.0460
Epoch [1/4] Batch [5750/6375] Loss: 0.3330
Epoch [1/4] Batch [5800/6375] Loss: 0.4008
Epoch [1/4] Batch [5850/6375] Loss: 0.0983
Epoch [1/4] Batch [5900/6375] Loss: 0.0359
Epoch [1/4] Batch [5950/6375] Loss: 0.4819
Epoch [1/4] Batch [6000/6375] Loss: 0.2197
Epoch [1/4] Batch [6050/6375] Loss: 0.0064
Epoch [1/4] Batch [6100/6375] Loss: 0.1758
Epoch [1/4] Batch [6150/6375] Loss: 0.0052
Epoch [1/4] Batch [6200/6375] Loss: 0.0147
Epoch [1/4] Batch [6250/6375] Loss: 0.0529
Epoch [1/4] Batch [6300/6375] Loss: 0.0222
Epoch [1/4] Batch [6350/6375] Loss: 0.3026
Trial 1: Epoch 1/4 | Val F1: 0.9406 | Val Loss: 0.1929
Epoch [2/4] Batch [50/6375] Loss: 0.0284
Epoch [2/4] Batch [100/6375] Loss: 0.0158
Epoch [2/4] Batch [150/6375] Loss: 0.0577
Epoch [2/4] Batch [200/6375] Loss: 0.1621
Epoch [2/4] Batch [250/6375] Loss: 0.0146
Epoch [2/4] Batch [300/6375] Loss: 0.1290
Epoch [2/4] Batch [350/6375] Loss: 0.3672
Epoch [2/4] Batch [400/6375] Loss: 0.2207
Epoch [2/4] Batch [450/6375] Loss: 0.0061
Epoch [2/4] Batch [500/6375] Loss: 0.6985
Epoch [2/4] Batch [550/6375] Loss: 0.0145
Epoch [2/4] Batch [600/6375] Loss: 0.1128
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Epoch [2/4] Batch [650/6375] Loss: 0.1682
Epoch [2/4] Batch [700/6375] Loss: 0.1953
Epoch [2/4] Batch [750/6375] Loss: 0.1248
Epoch [2/4] Batch [800/6375] Loss: 0.0102
Epoch [2/4] Batch [850/6375] Loss: 0.3744
Epoch [2/4] Batch [900/6375] Loss: 0.0036
Epoch [2/4] Batch [950/6375] Loss: 0.2162
Epoch [2/4] Batch [1000/6375] Loss: 0.0077
Epoch [2/4] Batch [1050/6375] Loss: 0.0146
Epoch [2/4] Batch [1100/6375] Loss: 0.0141
Epoch [2/4] Batch [1150/6375] Loss: 0.0732
Epoch [2/4] Batch [1200/6375] Loss: 0.1363
Epoch [2/4] Batch [1250/6375] Loss: 0.3351
Epoch [2/4] Batch [1300/6375] Loss: 0.0343
Epoch [2/4] Batch [1350/6375] Loss: 0.0115
Epoch [2/4] Batch [1400/6375] Loss: 0.0079
Epoch [2/4] Batch [1450/6375] Loss: 0.0075
Epoch [2/4] Batch [1500/6375] Loss: 0.3033
Epoch [2/4] Batch [1550/6375] Loss: 0.0156
Epoch [2/4] Batch [1600/6375] Loss: 0.0186
Epoch [2/4] Batch [1650/6375] Loss: 0.0071
Epoch [2/4] Batch [1700/6375] Loss: 0.0378
Epoch [2/4] Batch [1750/6375] Loss: 0.0025
Epoch [2/4] Batch [1800/6375] Loss: 0.2755
Epoch [2/4] Batch [1850/6375] Loss: 0.0205
Epoch [2/4] Batch [1900/6375] Loss: 0.0050
Epoch [2/4] Batch [1950/6375] Loss: 0.4717
Epoch [2/4] Batch [2000/6375] Loss: 0.1274
Epoch [2/4] Batch [2050/6375] Loss: 0.0848
Epoch [2/4] Batch [2100/6375] Loss: 0.4192
Epoch [2/4] Batch [2150/6375] Loss: 0.1521
Epoch [2/4] Batch [2200/6375] Loss: 0.2806
Epoch [2/4] Batch [2250/6375] Loss: 0.2935
Epoch [2/4] Batch [2300/6375] Loss: 0.0685
Epoch [2/4] Batch [2350/6375] Loss: 0.1880
Epoch [2/4] Batch [2400/6375] Loss: 0.0354
Epoch [2/4] Batch [2450/6375] Loss: 0.2312
Epoch [2/4] Batch [2500/6375] Loss: 0.0492
Epoch [2/4] Batch [2550/6375] Loss: 0.0907
Epoch [2/4] Batch [2600/6375] Loss: 0.1328
Epoch [2/4] Batch [2650/6375] Loss: 0.0059
Epoch [2/4] Batch [2700/6375] Loss: 0.0382
Epoch [2/4] Batch [2750/6375] Loss: 0.0735
Epoch [2/4] Batch [2800/6375] Loss: 0.0198
Epoch [2/4] Batch [2850/6375] Loss: 0.2071
Epoch [2/4] Batch [2900/6375] Loss: 0.0740
Epoch [2/4] Batch [2950/6375] Loss: 0.0226
Epoch [2/4] Batch [3000/6375] Loss: 0.1371
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Epoch [2/4] Batch [3050/6375] Loss: 0.0403
Epoch [2/4] Batch [3100/6375] Loss: 0.0385
Epoch [2/4] Batch [3150/6375] Loss: 0.0090
Epoch [2/4] Batch [3200/6375] Loss: 0.0042
Epoch [2/4] Batch [3250/6375] Loss: 0.1609
Epoch [2/4] Batch [3300/6375] Loss: 0.2833
Epoch [2/4] Batch [3350/6375] Loss: 0.3438
Epoch [2/4] Batch [3400/6375] Loss: 0.0154
Epoch [2/4] Batch [3450/6375] Loss: 0.1302
Epoch [2/4] Batch [3500/6375] Loss: 0.1278
Epoch [2/4] Batch [3550/6375] Loss: 0.2831
Epoch [2/4] Batch [3600/6375] Loss: 0.4172
Epoch [2/4] Batch [3650/6375] Loss: 0.1029
Epoch [2/4] Batch [3700/6375] Loss: 0.0203
Epoch [2/4] Batch [3750/6375] Loss: 0.2842
Epoch [2/4] Batch [3800/6375] Loss: 0.6359
Epoch [2/4] Batch [3850/6375] Loss: 0.0043
Epoch [2/4] Batch [3900/6375] Loss: 0.0050
Epoch [2/4] Batch [3950/6375] Loss: 0.0065
Epoch [2/4] Batch [4000/6375] Loss: 0.1757
Epoch [2/4] Batch [4050/6375] Loss: 0.2279
Epoch [2/4] Batch [4100/6375] Loss: 0.1335
Epoch [2/4] Batch [4150/6375] Loss: 0.4364
Epoch [2/4] Batch [4200/6375] Loss: 0.1510
Epoch [2/4] Batch [4250/6375] Loss: 0.0291
Epoch [2/4] Batch [4300/6375] Loss: 0.0814
Epoch [2/4] Batch [4350/6375] Loss: 0.2578
Epoch [2/4] Batch [4400/6375] Loss: 0.0193
Epoch [2/4] Batch [4450/6375] Loss: 0.0212
Epoch [2/4] Batch [4500/6375] Loss: 0.0086
Epoch [2/4] Batch [4550/6375] Loss: 0.1538
Epoch [2/4] Batch [4600/6375] Loss: 0.0495
Epoch [2/4] Batch [4650/6375] Loss: 0.2291
Epoch [2/4] Batch [4700/6375] Loss: 0.2199
Epoch [2/4] Batch [4750/6375] Loss: 0.2884
Epoch [2/4] Batch [4800/6375] Loss: 0.0181
Epoch [2/4] Batch [4850/6375] Loss: 0.4289
Epoch [2/4] Batch [4900/6375] Loss: 0.5037
Epoch [2/4] Batch [4950/6375] Loss: 0.1018
Epoch [2/4] Batch [5000/6375] Loss: 0.2699
Epoch [2/4] Batch [5050/6375] Loss: 0.1775
Epoch [2/4] Batch [5100/6375] Loss: 0.0070
Epoch [2/4] Batch [5150/6375] Loss: 0.2878
Epoch [2/4] Batch [5200/6375] Loss: 0.0068
Epoch [2/4] Batch [5250/6375] Loss: 0.2076
Epoch [2/4] Batch [5300/6375] Loss: 0.2178
Epoch [2/4] Batch [5350/6375] Loss: 0.2557
Epoch [2/4] Batch [5400/6375] Loss: 0.6475
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Epoch [2/4] Batch [5450/6375] Loss: 0.0101
Epoch [2/4] Batch [5500/6375] Loss: 0.0592
Epoch [2/4] Batch [5550/6375] Loss: 0.0069
Epoch [2/4] Batch [5600/6375] Loss: 0.1618
Epoch [2/4] Batch [5650/6375] Loss: 0.0437
Epoch [2/4] Batch [5700/6375] Loss: 0.0470
Epoch [2/4] Batch [5750/6375] Loss: 0.1435
Epoch [2/4] Batch [5800/6375] Loss: 0.0464
Epoch [2/4] Batch [5850/6375] Loss: 0.0331
Epoch [2/4] Batch [5900/6375] Loss: 0.2288
Epoch [2/4] Batch [5950/6375] Loss: 0.0426
Epoch [2/4] Batch [6000/6375] Loss: 0.0108
Epoch [2/4] Batch [6050/6375] Loss: 0.2127
Epoch [2/4] Batch [6100/6375] Loss: 0.0570
Epoch [2/4] Batch [6150/6375] Loss: 0.1605
Epoch [2/4] Batch [6200/6375] Loss: 0.0151
Epoch [2/4] Batch [6250/6375] Loss: 0.4377
Epoch [2/4] Batch [6300/6375] Loss: 0.2642
Epoch [2/4] Batch [6350/6375] Loss: 0.0396
Trial 1: Epoch 2/4 | Val F1: 0.9458 | Val Loss: 0.1899
Epoch [3/4] Batch [50/6375] Loss: 0.0053
Epoch [3/4] Batch [100/6375] Loss: 0.2871
Epoch [3/4] Batch [150/6375] Loss: 0.0112
Epoch [3/4] Batch [200/6375] Loss: 0.0031
Epoch [3/4] Batch [250/6375] Loss: 0.0074
Epoch [3/4] Batch [300/6375] Loss: 0.0031
Epoch [3/4] Batch [350/6375] Loss: 0.0041
Epoch [3/4] Batch [400/6375] Loss: 0.2904
Epoch [3/4] Batch [450/6375] Loss: 0.0040
Epoch [3/4] Batch [500/6375] Loss: 0.0032
Epoch [3/4] Batch [550/6375] Loss: 0.6153
Epoch [3/4] Batch [600/6375] Loss: 0.0378
Epoch [3/4] Batch [650/6375] Loss: 0.0047
Epoch [3/4] Batch [700/6375] Loss: 0.1427
Epoch [3/4] Batch [750/6375] Loss: 0.0046
Epoch [3/4] Batch [800/6375] Loss: 0.0094
Epoch [3/4] Batch [850/6375] Loss: 0.0024
Epoch [3/4] Batch [900/6375] Loss: 0.0008
Epoch [3/4] Batch [950/6375] Loss: 0.0050
Epoch [3/4] Batch [1000/6375] Loss: 0.0045
Epoch [3/4] Batch [1050/6375] Loss: 0.0072
Epoch [3/4] Batch [1100/6375] Loss: 0.0169
Epoch [3/4] Batch [1150/6375] Loss: 0.0019
Epoch [3/4] Batch [1200/6375] Loss: 0.0048
Epoch [3/4] Batch [1250/6375] Loss: 0.0011
Epoch [3/4] Batch [1300/6375] Loss: 0.0029
Epoch [3/4] Batch [1350/6375] Loss: 0.3496
Epoch [3/4] Batch [1400/6375] Loss: 0.0130
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Epoch [3/4] Batch [1450/6375] Loss: 0.0043
Epoch [3/4] Batch [1500/6375] Loss: 0.0019
Epoch [3/4] Batch [1550/6375] Loss: 0.3147
Epoch [3/4] Batch [1600/6375] Loss: 0.0795
Epoch [3/4] Batch [1650/6375] Loss: 0.0018
Epoch [3/4] Batch [1700/6375] Loss: 0.0033
Epoch [3/4] Batch [1750/6375] Loss: 0.0100
Epoch [3/4] Batch [1800/6375] Loss: 0.1826
Epoch [3/4] Batch [1850/6375] Loss: 0.0016
Epoch [3/4] Batch [1900/6375] Loss: 0.0018
Epoch [3/4] Batch [1950/6375] Loss: 0.0055
Epoch [3/4] Batch [2000/6375] Loss: 0.0058
Epoch [3/4] Batch [2050/6375] Loss: 0.0038
Epoch [3/4] Batch [2100/6375] Loss: 0.3160
Epoch [3/4] Batch [2150/6375] Loss: 0.0894
Epoch [3/4] Batch [2200/6375] Loss: 0.1707
Epoch [3/4] Batch [2250/6375] Loss: 0.1376
Epoch [3/4] Batch [2300/6375] Loss: 0.0018
Epoch [3/4] Batch [2350/6375] Loss: 0.2269
Epoch [3/4] Batch [2400/6375] Loss: 0.0129
Epoch [3/4] Batch [2450/6375] Loss: 0.0634
Epoch [3/4] Batch [2500/6375] Loss: 0.2983
Epoch [3/4] Batch [2550/6375] Loss: 0.0373
Epoch [3/4] Batch [2600/6375] Loss: 0.0012
Epoch [3/4] Batch [2650/6375] Loss: 0.0015
Epoch [3/4] Batch [2700/6375] Loss: 0.0025
Epoch [3/4] Batch [2750/6375] Loss: 0.3729
Epoch [3/4] Batch [2800/6375] Loss: 0.5183
Epoch [3/4] Batch [2850/6375] Loss: 0.0023
Epoch [3/4] Batch [2900/6375] Loss: 0.0032
Epoch [3/4] Batch [2950/6375] Loss: 0.0019
Epoch [3/4] Batch [3000/6375] Loss: 0.2433
Epoch [3/4] Batch [3050/6375] Loss: 0.0138
Epoch [3/4] Batch [3100/6375] Loss: 0.0043
Epoch [3/4] Batch [3150/6375] Loss: 0.0250
Epoch [3/4] Batch [3200/6375] Loss: 0.4583
Epoch [3/4] Batch [3250/6375] Loss: 0.2022
Epoch [3/4] Batch [3300/6375] Loss: 0.0019
Epoch [3/4] Batch [3350/6375] Loss: 0.0010
Epoch [3/4] Batch [3400/6375] Loss: 0.0024
Epoch [3/4] Batch [3450/6375] Loss: 0.0034
Epoch [3/4] Batch [3500/6375] Loss: 0.0384
Epoch [3/4] Batch [3550/6375] Loss: 0.0012
Epoch [3/4] Batch [3600/6375] Loss: 0.1727
Epoch [3/4] Batch [3650/6375] Loss: 0.0720
Epoch [3/4] Batch [3700/6375] Loss: 0.0028
Epoch [3/4] Batch [3750/6375] Loss: 0.0048
Epoch [3/4] Batch [3800/6375] Loss: 0.0056
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Epoch [3/4] Batch [3850/6375] Loss: 0.1434
Epoch [3/4] Batch [3900/6375] Loss: 0.0337
Epoch [3/4] Batch [3950/6375] Loss: 0.4126
Epoch [3/4] Batch [4000/6375] Loss: 0.0050
Epoch [3/4] Batch [4050/6375] Loss: 0.3775
Epoch [3/4] Batch [4100/6375] Loss: 0.1263
Epoch [3/4] Batch [4150/6375] Loss: 0.0055
Epoch [3/4] Batch [4200/6375] Loss: 0.0303
Epoch [3/4] Batch [4250/6375] Loss: 0.0009
Epoch [3/4] Batch [4300/6375] Loss: 0.0015
Epoch [3/4] Batch [4350/6375] Loss: 0.0014
Epoch [3/4] Batch [4400/6375] Loss: 0.0121
Epoch [3/4] Batch [4450/6375] Loss: 0.0352
Epoch [3/4] Batch [4500/6375] Loss: 0.3265
Epoch [3/4] Batch [4550/6375] Loss: 0.7176
Epoch [3/4] Batch [4600/6375] Loss: 0.0965
Epoch [3/4] Batch [4650/6375] Loss: 0.0010
Epoch [3/4] Batch [4700/6375] Loss: 0.0023
Epoch [3/4] Batch [4750/6375] Loss: 0.0016
Epoch [3/4] Batch [4800/6375] Loss: 0.0064
Epoch [3/4] Batch [4850/6375] Loss: 0.0046
Epoch [3/4] Batch [4900/6375] Loss: 0.0018
Epoch [3/4] Batch [4950/6375] Loss: 0.3011
Epoch [3/4] Batch [5000/6375] Loss: 0.0111
Epoch [3/4] Batch [5050/6375] Loss: 0.4403
Epoch [3/4] Batch [5100/6375] Loss: 0.0054
Epoch [3/4] Batch [5150/6375] Loss: 0.0071
Epoch [3/4] Batch [5200/6375] Loss: 0.0167
Epoch [3/4] Batch [5250/6375] Loss: 0.0017
Epoch [3/4] Batch [5300/6375] Loss: 0.0362
Epoch [3/4] Batch [5350/6375] Loss: 0.0108
Epoch [3/4] Batch [5400/6375] Loss: 0.3727
Epoch [3/4] Batch [5450/6375] Loss: 0.0144
Epoch [3/4] Batch [5500/6375] Loss: 0.4358
Epoch [3/4] Batch [5550/6375] Loss: 0.7504
Epoch [3/4] Batch [5600/6375] Loss: 0.0073
Epoch [3/4] Batch [5650/6375] Loss: 0.0045
Epoch [3/4] Batch [5700/6375] Loss: 0.4248
Epoch [3/4] Batch [5750/6375] Loss: 0.0383
Epoch [3/4] Batch [5800/6375] Loss: 0.4325
Epoch [3/4] Batch [5850/6375] Loss: 0.0209
Epoch [3/4] Batch [5900/6375] Loss: 0.0589
Epoch [3/4] Batch [5950/6375] Loss: 0.2250
Epoch [3/4] Batch [6000/6375] Loss: 0.7370
Epoch [3/4] Batch [6050/6375] Loss: 0.0028
Epoch [3/4] Batch [6100/6375] Loss: 0.0310
Epoch [3/4] Batch [6150/6375] Loss: 0.1025
Epoch [3/4] Batch [6200/6375] Loss: 0.0029
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Epoch [3/4] Batch [6250/6375] Loss: 0.4432
Epoch [3/4] Batch [6300/6375] Loss: 0.2146
Epoch [3/4] Batch [6350/6375] Loss: 0.0015
Trial 1: Epoch 3/4 | Val F1: 0.9479 | Val Loss: 0.2141
Epoch [4/4] Batch [50/6375] Loss: 0.0050
Epoch [4/4] Batch [100/6375] Loss: 0.0049
Epoch [4/4] Batch [150/6375] Loss: 0.0018
Epoch [4/4] Batch [200/6375] Loss: 0.2387
Epoch [4/4] Batch [250/6375] Loss: 0.0072
Epoch [4/4] Batch [300/6375] Loss: 0.0017
Epoch [4/4] Batch [350/6375] Loss: 0.0009
Epoch [4/4] Batch [400/6375] Loss: 0.0023
Epoch [4/4] Batch [450/6375] Loss: 0.0018
Epoch [4/4] Batch [500/6375] Loss: 0.1160
Epoch [4/4] Batch [550/6375] Loss: 0.0012
Epoch [4/4] Batch [600/6375] Loss: 0.0008
Epoch [4/4] Batch [650/6375] Loss: 0.0759
Epoch [4/4] Batch [700/6375] Loss: 0.0041
Epoch [4/4] Batch [750/6375] Loss: 0.0007
Epoch [4/4] Batch [800/6375] Loss: 0.0061
Epoch [4/4] Batch [850/6375] Loss: 0.0034
Epoch [4/4] Batch [900/6375] Loss: 0.4229
Epoch [4/4] Batch [950/6375] Loss: 0.0020
Epoch [4/4] Batch [1000/6375] Loss: 0.0015
Epoch [4/4] Batch [1050/6375] Loss: 0.0009
Epoch [4/4] Batch [1100/6375] Loss: 0.0008
Epoch [4/4] Batch [1150/6375] Loss: 0.0010
Epoch [4/4] Batch [1200/6375] Loss: 0.0006
Epoch [4/4] Batch [1250/6375] Loss: 0.0009
Epoch [4/4] Batch [1300/6375] Loss: 0.0020
Epoch [4/4] Batch [1350/6375] Loss: 0.0007
Epoch [4/4] Batch [1400/6375] Loss: 0.0012
Epoch [4/4] Batch [1450/6375] Loss: 0.0031
Epoch [4/4] Batch [1500/6375] Loss: 0.0039
Epoch [4/4] Batch [1550/6375] Loss: 0.0284
Epoch [4/4] Batch [1600/6375] Loss: 0.0023
Epoch [4/4] Batch [1650/6375] Loss: 0.0004
Epoch [4/4] Batch [1700/6375] Loss: 0.0010
Epoch [4/4] Batch [1750/6375] Loss: 0.0042
Epoch [4/4] Batch [1800/6375] Loss: 0.0009
Epoch [4/4] Batch [1850/6375] Loss: 0.0013
Epoch [4/4] Batch [1900/6375] Loss: 0.2998
Epoch [4/4] Batch [1950/6375] Loss: 0.0863
Epoch [4/4] Batch [2000/6375] Loss: 0.0906
Epoch [4/4] Batch [2050/6375] Loss: 0.0043
Epoch [4/4] Batch [2100/6375] Loss: 0.1937
Epoch [4/4] Batch [2150/6375] Loss: 0.0017
Epoch [4/4] Batch [2200/6375] Loss: 0.2644
```

```
Epoch [4/4] Batch [2250/6375] Loss: 0.3034
Epoch [4/4] Batch [2300/6375] Loss: 0.1593
Epoch [4/4] Batch [2350/6375] Loss: 0.0094
Epoch [4/4] Batch [2400/6375] Loss: 0.3058
Epoch [4/4] Batch [2450/6375] Loss: 0.3624
Epoch [4/4] Batch [2500/6375] Loss: 0.0011
Epoch [4/4] Batch [2550/6375] Loss: 0.0106
Epoch [4/4] Batch [2600/6375] Loss: 0.0361
Epoch [4/4] Batch [2650/6375] Loss: 0.0019
Epoch [4/4] Batch [2700/6375] Loss: 0.0017
Epoch [4/4] Batch [2750/6375] Loss: 0.0008
Epoch [4/4] Batch [2800/6375] Loss: 0.0006
Epoch [4/4] Batch [2850/6375] Loss: 0.0018
Epoch [4/4] Batch [2900/6375] Loss: 0.0193
Epoch [4/4] Batch [2950/6375] Loss: 0.0006
Epoch [4/4] Batch [3000/6375] Loss: 0.3559
Epoch [4/4] Batch [3050/6375] Loss: 0.0008
Epoch [4/4] Batch [3100/6375] Loss: 0.0090
Epoch [4/4] Batch [3150/6375] Loss: 0.3130
Epoch [4/4] Batch [3200/6375] Loss: 0.0006
Epoch [4/4] Batch [3250/6375] Loss: 0.0046
Epoch [4/4] Batch [3300/6375] Loss: 0.0014
Epoch [4/4] Batch [3350/6375] Loss: 0.0026
Epoch [4/4] Batch [3400/6375] Loss: 0.0005
Epoch [4/4] Batch [3450/6375] Loss: 0.3435
Epoch [4/4] Batch [3500/6375] Loss: 0.0009
Epoch [4/4] Batch [3550/6375] Loss: 0.0005
Epoch [4/4] Batch [3600/6375] Loss: 0.0016
Epoch [4/4] Batch [3650/6375] Loss: 0.0007
Epoch [4/4] Batch [3700/6375] Loss: 0.0049
Epoch [4/4] Batch [3750/6375] Loss: 0.0019
Epoch [4/4] Batch [3800/6375] Loss: 0.0987
Epoch [4/4] Batch [3850/6375] Loss: 0.0011
Epoch [4/4] Batch [3900/6375] Loss: 0.0004
Epoch [4/4] Batch [3950/6375] Loss: 0.0027
Epoch [4/4] Batch [4000/6375] Loss: 0.0117
Epoch [4/4] Batch [4050/6375] Loss: 0.0004
Epoch [4/4] Batch [4100/6375] Loss: 0.0040
Epoch [4/4] Batch [4150/6375] Loss: 0.0032
Epoch [4/4] Batch [4200/6375] Loss: 0.0888
Epoch [4/4] Batch [4250/6375] Loss: 0.0008
Epoch [4/4] Batch [4300/6375] Loss: 0.0007
Epoch [4/4] Batch [4350/6375] Loss: 0.0014
Epoch [4/4] Batch [4400/6375] Loss: 0.0151
Epoch [4/4] Batch [4450/6375] Loss: 0.0011
Epoch [4/4] Batch [4500/6375] Loss: 0.0216
Epoch [4/4] Batch [4550/6375] Loss: 0.0009
Epoch [4/4] Batch [4600/6375] Loss: 0.0006
```

```
Epoch [4/4] Batch [4650/6375] Loss: 0.0049
Epoch [4/4] Batch [4700/6375] Loss: 0.0007
Epoch [4/4] Batch [4750/6375] Loss: 0.0012
Epoch [4/4] Batch [4800/6375] Loss: 0.3977
Epoch [4/4] Batch [4850/6375] Loss: 0.0006
Epoch [4/4] Batch [4900/6375] Loss: 0.0003
Epoch [4/4] Batch [4950/6375] Loss: 0.0012
Epoch [4/4] Batch [5000/6375] Loss: 0.0355
Epoch [4/4] Batch [5050/6375] Loss: 0.2750
Epoch [4/4] Batch [5100/6375] Loss: 0.0007
Epoch [4/4] Batch [5150/6375] Loss: 0.0024
Epoch [4/4] Batch [5200/6375] Loss: 0.3595
Epoch [4/4] Batch [5250/6375] Loss: 0.0005
Epoch [4/4] Batch [5300/6375] Loss: 0.0012
Epoch [4/4] Batch [5350/6375] Loss: 0.1105
Epoch [4/4] Batch [5400/6375] Loss: 0.0004
Epoch [4/4] Batch [5450/6375] Loss: 0.0009
Epoch [4/4] Batch [5500/6375] Loss: 0.0007
Epoch [4/4] Batch [5550/6375] Loss: 0.2346
Epoch [4/4] Batch [5600/6375] Loss: 0.0581
Epoch [4/4] Batch [5650/6375] Loss: 0.0052
Epoch [4/4] Batch [5700/6375] Loss: 0.0667
Epoch [4/4] Batch [5750/6375] Loss: 0.0009
Epoch [4/4] Batch [5800/6375] Loss: 0.0010
Epoch [4/4] Batch [5850/6375] Loss: 0.2422
Epoch [4/4] Batch [5900/6375] Loss: 0.0012
Epoch [4/4] Batch [5950/6375] Loss: 0.0021
Epoch [4/4] Batch [6000/6375] Loss: 0.0060
Epoch [4/4] Batch [6050/6375] Loss: 0.0530
Epoch [4/4] Batch [6100/6375] Loss: 0.0007
Epoch [4/4] Batch [6150/6375] Loss: 0.0035
Epoch [4/4] Batch [6200/6375] Loss: 0.0184
Epoch [4/4] Batch [6250/6375] Loss: 0.0009
Epoch [4/4] Batch [6300/6375] Loss: 0.0008
Epoch [4/4] Batch [6350/6375] Loss: 0.0006
Trial 1: Epoch 4/4 | Val F1: 0.9460 | Val Loss: 0.2794
```

```
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.
```

```
Epoch [1/4] Batch [50/6375] Loss: 1.3951
Epoch [1/4] Batch [100/6375] Loss: 1.3536
Epoch [1/4] Batch [150/6375] Loss: 1.2499
Epoch [1/4] Batch [200/6375] Loss: 0.9934
Epoch [1/4] Batch [250/6375] Loss: 0.7752
```

```
Epoch [1/4] Batch [300/6375] Loss: 0.5290
Epoch [1/4] Batch [350/6375] Loss: 0.3910
Epoch [1/4] Batch [400/6375] Loss: 0.1691
Epoch [1/4] Batch [450/6375] Loss: 0.4844
Epoch [1/4] Batch [500/6375] Loss: 0.3538
Epoch [1/4] Batch [550/6375] Loss: 0.1965
Epoch [1/4] Batch [600/6375] Loss: 0.3178
Epoch [1/4] Batch [650/6375] Loss: 0.1672
Epoch [1/4] Batch [700/6375] Loss: 0.6186
Epoch [1/4] Batch [750/6375] Loss: 0.5924
Epoch [1/4] Batch [800/6375] Loss: 0.6317
Epoch [1/4] Batch [850/6375] Loss: 0.6145
Epoch [1/4] Batch [900/6375] Loss: 0.2645
Epoch [1/4] Batch [950/6375] Loss: 0.5941
Epoch [1/4] Batch [1000/6375] Loss: 0.4362
Epoch [1/4] Batch [1050/6375] Loss: 0.3938
Epoch [1/4] Batch [1100/6375] Loss: 0.4577
Epoch [1/4] Batch [1150/6375] Loss: 0.4026
Epoch [1/4] Batch [1200/6375] Loss: 0.4004
Epoch [1/4] Batch [1250/6375] Loss: 0.4105
Epoch [1/4] Batch [1300/6375] Loss: 0.2416
Epoch [1/4] Batch [1350/6375] Loss: 0.3688
Epoch [1/4] Batch [1400/6375] Loss: 0.2111
Epoch [1/4] Batch [1450/6375] Loss: 0.0557
Epoch [1/4] Batch [1500/6375] Loss: 0.2611
Epoch [1/4] Batch [1550/6375] Loss: 0.0355
Epoch [1/4] Batch [1600/6375] Loss: 0.3749
Epoch [1/4] Batch [1650/6375] Loss: 0.1278
Epoch [1/4] Batch [1700/6375] Loss: 0.3766
Epoch [1/4] Batch [1750/6375] Loss: 0.4196
Epoch [1/4] Batch [1800/6375] Loss: 0.0675
Epoch [1/4] Batch [1850/6375] Loss: 0.2937
Epoch [1/4] Batch [1900/6375] Loss: 0.1981
Epoch [1/4] Batch [1950/6375] Loss: 0.0578
Epoch [1/4] Batch [2000/6375] Loss: 0.0301
Epoch [1/4] Batch [2050/6375] Loss: 0.1100
Epoch [1/4] Batch [2100/6375] Loss: 0.0403
Epoch [1/4] Batch [2150/6375] Loss: 0.3250
Epoch [1/4] Batch [2200/6375] Loss: 0.3358
Epoch [1/4] Batch [2250/6375] Loss: 0.2067
Epoch [1/4] Batch [2300/6375] Loss: 0.0410
Epoch [1/4] Batch [2350/6375] Loss: 0.3371
Epoch [1/4] Batch [2400/6375] Loss: 0.2065
Epoch [1/4] Batch [2450/6375] Loss: 0.0287
Epoch [1/4] Batch [2500/6375] Loss: 0.2399
Epoch [1/4] Batch [2550/6375] Loss: 0.0230
Epoch [1/4] Batch [2600/6375] Loss: 0.3852
Epoch [1/4] Batch [2650/6375] Loss: 0.5940
```

```
Epoch [1/4] Batch [2700/6375] Loss: 0.4645
Epoch [1/4] Batch [2750/6375] Loss: 0.0377
Epoch [1/4] Batch [2800/6375] Loss: 0.0427
Epoch [1/4] Batch [2850/6375] Loss: 0.5078
Epoch [1/4] Batch [2900/6375] Loss: 0.0224
Epoch [1/4] Batch [2950/6375] Loss: 0.3283
Epoch [1/4] Batch [3000/6375] Loss: 0.3137
Epoch [1/4] Batch [3050/6375] Loss: 0.0305
Epoch [1/4] Batch [3100/6375] Loss: 0.0113
Epoch [1/4] Batch [3150/6375] Loss: 0.4247
Epoch [1/4] Batch [3200/6375] Loss: 0.3377
Epoch [1/4] Batch [3250/6375] Loss: 0.5886
Epoch [1/4] Batch [3300/6375] Loss: 0.0604
Epoch [1/4] Batch [3350/6375] Loss: 0.0924
Epoch [1/4] Batch [3400/6375] Loss: 0.8311
Epoch [1/4] Batch [3450/6375] Loss: 0.1029
Epoch [1/4] Batch [3500/6375] Loss: 0.0845
Epoch [1/4] Batch [3550/6375] Loss: 0.2664
Epoch [1/4] Batch [3600/6375] Loss: 0.1528
Epoch [1/4] Batch [3650/6375] Loss: 0.1400
Epoch [1/4] Batch [3700/6375] Loss: 0.2062
Epoch [1/4] Batch [3750/6375] Loss: 0.2797
Epoch [1/4] Batch [3800/6375] Loss: 0.2557
Epoch [1/4] Batch [3850/6375] Loss: 0.0239
Epoch [1/4] Batch [3900/6375] Loss: 0.1005
Epoch [1/4] Batch [3950/6375] Loss: 0.0985
Epoch [1/4] Batch [4000/6375] Loss: 0.6437
Epoch [1/4] Batch [4050/6375] Loss: 0.0726
Epoch [1/4] Batch [4100/6375] Loss: 0.0607
Epoch [1/4] Batch [4150/6375] Loss: 0.5385
Epoch [1/4] Batch [4200/6375] Loss: 0.7032
Epoch [1/4] Batch [4250/6375] Loss: 0.2575
Epoch [1/4] Batch [4300/6375] Loss: 0.7163
Epoch [1/4] Batch [4350/6375] Loss: 0.2733
Epoch [1/4] Batch [4400/6375] Loss: 0.2959
Epoch [1/4] Batch [4450/6375] Loss: 0.7191
Epoch [1/4] Batch [4500/6375] Loss: 0.0649
Epoch [1/4] Batch [4550/6375] Loss: 0.4259
Epoch [1/4] Batch [4600/6375] Loss: 0.5345
Epoch [1/4] Batch [4650/6375] Loss: 0.0507
Epoch [1/4] Batch [4700/6375] Loss: 0.7020
Epoch [1/4] Batch [4750/6375] Loss: 0.0225
Epoch [1/4] Batch [4800/6375] Loss: 0.2676
Epoch [1/4] Batch [4850/6375] Loss: 0.2227
Epoch [1/4] Batch [4900/6375] Loss: 0.3092
Epoch [1/4] Batch [4950/6375] Loss: 0.0792
Epoch [1/4] Batch [5000/6375] Loss: 0.0997
Epoch [1/4] Batch [5050/6375] Loss: 0.0169
```

```
Epoch [1/4] Batch [5100/6375] Loss: 0.2092
Epoch [1/4] Batch [5150/6375] Loss: 0.3124
Epoch [1/4] Batch [5200/6375] Loss: 0.0581
Epoch [1/4] Batch [5250/6375] Loss: 0.3478
Epoch [1/4] Batch [5300/6375] Loss: 0.3598
Epoch [1/4] Batch [5350/6375] Loss: 0.0652
Epoch [1/4] Batch [5400/6375] Loss: 0.3755
Epoch [1/4] Batch [5450/6375] Loss: 0.0686
Epoch [1/4] Batch [5500/6375] Loss: 0.2813
Epoch [1/4] Batch [5550/6375] Loss: 0.0270
Epoch [1/4] Batch [5600/6375] Loss: 0.1341
Epoch [1/4] Batch [5650/6375] Loss: 0.0070
Epoch [1/4] Batch [5700/6375] Loss: 0.2154
Epoch [1/4] Batch [5750/6375] Loss: 0.4196
Epoch [1/4] Batch [5800/6375] Loss: 0.3552
Epoch [1/4] Batch [5850/6375] Loss: 0.0348
Epoch [1/4] Batch [5900/6375] Loss: 0.2180
Epoch [1/4] Batch [5950/6375] Loss: 0.1599
Epoch [1/4] Batch [6000/6375] Loss: 0.4108
Epoch [1/4] Batch [6050/6375] Loss: 0.0582
Epoch [1/4] Batch [6100/6375] Loss: 0.0807
Epoch [1/4] Batch [6150/6375] Loss: 0.2872
Epoch [1/4] Batch [6200/6375] Loss: 0.2501
Epoch [1/4] Batch [6250/6375] Loss: 0.3135
Epoch [1/4] Batch [6300/6375] Loss: 0.0362
Epoch [1/4] Batch [6350/6375] Loss: 0.3643
Trial 2: Epoch 1/4 | Val F1: 0.9415 | Val Loss: 0.1853
Epoch [2/4] Batch [50/6375] Loss: 0.0093
Epoch [2/4] Batch [100/6375] Loss: 0.2858
Epoch [2/4] Batch [150/6375] Loss: 0.1039
Epoch [2/4] Batch [200/6375] Loss: 0.7422
Epoch [2/4] Batch [250/6375] Loss: 0.0158
Epoch [2/4] Batch [300/6375] Loss: 0.0272
Epoch [2/4] Batch [350/6375] Loss: 0.0813
Epoch [2/4] Batch [400/6375] Loss: 0.0860
Epoch [2/4] Batch [450/6375] Loss: 0.3755
Epoch [2/4] Batch [500/6375] Loss: 0.0819
Epoch [2/4] Batch [550/6375] Loss: 0.0872
Epoch [2/4] Batch [600/6375] Loss: 0.3620
Epoch [2/4] Batch [650/6375] Loss: 0.4031
Epoch [2/4] Batch [700/6375] Loss: 0.1522
Epoch [2/4] Batch [750/6375] Loss: 0.0343
Epoch [2/4] Batch [800/6375] Loss: 0.0668
Epoch [2/4] Batch [850/6375] Loss: 0.2487
Epoch [2/4] Batch [900/6375] Loss: 0.4226
Epoch [2/4] Batch [950/6375] Loss: 0.0221
Epoch [2/4] Batch [1000/6375] Loss: 0.0178
Epoch [2/4] Batch [1050/6375] Loss: 0.1337
```

```
Epoch [2/4] Batch [1100/6375] Loss: 0.1768
Epoch [2/4] Batch [1150/6375] Loss: 0.0739
Epoch [2/4] Batch [1200/6375] Loss: 0.0616
Epoch [2/4] Batch [1250/6375] Loss: 0.0174
Epoch [2/4] Batch [1300/6375] Loss: 0.6041
Epoch [2/4] Batch [1350/6375] Loss: 0.8177
Epoch [2/4] Batch [1400/6375] Loss: 0.0302
Epoch [2/4] Batch [1450/6375] Loss: 0.2902
Epoch [2/4] Batch [1500/6375] Loss: 0.0049
Epoch [2/4] Batch [1550/6375] Loss: 0.0067
Epoch [2/4] Batch [1600/6375] Loss: 0.2636
Epoch [2/4] Batch [1650/6375] Loss: 0.3976
Epoch [2/4] Batch [1700/6375] Loss: 0.2987
Epoch [2/4] Batch [1750/6375] Loss: 0.0070
Epoch [2/4] Batch [1800/6375] Loss: 0.1269
Epoch [2/4] Batch [1850/6375] Loss: 0.0399
Epoch [2/4] Batch [1900/6375] Loss: 0.3315
Epoch [2/4] Batch [1950/6375] Loss: 0.0465
Epoch [2/4] Batch [2000/6375] Loss: 0.0087
Epoch [2/4] Batch [2050/6375] Loss: 0.0838
Epoch [2/4] Batch [2100/6375] Loss: 0.0069
Epoch [2/4] Batch [2150/6375] Loss: 0.0063
Epoch [2/4] Batch [2200/6375] Loss: 0.0174
Epoch [2/4] Batch [2250/6375] Loss: 0.0201
Epoch [2/4] Batch [2300/6375] Loss: 0.0399
Epoch [2/4] Batch [2350/6375] Loss: 0.0045
Epoch [2/4] Batch [2400/6375] Loss: 0.6461
Epoch [2/4] Batch [2450/6375] Loss: 0.0368
Epoch [2/4] Batch [2500/6375] Loss: 0.1315
Epoch [2/4] Batch [2550/6375] Loss: 0.1911
Epoch [2/4] Batch [2600/6375] Loss: 0.0289
Epoch [2/4] Batch [2650/6375] Loss: 0.0017
Epoch [2/4] Batch [2700/6375] Loss: 0.0042
Epoch [2/4] Batch [2750/6375] Loss: 0.0349
Epoch [2/4] Batch [2800/6375] Loss: 0.0242
Epoch [2/4] Batch [2850/6375] Loss: 0.3721
Epoch [2/4] Batch [2900/6375] Loss: 0.5203
Epoch [2/4] Batch [2950/6375] Loss: 0.0336
Epoch [2/4] Batch [3000/6375] Loss: 0.0075
Epoch [2/4] Batch [3050/6375] Loss: 0.0383
Epoch [2/4] Batch [3100/6375] Loss: 0.0685
Epoch [2/4] Batch [3150/6375] Loss: 0.0741
Epoch [2/4] Batch [3200/6375] Loss: 0.0726
Epoch [2/4] Batch [3250/6375] Loss: 0.2124
Epoch [2/4] Batch [3300/6375] Loss: 0.0065
Epoch [2/4] Batch [3350/6375] Loss: 0.1811
Epoch [2/4] Batch [3400/6375] Loss: 0.5477
Epoch [2/4] Batch [3450/6375] Loss: 0.0056
```

```
Epoch [2/4] Batch [3500/6375] Loss: 0.3753
Epoch [2/4] Batch [3550/6375] Loss: 0.1027
Epoch [2/4] Batch [3600/6375] Loss: 0.0386
Epoch [2/4] Batch [3650/6375] Loss: 0.0111
Epoch [2/4] Batch [3700/6375] Loss: 0.2630
Epoch [2/4] Batch [3750/6375] Loss: 0.3572
Epoch [2/4] Batch [3800/6375] Loss: 0.1780
Epoch [2/4] Batch [3850/6375] Loss: 0.1378
Epoch [2/4] Batch [3900/6375] Loss: 0.4089
Epoch [2/4] Batch [3950/6375] Loss: 0.0266
Epoch [2/4] Batch [4000/6375] Loss: 0.0114
Epoch [2/4] Batch [4050/6375] Loss: 0.0100
Epoch [2/4] Batch [4100/6375] Loss: 0.1925
Epoch [2/4] Batch [4150/6375] Loss: 0.0305
Epoch [2/4] Batch [4200/6375] Loss: 0.0147
Epoch [2/4] Batch [4250/6375] Loss: 0.0090
Epoch [2/4] Batch [4300/6375] Loss: 0.0114
Epoch [2/4] Batch [4350/6375] Loss: 0.0491
Epoch [2/4] Batch [4400/6375] Loss: 0.8229
Epoch [2/4] Batch [4450/6375] Loss: 0.1349
Epoch [2/4] Batch [4500/6375] Loss: 0.0099
Epoch [2/4] Batch [4550/6375] Loss: 0.2309
Epoch [2/4] Batch [4600/6375] Loss: 0.0157
Epoch [2/4] Batch [4650/6375] Loss: 0.4085
Epoch [2/4] Batch [4700/6375] Loss: 0.3653
Epoch [2/4] Batch [4750/6375] Loss: 0.1342
Epoch [2/4] Batch [4800/6375] Loss: 0.1724
Epoch [2/4] Batch [4850/6375] Loss: 0.4335
Epoch [2/4] Batch [4900/6375] Loss: 0.9599
Epoch [2/4] Batch [4950/6375] Loss: 0.2579
Epoch [2/4] Batch [5000/6375] Loss: 0.3650
Epoch [2/4] Batch [5050/6375] Loss: 0.0176
Epoch [2/4] Batch [5100/6375] Loss: 0.1348
Epoch [2/4] Batch [5150/6375] Loss: 0.1530
Epoch [2/4] Batch [5200/6375] Loss: 0.0103
Epoch [2/4] Batch [5250/6375] Loss: 0.5882
Epoch [2/4] Batch [5300/6375] Loss: 0.1731
Epoch [2/4] Batch [5350/6375] Loss: 0.1135
Epoch [2/4] Batch [5400/6375] Loss: 0.0313
Epoch [2/4] Batch [5450/6375] Loss: 0.0140
Epoch [2/4] Batch [5500/6375] Loss: 0.0734
Epoch [2/4] Batch [5550/6375] Loss: 0.1107
Epoch [2/4] Batch [5600/6375] Loss: 0.3572
Epoch [2/4] Batch [5650/6375] Loss: 0.2841
Epoch [2/4] Batch [5700/6375] Loss: 0.0074
Epoch [2/4] Batch [5750/6375] Loss: 0.0093
Epoch [2/4] Batch [5800/6375] Loss: 0.0119
Epoch [2/4] Batch [5850/6375] Loss: 0.0060
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Epoch [2/4] Batch [5900/6375] Loss: 0.0089
Epoch [2/4] Batch [5950/6375] Loss: 0.0373
Epoch [2/4] Batch [6000/6375] Loss: 0.0059
Epoch [2/4] Batch [6050/6375] Loss: 0.0188
Epoch [2/4] Batch [6100/6375] Loss: 0.2867
Epoch [2/4] Batch [6150/6375] Loss: 0.2542
Epoch [2/4] Batch [6200/6375] Loss: 0.0078
Epoch [2/4] Batch [6250/6375] Loss: 0.3924
Epoch [2/4] Batch [6300/6375] Loss: 0.0346
Epoch [2/4] Batch [6350/6375] Loss: 0.0580
Trial 2: Epoch 2/4 | Val F1: 0.9459 | Val Loss: 0.1982
Epoch [3/4] Batch [50/6375] Loss: 0.1449
Epoch [3/4] Batch [100/6375] Loss: 0.0253
Epoch [3/4] Batch [150/6375] Loss: 0.0105
Epoch [3/4] Batch [200/6375] Loss: 0.0058
Epoch [3/4] Batch [250/6375] Loss: 0.0651
Epoch [3/4] Batch [300/6375] Loss: 0.0225
Epoch [3/4] Batch [350/6375] Loss: 0.0056
Epoch [3/4] Batch [400/6375] Loss: 0.0023
Epoch [3/4] Batch [450/6375] Loss: 0.0121
Epoch [3/4] Batch [500/6375] Loss: 0.0197
Epoch [3/4] Batch [550/6375] Loss: 0.0075
Epoch [3/4] Batch [600/6375] Loss: 0.5602
Epoch [3/4] Batch [650/6375] Loss: 0.0516
Epoch [3/4] Batch [700/6375] Loss: 0.0021
Epoch [3/4] Batch [750/6375] Loss: 0.1753
Epoch [3/4] Batch [800/6375] Loss: 0.2613
Epoch [3/4] Batch [850/6375] Loss: 0.0056
Epoch [3/4] Batch [900/6375] Loss: 0.0090
Epoch [3/4] Batch [950/6375] Loss: 0.0054
Epoch [3/4] Batch [1000/6375] Loss: 0.0064
Epoch [3/4] Batch [1050/6375] Loss: 0.3892
Epoch [3/4] Batch [1100/6375] Loss: 0.2134
Epoch [3/4] Batch [1150/6375] Loss: 0.0496
Epoch [3/4] Batch [1200/6375] Loss: 0.0018
Epoch [3/4] Batch [1250/6375] Loss: 0.5255
Epoch [3/4] Batch [1300/6375] Loss: 0.1954
Epoch [3/4] Batch [1350/6375] Loss: 0.0721
Epoch [3/4] Batch [1400/6375] Loss: 0.2385
Epoch [3/4] Batch [1450/6375] Loss: 0.1207
Epoch [3/4] Batch [1500/6375] Loss: 0.0012
Epoch [3/4] Batch [1550/6375] Loss: 0.0188
Epoch [3/4] Batch [1600/6375] Loss: 0.0035
Epoch [3/4] Batch [1650/6375] Loss: 0.0120
Epoch [3/4] Batch [1700/6375] Loss: 0.0125
Epoch [3/4] Batch [1750/6375] Loss: 0.6627
Epoch [3/4] Batch [1800/6375] Loss: 0.2524
Epoch [3/4] Batch [1850/6375] Loss: 0.3770
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Epoch [3/4] Batch [1900/6375] Loss: 0.0024
Epoch [3/4] Batch [1950/6375] Loss: 0.1758
Epoch [3/4] Batch [2000/6375] Loss: 0.0015
Epoch [3/4] Batch [2050/6375] Loss: 0.0799
Epoch [3/4] Batch [2100/6375] Loss: 0.0324
Epoch [3/4] Batch [2150/6375] Loss: 0.0085
Epoch [3/4] Batch [2200/6375] Loss: 0.0056
Epoch [3/4] Batch [2250/6375] Loss: 0.0028
Epoch [3/4] Batch [2300/6375] Loss: 0.0315
Epoch [3/4] Batch [2350/6375] Loss: 0.0216
Epoch [3/4] Batch [2400/6375] Loss: 0.0015
Epoch [3/4] Batch [2450/6375] Loss: 0.0043
Epoch [3/4] Batch [2500/6375] Loss: 0.0020
Epoch [3/4] Batch [2550/6375] Loss: 0.2218
Epoch [3/4] Batch [2600/6375] Loss: 0.0673
Epoch [3/4] Batch [2650/6375] Loss: 0.0117
Epoch [3/4] Batch [2700/6375] Loss: 0.3225
Epoch [3/4] Batch [2750/6375] Loss: 0.2111
Epoch [3/4] Batch [2800/6375] Loss: 0.0057
Epoch [3/4] Batch [2850/6375] Loss: 0.2737
Epoch [3/4] Batch [2900/6375] Loss: 0.1225
Epoch [3/4] Batch [2950/6375] Loss: 0.2837
Epoch [3/4] Batch [3000/6375] Loss: 0.0014
Epoch [3/4] Batch [3050/6375] Loss: 0.0012
Epoch [3/4] Batch [3100/6375] Loss: 0.0026
Epoch [3/4] Batch [3150/6375] Loss: 0.3608
Epoch [3/4] Batch [3200/6375] Loss: 0.0597
Epoch [3/4] Batch [3250/6375] Loss: 0.0031
Epoch [3/4] Batch [3300/6375] Loss: 0.4111
Epoch [3/4] Batch [3350/6375] Loss: 0.3414
Epoch [3/4] Batch [3400/6375] Loss: 0.0197
Epoch [3/4] Batch [3450/6375] Loss: 0.0171
Epoch [3/4] Batch [3500/6375] Loss: 0.1153
Epoch [3/4] Batch [3550/6375] Loss: 0.1700
Epoch [3/4] Batch [3600/6375] Loss: 0.1871
Epoch [3/4] Batch [3650/6375] Loss: 0.0014
Epoch [3/4] Batch [3700/6375] Loss: 0.3115
Epoch [3/4] Batch [3750/6375] Loss: 0.0228
Epoch [3/4] Batch [3800/6375] Loss: 0.0030
Epoch [3/4] Batch [3850/6375] Loss: 0.0008
Epoch [3/4] Batch [3900/6375] Loss: 0.0063
Epoch [3/4] Batch [3950/6375] Loss: 0.2739
Epoch [3/4] Batch [4000/6375] Loss: 0.1388
Epoch [3/4] Batch [4050/6375] Loss: 0.0052
Epoch [3/4] Batch [4100/6375] Loss: 0.3149
Epoch [3/4] Batch [4150/6375] Loss: 0.0534
Epoch [3/4] Batch [4200/6375] Loss: 0.1625
Epoch [3/4] Batch [4250/6375] Loss: 0.4030
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Epoch [3/4] Batch [4300/6375] Loss: 0.0054
Epoch [3/4] Batch [4350/6375] Loss: 0.1857
Epoch [3/4] Batch [4400/6375] Loss: 0.0017
Epoch [3/4] Batch [4450/6375] Loss: 0.0019
Epoch [3/4] Batch [4500/6375] Loss: 0.0151
Epoch [3/4] Batch [4550/6375] Loss: 0.0008
Epoch [3/4] Batch [4600/6375] Loss: 0.0974
Epoch [3/4] Batch [4650/6375] Loss: 0.3235
Epoch [3/4] Batch [4700/6375] Loss: 0.0398
Epoch [3/4] Batch [4750/6375] Loss: 0.0025
Epoch [3/4] Batch [4800/6375] Loss: 0.0011
Epoch [3/4] Batch [4850/6375] Loss: 0.0199
Epoch [3/4] Batch [4900/6375] Loss: 0.0014
Epoch [3/4] Batch [4950/6375] Loss: 0.0019
Epoch [3/4] Batch [5000/6375] Loss: 0.2741
Epoch [3/4] Batch [5050/6375] Loss: 0.3085
Epoch [3/4] Batch [5100/6375] Loss: 0.0031
Epoch [3/4] Batch [5150/6375] Loss: 0.0031
Epoch [3/4] Batch [5200/6375] Loss: 0.0012
Epoch [3/4] Batch [5250/6375] Loss: 0.0014
Epoch [3/4] Batch [5300/6375] Loss: 0.0051
Epoch [3/4] Batch [5350/6375] Loss: 0.0825
Epoch [3/4] Batch [5400/6375] Loss: 0.0069
Epoch [3/4] Batch [5450/6375] Loss: 0.0672
Epoch [3/4] Batch [5500/6375] Loss: 0.0973
Epoch [3/4] Batch [5550/6375] Loss: 0.0085
Epoch [3/4] Batch [5600/6375] Loss: 0.0050
Epoch [3/4] Batch [5650/6375] Loss: 0.0056
Epoch [3/4] Batch [5700/6375] Loss: 0.0226
Epoch [3/4] Batch [5750/6375] Loss: 0.0018
Epoch [3/4] Batch [5800/6375] Loss: 0.0279
Epoch [3/4] Batch [5850/6375] Loss: 0.0075
Epoch [3/4] Batch [5900/6375] Loss: 0.2831
Epoch [3/4] Batch [5950/6375] Loss: 0.0013
Epoch [3/4] Batch [6000/6375] Loss: 0.0012
Epoch [3/4] Batch [6050/6375] Loss: 0.1079
Epoch [3/4] Batch [6100/6375] Loss: 0.4616
Epoch [3/4] Batch [6150/6375] Loss: 0.2177
Epoch [3/4] Batch [6200/6375] Loss: 0.0123
Epoch [3/4] Batch [6250/6375] Loss: 0.0027
Epoch [3/4] Batch [6300/6375] Loss: 0.0058
Epoch [3/4] Batch [6350/6375] Loss: 0.0090
Trial 2: Epoch 3/4 | Val F1: 0.9475 | Val Loss: 0.2227
Epoch [4/4] Batch [50/6375] Loss: 0.0873
Epoch [4/4] Batch [100/6375] Loss: 0.0031
Epoch [4/4] Batch [150/6375] Loss: 0.0379
Epoch [4/4] Batch [200/6375] Loss: 0.0010
Epoch [4/4] Batch [250/6375] Loss: 0.0015
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Epoch [4/4] Batch [300/6375] Loss: 0.0044
Epoch [4/4] Batch [350/6375] Loss: 0.0203
Epoch [4/4] Batch [400/6375] Loss: 0.1230
Epoch [4/4] Batch [450/6375] Loss: 0.0059
Epoch [4/4] Batch [500/6375] Loss: 0.0037
Epoch [4/4] Batch [550/6375] Loss: 0.0252
Epoch [4/4] Batch [600/6375] Loss: 0.0058
Epoch [4/4] Batch [650/6375] Loss: 0.0034
Epoch [4/4] Batch [700/6375] Loss: 0.0011
Epoch [4/4] Batch [750/6375] Loss: 0.0026
Epoch [4/4] Batch [800/6375] Loss: 0.0024
Epoch [4/4] Batch [850/6375] Loss: 0.0014
Epoch [4/4] Batch [900/6375] Loss: 0.0013
Epoch [4/4] Batch [950/6375] Loss: 0.0056
Epoch [4/4] Batch [1000/6375] Loss: 0.0008
Epoch [4/4] Batch [1050/6375] Loss: 0.0274
Epoch [4/4] Batch [1100/6375] Loss: 0.0047
Epoch [4/4] Batch [1150/6375] Loss: 0.1289
Epoch [4/4] Batch [1200/6375] Loss: 0.0014
Epoch [4/4] Batch [1250/6375] Loss: 0.0031
Epoch [4/4] Batch [1300/6375] Loss: 0.0008
Epoch [4/4] Batch [1350/6375] Loss: 0.0009
Epoch [4/4] Batch [1400/6375] Loss: 0.0006
Epoch [4/4] Batch [1450/6375] Loss: 0.0013
Epoch [4/4] Batch [1500/6375] Loss: 0.0016
Epoch [4/4] Batch [1550/6375] Loss: 0.0015
Epoch [4/4] Batch [1600/6375] Loss: 0.0010
Epoch [4/4] Batch [1650/6375] Loss: 0.0009
Epoch [4/4] Batch [1700/6375] Loss: 0.3821
Epoch [4/4] Batch [1750/6375] Loss: 0.4189
Epoch [4/4] Batch [1800/6375] Loss: 0.0008
Epoch [4/4] Batch [1850/6375] Loss: 0.0026
Epoch [4/4] Batch [1900/6375] Loss: 0.0033
Epoch [4/4] Batch [1950/6375] Loss: 0.0010
Epoch [4/4] Batch [2000/6375] Loss: 0.0079
Epoch [4/4] Batch [2050/6375] Loss: 0.0011
Epoch [4/4] Batch [2100/6375] Loss: 0.0048
Epoch [4/4] Batch [2150/6375] Loss: 0.0005
Epoch [4/4] Batch [2200/6375] Loss: 0.0032
Epoch [4/4] Batch [2250/6375] Loss: 0.0017
Epoch [4/4] Batch [2300/6375] Loss: 0.0029
Epoch [4/4] Batch [2350/6375] Loss: 0.0097
Epoch [4/4] Batch [2400/6375] Loss: 0.0023
Epoch [4/4] Batch [2450/6375] Loss: 0.0005
Epoch [4/4] Batch [2500/6375] Loss: 0.0235
Epoch [4/4] Batch [2550/6375] Loss: 0.3780
Epoch [4/4] Batch [2600/6375] Loss: 0.0008
Epoch [4/4] Batch [2650/6375] Loss: 0.0023
```

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Epoch [4/4] Batch [2700/6375] Loss: 0.0004
Epoch [4/4] Batch [2750/6375] Loss: 0.0023
Epoch [4/4] Batch [2800/6375] Loss: 0.0007
Epoch [4/4] Batch [2850/6375] Loss: 0.0005
Epoch [4/4] Batch [2900/6375] Loss: 0.1129
Epoch [4/4] Batch [2950/6375] Loss: 0.4721
Epoch [4/4] Batch [3000/6375] Loss: 0.0150
Epoch [4/4] Batch [3050/6375] Loss: 0.0013
Epoch [4/4] Batch [3100/6375] Loss: 0.0018
Epoch [4/4] Batch [3150/6375] Loss: 0.0046
Epoch [4/4] Batch [3200/6375] Loss: 0.0014
Epoch [4/4] Batch [3250/6375] Loss: 0.0007
Epoch [4/4] Batch [3300/6375] Loss: 0.0004
Epoch [4/4] Batch [3350/6375] Loss: 0.0003
Epoch [4/4] Batch [3400/6375] Loss: 0.0009
Epoch [4/4] Batch [3450/6375] Loss: 0.0005
Epoch [4/4] Batch [3500/6375] Loss: 0.4018
Epoch [4/4] Batch [3550/6375] Loss: 0.0006
Epoch [4/4] Batch [3600/6375] Loss: 0.0008
Epoch [4/4] Batch [3650/6375] Loss: 0.0005
Epoch [4/4] Batch [3700/6375] Loss: 0.0007
Epoch [4/4] Batch [3750/6375] Loss: 0.0029
Epoch [4/4] Batch [3800/6375] Loss: 0.0189
Epoch [4/4] Batch [3850/6375] Loss: 0.0017
Epoch [4/4] Batch [3900/6375] Loss: 0.0134
Epoch [4/4] Batch [3950/6375] Loss: 0.0055
Epoch [4/4] Batch [4000/6375] Loss: 0.0034
Epoch [4/4] Batch [4050/6375] Loss: 0.0191
Epoch [4/4] Batch [4100/6375] Loss: 0.0005
Epoch [4/4] Batch [4150/6375] Loss: 0.0006
Epoch [4/4] Batch [4200/6375] Loss: 0.0017
Epoch [4/4] Batch [4250/6375] Loss: 0.0003
Epoch [4/4] Batch [4300/6375] Loss: 0.0493
Epoch [4/4] Batch [4350/6375] Loss: 0.0022
Epoch [4/4] Batch [4400/6375] Loss: 0.0016
Epoch [4/4] Batch [4450/6375] Loss: 0.0009
Epoch [4/4] Batch [4500/6375] Loss: 0.2119
Epoch [4/4] Batch [4550/6375] Loss: 0.0012
Epoch [4/4] Batch [4600/6375] Loss: 0.0099
Epoch [4/4] Batch [4650/6375] Loss: 0.0211
Epoch [4/4] Batch [4700/6375] Loss: 0.0009
Epoch [4/4] Batch [4750/6375] Loss: 0.0014
Epoch [4/4] Batch [4800/6375] Loss: 0.0009
Epoch [4/4] Batch [4850/6375] Loss: 0.0005
Epoch [4/4] Batch [4900/6375] Loss: 0.0100
Epoch [4/4] Batch [4950/6375] Loss: 0.0008
Epoch [4/4] Batch [5000/6375] Loss: 0.0026
Epoch [4/4] Batch [5050/6375] Loss: 0.0032
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Epoch [4/4] Batch [5100/6375] Loss: 0.0004
Epoch [4/4] Batch [5150/6375] Loss: 0.2549
Epoch [4/4] Batch [5200/6375] Loss: 0.0013
Epoch [4/4] Batch [5250/6375] Loss: 0.3071
Epoch [4/4] Batch [5300/6375] Loss: 0.0012
Epoch [4/4] Batch [5350/6375] Loss: 0.0004
Epoch [4/4] Batch [5400/6375] Loss: 0.0007
Epoch [4/4] Batch [5450/6375] Loss: 0.3477
Epoch [4/4] Batch [5500/6375] Loss: 0.0010
Epoch [4/4] Batch [5550/6375] Loss: 0.0007
Epoch [4/4] Batch [5600/6375] Loss: 0.0737
Epoch [4/4] Batch [5650/6375] Loss: 0.0003
Epoch [4/4] Batch [5700/6375] Loss: 0.0003
Epoch [4/4] Batch [5750/6375] Loss: 0.2277
Epoch [4/4] Batch [5800/6375] Loss: 0.0009
Epoch [4/4] Batch [5850/6375] Loss: 0.0005
Epoch [4/4] Batch [5900/6375] Loss: 0.0006
Epoch [4/4] Batch [5950/6375] Loss: 0.0010
Epoch [4/4] Batch [6000/6375] Loss: 0.0005
Epoch [4/4] Batch [6050/6375] Loss: 0.0048
Epoch [4/4] Batch [6100/6375] Loss: 0.2264
Epoch [4/4] Batch [6150/6375] Loss: 0.0008
Epoch [4/4] Batch [6200/6375] Loss: 0.0016
Epoch [4/4] Batch [6250/6375] Loss: 0.0012
Epoch [4/4] Batch [6300/6375] Loss: 0.4405
Epoch [4/4] Batch [6350/6375] Loss: 0.1575
Trial 2: Epoch 4/4 | Val F1: 0.9470 | Val Loss: 0.2726

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.

Epoch [1/4] Batch [50/1594] Loss: 1.3719
Epoch [1/4] Batch [100/1594] Loss: 1.2973
Epoch [1/4] Batch [150/1594] Loss: 1.0539
Epoch [1/4] Batch [200/1594] Loss: 0.6777
Epoch [1/4] Batch [250/1594] Loss: 0.4197
Epoch [1/4] Batch [300/1594] Loss: 0.3673
Epoch [1/4] Batch [350/1594] Loss: 0.3154
Epoch [1/4] Batch [400/1594] Loss: 0.3223
Epoch [1/4] Batch [450/1594] Loss: 0.3026
Epoch [1/4] Batch [500/1594] Loss: 0.2160
Epoch [1/4] Batch [550/1594] Loss: 0.4060
Epoch [1/4] Batch [600/1594] Loss: 0.4596
Epoch [1/4] Batch [650/1594] Loss: 0.2755
Epoch [1/4] Batch [700/1594] Loss: 0.1465
```

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Epoch [1/4] Batch [750/1594] Loss: 0.2771
Epoch [1/4] Batch [800/1594] Loss: 0.2244
Epoch [1/4] Batch [850/1594] Loss: 0.2644
Epoch [1/4] Batch [900/1594] Loss: 0.2560
Epoch [1/4] Batch [950/1594] Loss: 0.3183
Epoch [1/4] Batch [1000/1594] Loss: 0.1774
Epoch [1/4] Batch [1050/1594] Loss: 0.1765
Epoch [1/4] Batch [1100/1594] Loss: 0.2454
Epoch [1/4] Batch [1150/1594] Loss: 0.2933
Epoch [1/4] Batch [1200/1594] Loss: 0.3267
Epoch [1/4] Batch [1250/1594] Loss: 0.1214
Epoch [1/4] Batch [1300/1594] Loss: 0.5133
Epoch [1/4] Batch [1350/1594] Loss: 0.1245
Epoch [1/4] Batch [1400/1594] Loss: 0.2176
Epoch [1/4] Batch [1450/1594] Loss: 0.3047
Epoch [1/4] Batch [1500/1594] Loss: 0.1387
Epoch [1/4] Batch [1550/1594] Loss: 0.3195
Trial 3: Epoch 1/4 | Val F1: 0.9365 | Val Loss: 0.1891
Epoch [2/4] Batch [50/1594] Loss: 0.1830
Epoch [2/4] Batch [100/1594] Loss: 0.1915
Epoch [2/4] Batch [150/1594] Loss: 0.2623
Epoch [2/4] Batch [200/1594] Loss: 0.1696
Epoch [2/4] Batch [250/1594] Loss: 0.2775
Epoch [2/4] Batch [300/1594] Loss: 0.1067
Epoch [2/4] Batch [350/1594] Loss: 0.2039
Epoch [2/4] Batch [400/1594] Loss: 0.1647
Epoch [2/4] Batch [450/1594] Loss: 0.0362
Epoch [2/4] Batch [500/1594] Loss: 0.2496
Epoch [2/4] Batch [550/1594] Loss: 0.2366
Epoch [2/4] Batch [600/1594] Loss: 0.1465
Epoch [2/4] Batch [650/1594] Loss: 0.2015
Epoch [2/4] Batch [700/1594] Loss: 0.3014
Epoch [2/4] Batch [750/1594] Loss: 0.1645
Epoch [2/4] Batch [800/1594] Loss: 0.1631
Epoch [2/4] Batch [850/1594] Loss: 0.1002
Epoch [2/4] Batch [900/1594] Loss: 0.1001
Epoch [2/4] Batch [950/1594] Loss: 0.0622
Epoch [2/4] Batch [1000/1594] Loss: 0.2363
Epoch [2/4] Batch [1050/1594] Loss: 0.3221
Epoch [2/4] Batch [1100/1594] Loss: 0.3242
Epoch [2/4] Batch [1150/1594] Loss: 0.1397
Epoch [2/4] Batch [1200/1594] Loss: 0.1863
Epoch [2/4] Batch [1250/1594] Loss: 0.1059
Epoch [2/4] Batch [1300/1594] Loss: 0.1172
Epoch [2/4] Batch [1350/1594] Loss: 0.3825
Epoch [2/4] Batch [1400/1594] Loss: 0.1954
Epoch [2/4] Batch [1450/1594] Loss: 0.2887
Epoch [2/4] Batch [1500/1594] Loss: 0.1078
```

```
Epoch [2/4] Batch [1550/1594] Loss: 0.1784
Trial 3: Epoch 2/4 | Val F1: 0.9415 | Val Loss: 0.1722
Epoch [3/4] Batch [50/1594] Loss: 0.1146
Epoch [3/4] Batch [100/1594] Loss: 0.0781
Epoch [3/4] Batch [150/1594] Loss: 0.1374
Epoch [3/4] Batch [200/1594] Loss: 0.0657
Epoch [3/4] Batch [250/1594] Loss: 0.0646
Epoch [3/4] Batch [300/1594] Loss: 0.0699
Epoch [3/4] Batch [350/1594] Loss: 0.0773
Epoch [3/4] Batch [400/1594] Loss: 0.0749
Epoch [3/4] Batch [450/1594] Loss: 0.0769
Epoch [3/4] Batch [500/1594] Loss: 0.1033
Epoch [3/4] Batch [550/1594] Loss: 0.0960
Epoch [3/4] Batch [600/1594] Loss: 0.0584
Epoch [3/4] Batch [650/1594] Loss: 0.2292
Epoch [3/4] Batch [700/1594] Loss: 0.0609
Epoch [3/4] Batch [750/1594] Loss: 0.0984
Epoch [3/4] Batch [800/1594] Loss: 0.1565
Epoch [3/4] Batch [850/1594] Loss: 0.0466
Epoch [3/4] Batch [900/1594] Loss: 0.0479
Epoch [3/4] Batch [950/1594] Loss: 0.1163
Epoch [3/4] Batch [1000/1594] Loss: 0.0860
Epoch [3/4] Batch [1050/1594] Loss: 0.1135
Epoch [3/4] Batch [1100/1594] Loss: 0.1100
Epoch [3/4] Batch [1150/1594] Loss: 0.1219
Epoch [3/4] Batch [1200/1594] Loss: 0.1382
Epoch [3/4] Batch [1250/1594] Loss: 0.0784
Epoch [3/4] Batch [1300/1594] Loss: 0.1368
Epoch [3/4] Batch [1350/1594] Loss: 0.1473
Epoch [3/4] Batch [1400/1594] Loss: 0.2474
Epoch [3/4] Batch [1450/1594] Loss: 0.1030
Epoch [3/4] Batch [1500/1594] Loss: 0.1378
Epoch [3/4] Batch [1550/1594] Loss: 0.1597
Trial 3: Epoch 3/4 | Val F1: 0.9443 | Val Loss: 0.1672
Epoch [4/4] Batch [50/1594] Loss: 0.2107
Epoch [4/4] Batch [100/1594] Loss: 0.0470
Epoch [4/4] Batch [150/1594] Loss: 0.0558
Epoch [4/4] Batch [200/1594] Loss: 0.1503
Epoch [4/4] Batch [250/1594] Loss: 0.1650
Epoch [4/4] Batch [300/1594] Loss: 0.1533
Epoch [4/4] Batch [350/1594] Loss: 0.1719
Epoch [4/4] Batch [400/1594] Loss: 0.0259
Epoch [4/4] Batch [450/1594] Loss: 0.0203
Epoch [4/4] Batch [500/1594] Loss: 0.2944
Epoch [4/4] Batch [550/1594] Loss: 0.1476
Epoch [4/4] Batch [600/1594] Loss: 0.0594
Epoch [4/4] Batch [650/1594] Loss: 0.0208
Epoch [4/4] Batch [700/1594] Loss: 0.1407
```

```
Epoch [4/4] Batch [750/1594] Loss: 0.0507
Epoch [4/4] Batch [800/1594] Loss: 0.1368
Epoch [4/4] Batch [850/1594] Loss: 0.1204
Epoch [4/4] Batch [900/1594] Loss: 0.0937
Epoch [4/4] Batch [950/1594] Loss: 0.0101
Epoch [4/4] Batch [1000/1594] Loss: 0.0596
Epoch [4/4] Batch [1050/1594] Loss: 0.0980
Epoch [4/4] Batch [1100/1594] Loss: 0.0647
Epoch [4/4] Batch [1150/1594] Loss: 0.2812
Epoch [4/4] Batch [1200/1594] Loss: 0.0960
Epoch [4/4] Batch [1250/1594] Loss: 0.1298
Epoch [4/4] Batch [1300/1594] Loss: 0.0783
Epoch [4/4] Batch [1350/1594] Loss: 0.0784
Epoch [4/4] Batch [1400/1594] Loss: 0.0759
Epoch [4/4] Batch [1450/1594] Loss: 0.1270
Epoch [4/4] Batch [1500/1594] Loss: 0.0792
Epoch [4/4] Batch [1550/1594] Loss: 0.0709
Trial 3: Epoch 4/4 | Val F1: 0.9451 | Val Loss: 0.1720
```

```
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.
```

```
Epoch [1/4] Batch [50/3188] Loss: 1.4019
Epoch [1/4] Batch [100/3188] Loss: 1.3599
Epoch [1/4] Batch [150/3188] Loss: 1.2275
Epoch [1/4] Batch [200/3188] Loss: 0.8179
Epoch [1/4] Batch [250/3188] Loss: 0.6219
Epoch [1/4] Batch [300/3188] Loss: 0.3929
Epoch [1/4] Batch [350/3188] Loss: 0.1903
Epoch [1/4] Batch [400/3188] Loss: 0.3658
Epoch [1/4] Batch [450/3188] Loss: 0.2194
Epoch [1/4] Batch [500/3188] Loss: 0.4303
Epoch [1/4] Batch [550/3188] Loss: 0.4212
Epoch [1/4] Batch [600/3188] Loss: 0.3557
Epoch [1/4] Batch [650/3188] Loss: 0.3756
Epoch [1/4] Batch [700/3188] Loss: 0.1607
Epoch [1/4] Batch [750/3188] Loss: 0.2265
Epoch [1/4] Batch [800/3188] Loss: 0.2704
Epoch [1/4] Batch [850/3188] Loss: 0.4575
Epoch [1/4] Batch [900/3188] Loss: 0.1138
Epoch [1/4] Batch [950/3188] Loss: 0.3309
Epoch [1/4] Batch [1000/3188] Loss: 0.0648
Epoch [1/4] Batch [1050/3188] Loss: 0.3042
Epoch [1/4] Batch [1100/3188] Loss: 0.2275
Epoch [1/4] Batch [1150/3188] Loss: 0.5009
```

```
Epoch [1/4] Batch [1200/3188] Loss: 0.2005
Epoch [1/4] Batch [1250/3188] Loss: 0.0640
Epoch [1/4] Batch [1300/3188] Loss: 0.2795
Epoch [1/4] Batch [1350/3188] Loss: 0.2619
Epoch [1/4] Batch [1400/3188] Loss: 0.4805
Epoch [1/4] Batch [1450/3188] Loss: 0.1175
Epoch [1/4] Batch [1500/3188] Loss: 0.2352
Epoch [1/4] Batch [1550/3188] Loss: 0.2021
Epoch [1/4] Batch [1600/3188] Loss: 0.3826
Epoch [1/4] Batch [1650/3188] Loss: 0.3992
Epoch [1/4] Batch [1700/3188] Loss: 0.2156
Epoch [1/4] Batch [1750/3188] Loss: 0.1108
Epoch [1/4] Batch [1800/3188] Loss: 0.0414
Epoch [1/4] Batch [1850/3188] Loss: 0.1469
Epoch [1/4] Batch [1900/3188] Loss: 0.3392
Epoch [1/4] Batch [1950/3188] Loss: 0.0983
Epoch [1/4] Batch [2000/3188] Loss: 0.5165
Epoch [1/4] Batch [2050/3188] Loss: 0.2684
Epoch [1/4] Batch [2100/3188] Loss: 0.0492
Epoch [1/4] Batch [2150/3188] Loss: 0.2214
Epoch [1/4] Batch [2200/3188] Loss: 0.1757
Epoch [1/4] Batch [2250/3188] Loss: 0.3153
Epoch [1/4] Batch [2300/3188] Loss: 0.1955
Epoch [1/4] Batch [2350/3188] Loss: 0.1996
Epoch [1/4] Batch [2400/3188] Loss: 0.1205
Epoch [1/4] Batch [2450/3188] Loss: 0.4098
Epoch [1/4] Batch [2500/3188] Loss: 0.3046
Epoch [1/4] Batch [2550/3188] Loss: 0.2026
Epoch [1/4] Batch [2600/3188] Loss: 0.2991
Epoch [1/4] Batch [2650/3188] Loss: 0.2605
Epoch [1/4] Batch [2700/3188] Loss: 0.1113
Epoch [1/4] Batch [2750/3188] Loss: 0.1814
Epoch [1/4] Batch [2800/3188] Loss: 0.1588
Epoch [1/4] Batch [2850/3188] Loss: 0.0686
Epoch [1/4] Batch [2900/3188] Loss: 0.1461
Epoch [1/4] Batch [2950/3188] Loss: 0.1146
Epoch [1/4] Batch [3000/3188] Loss: 0.1075
Epoch [1/4] Batch [3050/3188] Loss: 0.2138
Epoch [1/4] Batch [3100/3188] Loss: 0.4839
Epoch [1/4] Batch [3150/3188] Loss: 0.0370
Trial 4: Epoch 1/4 | Val F1: 0.9414 | Val Loss: 0.1844
Epoch [2/4] Batch [50/3188] Loss: 0.3471
Epoch [2/4] Batch [100/3188] Loss: 0.1293
Epoch [2/4] Batch [150/3188] Loss: 0.4096
Epoch [2/4] Batch [200/3188] Loss: 0.2210
Epoch [2/4] Batch [250/3188] Loss: 0.0435
Epoch [2/4] Batch [300/3188] Loss: 0.6348
Epoch [2/4] Batch [350/3188] Loss: 0.5102
```

```
Epoch [2/4] Batch [400/3188] Loss: 0.2299
Epoch [2/4] Batch [450/3188] Loss: 0.0917
Epoch [2/4] Batch [500/3188] Loss: 0.3021
Epoch [2/4] Batch [550/3188] Loss: 0.1936
Epoch [2/4] Batch [600/3188] Loss: 0.0478
Epoch [2/4] Batch [650/3188] Loss: 0.3115
Epoch [2/4] Batch [700/3188] Loss: 0.0679
Epoch [2/4] Batch [750/3188] Loss: 0.0406
Epoch [2/4] Batch [800/3188] Loss: 0.0622
Epoch [2/4] Batch [850/3188] Loss: 0.1674
Epoch [2/4] Batch [900/3188] Loss: 0.0855
Epoch [2/4] Batch [950/3188] Loss: 0.1755
Epoch [2/4] Batch [1000/3188] Loss: 0.0817
Epoch [2/4] Batch [1050/3188] Loss: 0.1770
Epoch [2/4] Batch [1100/3188] Loss: 0.0790
Epoch [2/4] Batch [1150/3188] Loss: 0.0646
Epoch [2/4] Batch [1200/3188] Loss: 0.2066
Epoch [2/4] Batch [1250/3188] Loss: 0.0457
Epoch [2/4] Batch [1300/3188] Loss: 0.0726
Epoch [2/4] Batch [1350/3188] Loss: 0.1374
Epoch [2/4] Batch [1400/3188] Loss: 0.0775
Epoch [2/4] Batch [1450/3188] Loss: 0.1356
Epoch [2/4] Batch [1500/3188] Loss: 0.2408
Epoch [2/4] Batch [1550/3188] Loss: 0.0663
Epoch [2/4] Batch [1600/3188] Loss: 0.0335
Epoch [2/4] Batch [1650/3188] Loss: 0.0487
Epoch [2/4] Batch [1700/3188] Loss: 0.1338
Epoch [2/4] Batch [1750/3188] Loss: 0.3339
Epoch [2/4] Batch [1800/3188] Loss: 0.1935
Epoch [2/4] Batch [1850/3188] Loss: 0.1621
Epoch [2/4] Batch [1900/3188] Loss: 0.1656
Epoch [2/4] Batch [1950/3188] Loss: 0.2305
Epoch [2/4] Batch [2000/3188] Loss: 0.0167
Epoch [2/4] Batch [2050/3188] Loss: 0.2416
Epoch [2/4] Batch [2100/3188] Loss: 0.3908
Epoch [2/4] Batch [2150/3188] Loss: 0.0351
Epoch [2/4] Batch [2200/3188] Loss: 0.0903
Epoch [2/4] Batch [2250/3188] Loss: 0.1272
Epoch [2/4] Batch [2300/3188] Loss: 0.2319
Epoch [2/4] Batch [2350/3188] Loss: 0.0188
Epoch [2/4] Batch [2400/3188] Loss: 0.1002
Epoch [2/4] Batch [2450/3188] Loss: 0.0953
Epoch [2/4] Batch [2500/3188] Loss: 0.0958
Epoch [2/4] Batch [2550/3188] Loss: 0.2064
Epoch [2/4] Batch [2600/3188] Loss: 0.1815
Epoch [2/4] Batch [2650/3188] Loss: 0.0777
Epoch [2/4] Batch [2700/3188] Loss: 0.0652
Epoch [2/4] Batch [2750/3188] Loss: 0.1447
```

```
Epoch [2/4] Batch [2800/3188] Loss: 0.1206
Epoch [2/4] Batch [2850/3188] Loss: 0.1189
Epoch [2/4] Batch [2900/3188] Loss: 0.1170
Epoch [2/4] Batch [2950/3188] Loss: 0.3538
Epoch [2/4] Batch [3000/3188] Loss: 0.0215
Epoch [2/4] Batch [3050/3188] Loss: 0.0465
Epoch [2/4] Batch [3100/3188] Loss: 0.0458
Epoch [2/4] Batch [3150/3188] Loss: 0.1964
Trial 4: Epoch 2/4 | Val F1: 0.9457 | Val Loss: 0.1716
Epoch [3/4] Batch [50/3188] Loss: 0.0424
Epoch [3/4] Batch [100/3188] Loss: 0.0631
Epoch [3/4] Batch [150/3188] Loss: 0.1118
Epoch [3/4] Batch [200/3188] Loss: 0.0762
Epoch [3/4] Batch [250/3188] Loss: 0.0244
Epoch [3/4] Batch [300/3188] Loss: 0.1235
Epoch [3/4] Batch [350/3188] Loss: 0.0077
Epoch [3/4] Batch [400/3188] Loss: 0.0487
Epoch [3/4] Batch [450/3188] Loss: 0.0165
Epoch [3/4] Batch [500/3188] Loss: 0.1473
Epoch [3/4] Batch [550/3188] Loss: 0.0740
Epoch [3/4] Batch [600/3188] Loss: 0.1649
Epoch [3/4] Batch [650/3188] Loss: 0.0104
Epoch [3/4] Batch [700/3188] Loss: 0.1224
Epoch [3/4] Batch [750/3188] Loss: 0.0669
Epoch [3/4] Batch [800/3188] Loss: 0.0186
Epoch [3/4] Batch [850/3188] Loss: 0.0226
Epoch [3/4] Batch [900/3188] Loss: 0.0124
Epoch [3/4] Batch [950/3188] Loss: 0.0204
Epoch [3/4] Batch [1000/3188] Loss: 0.0093
Epoch [3/4] Batch [1050/3188] Loss: 0.0058
Epoch [3/4] Batch [1100/3188] Loss: 0.1388
Epoch [3/4] Batch [1150/3188] Loss: 0.0077
Epoch [3/4] Batch [1200/3188] Loss: 0.1585
Epoch [3/4] Batch [1250/3188] Loss: 0.0566
Epoch [3/4] Batch [1300/3188] Loss: 0.0068
Epoch [3/4] Batch [1350/3188] Loss: 0.0141
Epoch [3/4] Batch [1400/3188] Loss: 0.0767
Epoch [3/4] Batch [1450/3188] Loss: 0.0802
Epoch [3/4] Batch [1500/3188] Loss: 0.1475
Epoch [3/4] Batch [1550/3188] Loss: 0.0546
Epoch [3/4] Batch [1600/3188] Loss: 0.0089
Epoch [3/4] Batch [1650/3188] Loss: 0.1605
Epoch [3/4] Batch [1700/3188] Loss: 0.0149
Epoch [3/4] Batch [1750/3188] Loss: 0.2163
Epoch [3/4] Batch [1800/3188] Loss: 0.0868
Epoch [3/4] Batch [1850/3188] Loss: 0.0392
Epoch [3/4] Batch [1900/3188] Loss: 0.1934
Epoch [3/4] Batch [1950/3188] Loss: 0.1386
```

```
Epoch [3/4] Batch [2000/3188] Loss: 0.0215
Epoch [3/4] Batch [2050/3188] Loss: 0.0200
Epoch [3/4] Batch [2100/3188] Loss: 0.0720
Epoch [3/4] Batch [2150/3188] Loss: 0.1674
Epoch [3/4] Batch [2200/3188] Loss: 0.0028
Epoch [3/4] Batch [2250/3188] Loss: 0.0079
Epoch [3/4] Batch [2300/3188] Loss: 0.0195
Epoch [3/4] Batch [2350/3188] Loss: 0.1607
Epoch [3/4] Batch [2400/3188] Loss: 0.0620
Epoch [3/4] Batch [2450/3188] Loss: 0.1132
Epoch [3/4] Batch [2500/3188] Loss: 0.0748
Epoch [3/4] Batch [2550/3188] Loss: 0.1390
Epoch [3/4] Batch [2600/3188] Loss: 0.0521
Epoch [3/4] Batch [2650/3188] Loss: 0.0069
Epoch [3/4] Batch [2700/3188] Loss: 0.0300
Epoch [3/4] Batch [2750/3188] Loss: 0.0977
Epoch [3/4] Batch [2800/3188] Loss: 0.1281
Epoch [3/4] Batch [2850/3188] Loss: 0.1179
Epoch [3/4] Batch [2900/3188] Loss: 0.0593
Epoch [3/4] Batch [2950/3188] Loss: 0.0823
Epoch [3/4] Batch [3000/3188] Loss: 0.1272
Epoch [3/4] Batch [3050/3188] Loss: 0.1356
Epoch [3/4] Batch [3100/3188] Loss: 0.0049
Epoch [3/4] Batch [3150/3188] Loss: 0.2257
Trial 4: Epoch 3/4 | Val F1: 0.9456 | Val Loss: 0.2037
Epoch [4/4] Batch [50/3188] Loss: 0.0069
Epoch [4/4] Batch [100/3188] Loss: 0.3060
Epoch [4/4] Batch [150/3188] Loss: 0.0027
Epoch [4/4] Batch [200/3188] Loss: 0.0060
Epoch [4/4] Batch [250/3188] Loss: 0.0322
Epoch [4/4] Batch [300/3188] Loss: 0.1155
Epoch [4/4] Batch [350/3188] Loss: 0.0011
Epoch [4/4] Batch [400/3188] Loss: 0.0046
Epoch [4/4] Batch [450/3188] Loss: 0.0067
Epoch [4/4] Batch [500/3188] Loss: 0.2185
Epoch [4/4] Batch [550/3188] Loss: 0.0076
Epoch [4/4] Batch [600/3188] Loss: 0.0015
Epoch [4/4] Batch [650/3188] Loss: 0.0082
Epoch [4/4] Batch [700/3188] Loss: 0.0049
Epoch [4/4] Batch [750/3188] Loss: 0.0013
Epoch [4/4] Batch [800/3188] Loss: 0.0024
Epoch [4/4] Batch [850/3188] Loss: 0.0085
Epoch [4/4] Batch [900/3188] Loss: 0.0118
Epoch [4/4] Batch [950/3188] Loss: 0.0029
Epoch [4/4] Batch [1000/3188] Loss: 0.0013
Epoch [4/4] Batch [1050/3188] Loss: 0.0011
Epoch [4/4] Batch [1100/3188] Loss: 0.0024
Epoch [4/4] Batch [1150/3188] Loss: 0.0020
```

```
Epoch [4/4] Batch [1200/3188] Loss: 0.0389
Epoch [4/4] Batch [1250/3188] Loss: 0.0025
Epoch [4/4] Batch [1300/3188] Loss: 0.0022
Epoch [4/4] Batch [1350/3188] Loss: 0.0526
Epoch [4/4] Batch [1400/3188] Loss: 0.1490
Epoch [4/4] Batch [1450/3188] Loss: 0.0047
Epoch [4/4] Batch [1500/3188] Loss: 0.0652
Epoch [4/4] Batch [1550/3188] Loss: 0.0278
Epoch [4/4] Batch [1600/3188] Loss: 0.0660
Epoch [4/4] Batch [1650/3188] Loss: 0.0240
Epoch [4/4] Batch [1700/3188] Loss: 0.1423
Epoch [4/4] Batch [1750/3188] Loss: 0.0243
Epoch [4/4] Batch [1800/3188] Loss: 0.0019
Epoch [4/4] Batch [1850/3188] Loss: 0.0166
Epoch [4/4] Batch [1900/3188] Loss: 0.0341
Epoch [4/4] Batch [1950/3188] Loss: 0.0025
Epoch [4/4] Batch [2000/3188] Loss: 0.0033
Epoch [4/4] Batch [2050/3188] Loss: 0.1096
Epoch [4/4] Batch [2100/3188] Loss: 0.0019
Epoch [4/4] Batch [2150/3188] Loss: 0.0041
Epoch [4/4] Batch [2200/3188] Loss: 0.1123
Epoch [4/4] Batch [2250/3188] Loss: 0.1385
Epoch [4/4] Batch [2300/3188] Loss: 0.1563
Epoch [4/4] Batch [2350/3188] Loss: 0.0771
Epoch [4/4] Batch [2400/3188] Loss: 0.0023
Epoch [4/4] Batch [2450/3188] Loss: 0.0041
Epoch [4/4] Batch [2500/3188] Loss: 0.0033
Epoch [4/4] Batch [2550/3188] Loss: 0.2496
Epoch [4/4] Batch [2600/3188] Loss: 0.2319
Epoch [4/4] Batch [2650/3188] Loss: 0.0014
Epoch [4/4] Batch [2700/3188] Loss: 0.0039
Epoch [4/4] Batch [2750/3188] Loss: 0.1196
Epoch [4/4] Batch [2800/3188] Loss: 0.0230
Epoch [4/4] Batch [2850/3188] Loss: 0.0971
Epoch [4/4] Batch [2900/3188] Loss: 0.0083
Epoch [4/4] Batch [2950/3188] Loss: 0.0019
Epoch [4/4] Batch [3000/3188] Loss: 0.0048
Epoch [4/4] Batch [3050/3188] Loss: 0.0724
Epoch [4/4] Batch [3100/3188] Loss: 0.2575
Epoch [4/4] Batch [3150/3188] Loss: 0.0494
Trial 4: Epoch 4/4 | Val F1: 0.9485 | Val Loss: 0.2316
```

```
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.
```

```
Epoch [1/4] Batch [50/6375] Loss: 1.3957
Epoch [1/4] Batch [100/6375] Loss: 1.3765
Epoch [1/4] Batch [150/6375] Loss: 1.3644
Epoch [1/4] Batch [200/6375] Loss: 1.3439
Epoch [1/4] Batch [250/6375] Loss: 1.3536
Epoch [1/4] Batch [300/6375] Loss: 1.2218
Epoch [1/4] Batch [350/6375] Loss: 1.0472
Epoch [1/4] Batch [400/6375] Loss: 0.9203
Epoch [1/4] Batch [450/6375] Loss: 0.9045
Epoch [1/4] Batch [500/6375] Loss: 0.7847
Epoch [1/4] Batch [550/6375] Loss: 0.6270
Epoch [1/4] Batch [600/6375] Loss: 0.4874
Epoch [1/4] Batch [650/6375] Loss: 0.5151
Epoch [1/4] Batch [700/6375] Loss: 0.2743
Epoch [1/4] Batch [750/6375] Loss: 0.5950
Epoch [1/4] Batch [800/6375] Loss: 0.3559
Epoch [1/4] Batch [850/6375] Loss: 0.2308
Epoch [1/4] Batch [900/6375] Loss: 0.2203
Epoch [1/4] Batch [950/6375] Loss: 0.4587
Epoch [1/4] Batch [1000/6375] Loss: 0.3610
Epoch [1/4] Batch [1050/6375] Loss: 0.3076
Epoch [1/4] Batch [1100/6375] Loss: 0.4214
Epoch [1/4] Batch [1150/6375] Loss: 0.0925
Epoch [1/4] Batch [1200/6375] Loss: 0.2681
Epoch [1/4] Batch [1250/6375] Loss: 0.4060
Epoch [1/4] Batch [1300/6375] Loss: 0.3110
Epoch [1/4] Batch [1350/6375] Loss: 0.3093
Epoch [1/4] Batch [1400/6375] Loss: 0.0668
Epoch [1/4] Batch [1450/6375] Loss: 0.5028
Epoch [1/4] Batch [1500/6375] Loss: 0.3474
Epoch [1/4] Batch [1550/6375] Loss: 0.2361
Epoch [1/4] Batch [1600/6375] Loss: 0.1008
Epoch [1/4] Batch [1650/6375] Loss: 0.0908
Epoch [1/4] Batch [1700/6375] Loss: 0.1297
Epoch [1/4] Batch [1750/6375] Loss: 0.1620
Epoch [1/4] Batch [1800/6375] Loss: 0.4359
Epoch [1/4] Batch [1850/6375] Loss: 0.5092
Epoch [1/4] Batch [1900/6375] Loss: 1.0932
Epoch [1/4] Batch [1950/6375] Loss: 0.2745
Epoch [1/4] Batch [2000/6375] Loss: 0.2903
Epoch [1/4] Batch [2050/6375] Loss: 0.5833
Epoch [1/4] Batch [2100/6375] Loss: 0.0949
Epoch [1/4] Batch [2150/6375] Loss: 0.0344
Epoch [1/4] Batch [2200/6375] Loss: 0.4263
Epoch [1/4] Batch [2250/6375] Loss: 0.2480
Epoch [1/4] Batch [2300/6375] Loss: 0.7362
Epoch [1/4] Batch [2350/6375] Loss: 0.4015
Epoch [1/4] Batch [2400/6375] Loss: 0.2093
```

```
Epoch [1/4] Batch [2450/6375] Loss: 0.1430
Epoch [1/4] Batch [2500/6375] Loss: 0.3936
Epoch [1/4] Batch [2550/6375] Loss: 0.0955
Epoch [1/4] Batch [2600/6375] Loss: 0.1067
Epoch [1/4] Batch [2650/6375] Loss: 0.1439
Epoch [1/4] Batch [2700/6375] Loss: 0.0844
Epoch [1/4] Batch [2750/6375] Loss: 0.1076
Epoch [1/4] Batch [2800/6375] Loss: 0.3603
Epoch [1/4] Batch [2850/6375] Loss: 0.3863
Epoch [1/4] Batch [2900/6375] Loss: 0.1431
Epoch [1/4] Batch [2950/6375] Loss: 0.0567
Epoch [1/4] Batch [3000/6375] Loss: 0.1406
Epoch [1/4] Batch [3050/6375] Loss: 0.2495
Epoch [1/4] Batch [3100/6375] Loss: 0.0836
Epoch [1/4] Batch [3150/6375] Loss: 0.1768
Epoch [1/4] Batch [3200/6375] Loss: 0.1565
Epoch [1/4] Batch [3250/6375] Loss: 0.1977
Epoch [1/4] Batch [3300/6375] Loss: 0.5329
Epoch [1/4] Batch [3350/6375] Loss: 0.1990
Epoch [1/4] Batch [3400/6375] Loss: 0.2008
Epoch [1/4] Batch [3450/6375] Loss: 0.5023
Epoch [1/4] Batch [3500/6375] Loss: 0.3292
Epoch [1/4] Batch [3550/6375] Loss: 0.1456
Epoch [1/4] Batch [3600/6375] Loss: 0.4076
Epoch [1/4] Batch [3650/6375] Loss: 0.3539
Epoch [1/4] Batch [3700/6375] Loss: 0.4170
Epoch [1/4] Batch [3750/6375] Loss: 0.5800
Epoch [1/4] Batch [3800/6375] Loss: 0.0349
Epoch [1/4] Batch [3850/6375] Loss: 0.0450
Epoch [1/4] Batch [3900/6375] Loss: 0.0474
Epoch [1/4] Batch [3950/6375] Loss: 0.6059
Epoch [1/4] Batch [4000/6375] Loss: 0.0676
Epoch [1/4] Batch [4050/6375] Loss: 0.1089
Epoch [1/4] Batch [4100/6375] Loss: 0.8105
Epoch [1/4] Batch [4150/6375] Loss: 0.2592
Epoch [1/4] Batch [4200/6375] Loss: 0.1014
Epoch [1/4] Batch [4250/6375] Loss: 0.5938
Epoch [1/4] Batch [4300/6375] Loss: 0.1177
Epoch [1/4] Batch [4350/6375] Loss: 0.1865
Epoch [1/4] Batch [4400/6375] Loss: 0.2536
Epoch [1/4] Batch [4450/6375] Loss: 0.1392
Epoch [1/4] Batch [4500/6375] Loss: 0.2757
Epoch [1/4] Batch [4550/6375] Loss: 0.2500
Epoch [1/4] Batch [4600/6375] Loss: 0.6835
Epoch [1/4] Batch [4650/6375] Loss: 0.0552
Epoch [1/4] Batch [4700/6375] Loss: 0.3458
Epoch [1/4] Batch [4750/6375] Loss: 0.4403
Epoch [1/4] Batch [4800/6375] Loss: 0.1170
```

```
Epoch [1/4] Batch [4850/6375] Loss: 0.0283
Epoch [1/4] Batch [4900/6375] Loss: 0.3965
Epoch [1/4] Batch [4950/6375] Loss: 0.0211
Epoch [1/4] Batch [5000/6375] Loss: 0.1100
Epoch [1/4] Batch [5050/6375] Loss: 0.3245
Epoch [1/4] Batch [5100/6375] Loss: 0.4106
Epoch [1/4] Batch [5150/6375] Loss: 0.4346
Epoch [1/4] Batch [5200/6375] Loss: 0.3603
Epoch [1/4] Batch [5250/6375] Loss: 0.2117
Epoch [1/4] Batch [5300/6375] Loss: 0.3632
Epoch [1/4] Batch [5350/6375] Loss: 0.0632
Epoch [1/4] Batch [5400/6375] Loss: 0.0832
Epoch [1/4] Batch [5450/6375] Loss: 0.1147
Epoch [1/4] Batch [5500/6375] Loss: 0.1416
Epoch [1/4] Batch [5550/6375] Loss: 0.3025
Epoch [1/4] Batch [5600/6375] Loss: 0.5635
Epoch [1/4] Batch [5650/6375] Loss: 0.1858
Epoch [1/4] Batch [5700/6375] Loss: 0.2498
Epoch [1/4] Batch [5750/6375] Loss: 0.0385
Epoch [1/4] Batch [5800/6375] Loss: 0.2974
Epoch [1/4] Batch [5850/6375] Loss: 0.0435
Epoch [1/4] Batch [5900/6375] Loss: 0.2412
Epoch [1/4] Batch [5950/6375] Loss: 0.3823
Epoch [1/4] Batch [6000/6375] Loss: 0.0336
Epoch [1/4] Batch [6050/6375] Loss: 0.2622
Epoch [1/4] Batch [6100/6375] Loss: 0.0157
Epoch [1/4] Batch [6150/6375] Loss: 0.0689
Epoch [1/4] Batch [6200/6375] Loss: 0.1298
Epoch [1/4] Batch [6250/6375] Loss: 0.0532
Epoch [1/4] Batch [6300/6375] Loss: 0.0170
Epoch [1/4] Batch [6350/6375] Loss: 0.2992
Trial 5: Epoch 1/4 | Val F1: 0.9352 | Val Loss: 0.2003

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.

Epoch [1/4] Batch [50/1594] Loss: 1.3343
Epoch [1/4] Batch [100/1594] Loss: 0.6775
Epoch [1/4] Batch [150/1594] Loss: 0.3801
Epoch [1/4] Batch [200/1594] Loss: 0.3015
Epoch [1/4] Batch [250/1594] Loss: 0.2176
Epoch [1/4] Batch [300/1594] Loss: 0.2284
Epoch [1/4] Batch [350/1594] Loss: 0.1886
Epoch [1/4] Batch [400/1594] Loss: 0.2581
Epoch [1/4] Batch [450/1594] Loss: 0.3781
```

```
Epoch [1/4] Batch [500/1594] Loss: 0.1735
Epoch [1/4] Batch [550/1594] Loss: 0.2230
Epoch [1/4] Batch [600/1594] Loss: 0.2202
Epoch [1/4] Batch [650/1594] Loss: 0.1214
Epoch [1/4] Batch [700/1594] Loss: 0.1492
Epoch [1/4] Batch [750/1594] Loss: 0.1643
Epoch [1/4] Batch [800/1594] Loss: 0.1083
Epoch [1/4] Batch [850/1594] Loss: 0.3222
Epoch [1/4] Batch [900/1594] Loss: 0.3280
Epoch [1/4] Batch [950/1594] Loss: 0.2615
Epoch [1/4] Batch [1000/1594] Loss: 0.1953
Epoch [1/4] Batch [1050/1594] Loss: 0.2652
Epoch [1/4] Batch [1100/1594] Loss: 0.1307
Epoch [1/4] Batch [1150/1594] Loss: 0.1172
Epoch [1/4] Batch [1200/1594] Loss: 0.2034
Epoch [1/4] Batch [1250/1594] Loss: 0.2260
Epoch [1/4] Batch [1300/1594] Loss: 0.1091
Epoch [1/4] Batch [1350/1594] Loss: 0.2277
Epoch [1/4] Batch [1400/1594] Loss: 0.2531
Epoch [1/4] Batch [1450/1594] Loss: 0.2207
Epoch [1/4] Batch [1500/1594] Loss: 0.2057
Epoch [1/4] Batch [1550/1594] Loss: 0.2495
Trial 6: Epoch 1/4 | Val F1: 0.9407 | Val Loss: 0.1694
Epoch [2/4] Batch [50/1594] Loss: 0.2267
Epoch [2/4] Batch [100/1594] Loss: 0.1136
Epoch [2/4] Batch [150/1594] Loss: 0.1338
Epoch [2/4] Batch [200/1594] Loss: 0.1669
Epoch [2/4] Batch [250/1594] Loss: 0.1111
Epoch [2/4] Batch [300/1594] Loss: 0.1611
Epoch [2/4] Batch [350/1594] Loss: 0.1476
Epoch [2/4] Batch [400/1594] Loss: 0.2483
Epoch [2/4] Batch [450/1594] Loss: 0.3694
Epoch [2/4] Batch [500/1594] Loss: 0.1845
Epoch [2/4] Batch [550/1594] Loss: 0.2098
Epoch [2/4] Batch [600/1594] Loss: 0.1000
Epoch [2/4] Batch [650/1594] Loss: 0.1622
Epoch [2/4] Batch [700/1594] Loss: 0.1105
Epoch [2/4] Batch [750/1594] Loss: 0.1822
Epoch [2/4] Batch [800/1594] Loss: 0.1603
Epoch [2/4] Batch [850/1594] Loss: 0.0602
Epoch [2/4] Batch [900/1594] Loss: 0.1109
Epoch [2/4] Batch [950/1594] Loss: 0.3105
Epoch [2/4] Batch [1000/1594] Loss: 0.0958
Epoch [2/4] Batch [1050/1594] Loss: 0.2002
Epoch [2/4] Batch [1100/1594] Loss: 0.0868
Epoch [2/4] Batch [1150/1594] Loss: 0.1141
Epoch [2/4] Batch [1200/1594] Loss: 0.1533
Epoch [2/4] Batch [1250/1594] Loss: 0.1628
```

```
Epoch [2/4] Batch [1300/1594] Loss: 0.2656
Epoch [2/4] Batch [1350/1594] Loss: 0.1285
Epoch [2/4] Batch [1400/1594] Loss: 0.2377
Epoch [2/4] Batch [1450/1594] Loss: 0.2239
Epoch [2/4] Batch [1500/1594] Loss: 0.1808
Epoch [2/4] Batch [1550/1594] Loss: 0.2760
Trial 6: Epoch 2/4 | Val F1: 0.9480 | Val Loss: 0.1599
Epoch [3/4] Batch [50/1594] Loss: 0.1291
Epoch [3/4] Batch [100/1594] Loss: 0.0742
Epoch [3/4] Batch [150/1594] Loss: 0.1736
Epoch [3/4] Batch [200/1594] Loss: 0.0856
Epoch [3/4] Batch [250/1594] Loss: 0.0596
Epoch [3/4] Batch [300/1594] Loss: 0.0625
Epoch [3/4] Batch [350/1594] Loss: 0.0609
Epoch [3/4] Batch [400/1594] Loss: 0.0100
Epoch [3/4] Batch [450/1594] Loss: 0.1040
Epoch [3/4] Batch [500/1594] Loss: 0.1159
Epoch [3/4] Batch [550/1594] Loss: 0.0799
Epoch [3/4] Batch [600/1594] Loss: 0.1167
Epoch [3/4] Batch [650/1594] Loss: 0.0283
Epoch [3/4] Batch [700/1594] Loss: 0.0060
Epoch [3/4] Batch [750/1594] Loss: 0.0247
Epoch [3/4] Batch [800/1594] Loss: 0.0170
Epoch [3/4] Batch [850/1594] Loss: 0.2651
Epoch [3/4] Batch [900/1594] Loss: 0.0979
Epoch [3/4] Batch [950/1594] Loss: 0.2113
Epoch [3/4] Batch [1000/1594] Loss: 0.0213
Epoch [3/4] Batch [1050/1594] Loss: 0.1342
Epoch [3/4] Batch [1100/1594] Loss: 0.2980
Epoch [3/4] Batch [1150/1594] Loss: 0.1577
Epoch [3/4] Batch [1200/1594] Loss: 0.0099
Epoch [3/4] Batch [1250/1594] Loss: 0.1036
Epoch [3/4] Batch [1300/1594] Loss: 0.0429
Epoch [3/4] Batch [1350/1594] Loss: 0.0597
Epoch [3/4] Batch [1400/1594] Loss: 0.1088
Epoch [3/4] Batch [1450/1594] Loss: 0.0460
Epoch [3/4] Batch [1500/1594] Loss: 0.0674
Epoch [3/4] Batch [1550/1594] Loss: 0.0429
Trial 6: Epoch 3/4 | Val F1: 0.9487 | Val Loss: 0.1762
Epoch [4/4] Batch [50/1594] Loss: 0.0670
Epoch [4/4] Batch [100/1594] Loss: 0.0670
Epoch [4/4] Batch [150/1594] Loss: 0.1335
Epoch [4/4] Batch [200/1594] Loss: 0.0122
Epoch [4/4] Batch [250/1594] Loss: 0.0097
Epoch [4/4] Batch [300/1594] Loss: 0.0657
Epoch [4/4] Batch [350/1594] Loss: 0.0880
Epoch [4/4] Batch [400/1594] Loss: 0.0320
Epoch [4/4] Batch [450/1594] Loss: 0.0202
```

```
Epoch [4/4] Batch [500/1594] Loss: 0.0145
Epoch [4/4] Batch [550/1594] Loss: 0.0308
Epoch [4/4] Batch [600/1594] Loss: 0.1161
Epoch [4/4] Batch [650/1594] Loss: 0.0669
Epoch [4/4] Batch [700/1594] Loss: 0.0304
Epoch [4/4] Batch [750/1594] Loss: 0.1048
Epoch [4/4] Batch [800/1594] Loss: 0.0359
Epoch [4/4] Batch [850/1594] Loss: 0.0366
Epoch [4/4] Batch [900/1594] Loss: 0.0050
Epoch [4/4] Batch [950/1594] Loss: 0.0443
Epoch [4/4] Batch [1000/1594] Loss: 0.0783
Epoch [4/4] Batch [1050/1594] Loss: 0.0382
Epoch [4/4] Batch [1100/1594] Loss: 0.0409
Epoch [4/4] Batch [1150/1594] Loss: 0.0379
Epoch [4/4] Batch [1200/1594] Loss: 0.1829
Epoch [4/4] Batch [1250/1594] Loss: 0.0343
Epoch [4/4] Batch [1300/1594] Loss: 0.0097
Epoch [4/4] Batch [1350/1594] Loss: 0.1600
Epoch [4/4] Batch [1400/1594] Loss: 0.0080
Epoch [4/4] Batch [1450/1594] Loss: 0.0090
Epoch [4/4] Batch [1500/1594] Loss: 0.1503
Epoch [4/4] Batch [1550/1594] Loss: 0.0327
Trial 6: Epoch 4/4 | Val F1: 0.9451 | Val Loss: 0.1956
```

```
'(ReadTimeoutError("HTTPSConnectionPool(host='huggingface.co', port=443): Read
timed out. (read timeout=10)"), '(Request ID: 4f529bff-
af5e-4834-ab93-cf3a67d00beb)')' thrown while requesting HEAD
https://huggingface.co/distilbert-base-uncased/resolve/main/config.json
Retrying in 1s [Retry 1/5].
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.
```

```
Epoch [1/4] Batch [50/6375] Loss: 1.4072
Epoch [1/4] Batch [100/6375] Loss: 1.3809
Epoch [1/4] Batch [150/6375] Loss: 1.3224
Epoch [1/4] Batch [200/6375] Loss: 1.3012
Epoch [1/4] Batch [250/6375] Loss: 1.2321
Epoch [1/4] Batch [300/6375] Loss: 1.1375
Epoch [1/4] Batch [350/6375] Loss: 0.7747
Epoch [1/4] Batch [400/6375] Loss: 0.7930
Epoch [1/4] Batch [450/6375] Loss: 0.5058
Epoch [1/4] Batch [500/6375] Loss: 0.3500
Epoch [1/4] Batch [550/6375] Loss: 0.6804
Epoch [1/4] Batch [600/6375] Loss: 0.3138
Epoch [1/4] Batch [650/6375] Loss: 0.3602
```

```
Epoch [1/4] Batch [700/6375] Loss: 0.8109
Epoch [1/4] Batch [750/6375] Loss: 0.2681
Epoch [1/4] Batch [800/6375] Loss: 0.2071
Epoch [1/4] Batch [850/6375] Loss: 0.2255
Epoch [1/4] Batch [900/6375] Loss: 0.3588
Epoch [1/4] Batch [950/6375] Loss: 0.4948
Epoch [1/4] Batch [1000/6375] Loss: 0.4071
Epoch [1/4] Batch [1050/6375] Loss: 0.2521
Epoch [1/4] Batch [1100/6375] Loss: 0.2570
Epoch [1/4] Batch [1150/6375] Loss: 0.2005
Epoch [1/4] Batch [1200/6375] Loss: 0.3520
Epoch [1/4] Batch [1250/6375] Loss: 0.0630
Epoch [1/4] Batch [1300/6375] Loss: 0.1343
Epoch [1/4] Batch [1350/6375] Loss: 0.3191
Epoch [1/4] Batch [1400/6375] Loss: 0.2800
Epoch [1/4] Batch [1450/6375] Loss: 0.1128
Epoch [1/4] Batch [1500/6375] Loss: 0.0960
Epoch [1/4] Batch [1550/6375] Loss: 0.2814
Epoch [1/4] Batch [1600/6375] Loss: 0.2587
Epoch [1/4] Batch [1650/6375] Loss: 0.2217
Epoch [1/4] Batch [1700/6375] Loss: 0.6263
Epoch [1/4] Batch [1750/6375] Loss: 0.2016
Epoch [1/4] Batch [1800/6375] Loss: 0.4736
Epoch [1/4] Batch [1850/6375] Loss: 0.1344
Epoch [1/4] Batch [1900/6375] Loss: 0.4142
Epoch [1/4] Batch [1950/6375] Loss: 0.4512
Epoch [1/4] Batch [2000/6375] Loss: 0.0467
Epoch [1/4] Batch [2050/6375] Loss: 0.3049
Epoch [1/4] Batch [2100/6375] Loss: 0.3782
Epoch [1/4] Batch [2150/6375] Loss: 0.1951
Epoch [1/4] Batch [2200/6375] Loss: 0.4966
Epoch [1/4] Batch [2250/6375] Loss: 0.3080
Epoch [1/4] Batch [2300/6375] Loss: 0.3812
Epoch [1/4] Batch [2350/6375] Loss: 0.2087
Epoch [1/4] Batch [2400/6375] Loss: 0.0873
Epoch [1/4] Batch [2450/6375] Loss: 0.0547
Epoch [1/4] Batch [2500/6375] Loss: 0.3089
Epoch [1/4] Batch [2550/6375] Loss: 0.4396
Epoch [1/4] Batch [2600/6375] Loss: 0.0901
Epoch [1/4] Batch [2650/6375] Loss: 0.2263
Epoch [1/4] Batch [2700/6375] Loss: 0.2263
Epoch [1/4] Batch [2750/6375] Loss: 0.2724
Epoch [1/4] Batch [2800/6375] Loss: 0.2949
Epoch [1/4] Batch [2850/6375] Loss: 0.2181
Epoch [1/4] Batch [2900/6375] Loss: 0.1332
Epoch [1/4] Batch [2950/6375] Loss: 0.1739
Epoch [1/4] Batch [3000/6375] Loss: 0.1547
Epoch [1/4] Batch [3050/6375] Loss: 0.0896
```

```
Epoch [1/4] Batch [3100/6375] Loss: 0.2363
Epoch [1/4] Batch [3150/6375] Loss: 0.1987
Epoch [1/4] Batch [3200/6375] Loss: 0.0138
Epoch [1/4] Batch [3250/6375] Loss: 0.0773
Epoch [1/4] Batch [3300/6375] Loss: 0.0141
Epoch [1/4] Batch [3350/6375] Loss: 0.8311
Epoch [1/4] Batch [3400/6375] Loss: 0.1899
Epoch [1/4] Batch [3450/6375] Loss: 0.3528
Epoch [1/4] Batch [3500/6375] Loss: 0.9753
Epoch [1/4] Batch [3550/6375] Loss: 0.2617
Epoch [1/4] Batch [3600/6375] Loss: 0.4452
Epoch [1/4] Batch [3650/6375] Loss: 0.0811
Epoch [1/4] Batch [3700/6375] Loss: 0.1785
Epoch [1/4] Batch [3750/6375] Loss: 0.0449
Epoch [1/4] Batch [3800/6375] Loss: 0.8433
Epoch [1/4] Batch [3850/6375] Loss: 0.3659
Epoch [1/4] Batch [3900/6375] Loss: 0.4196
Epoch [1/4] Batch [3950/6375] Loss: 0.5232
Epoch [1/4] Batch [4000/6375] Loss: 0.0125
Epoch [1/4] Batch [4050/6375] Loss: 0.1288
Epoch [1/4] Batch [4100/6375] Loss: 0.0301
Epoch [1/4] Batch [4150/6375] Loss: 0.2247
Epoch [1/4] Batch [4200/6375] Loss: 0.3683
Epoch [1/4] Batch [4250/6375] Loss: 0.1360
Epoch [1/4] Batch [4300/6375] Loss: 0.4415
Epoch [1/4] Batch [4350/6375] Loss: 0.0304
Epoch [1/4] Batch [4400/6375] Loss: 0.2318
Epoch [1/4] Batch [4450/6375] Loss: 0.1889
Epoch [1/4] Batch [4500/6375] Loss: 0.3270
Epoch [1/4] Batch [4550/6375] Loss: 0.0402
Epoch [1/4] Batch [4600/6375] Loss: 0.0659
Epoch [1/4] Batch [4650/6375] Loss: 0.2107
Epoch [1/4] Batch [4700/6375] Loss: 0.0585
Epoch [1/4] Batch [4750/6375] Loss: 0.5617
Epoch [1/4] Batch [4800/6375] Loss: 0.1893
Epoch [1/4] Batch [4850/6375] Loss: 0.1431
Epoch [1/4] Batch [4900/6375] Loss: 0.0421
Epoch [1/4] Batch [4950/6375] Loss: 0.0930
Epoch [1/4] Batch [5000/6375] Loss: 0.0311
Epoch [1/4] Batch [5050/6375] Loss: 0.4853
Epoch [1/4] Batch [5100/6375] Loss: 0.0378
Epoch [1/4] Batch [5150/6375] Loss: 0.4711
Epoch [1/4] Batch [5200/6375] Loss: 0.0204
Epoch [1/4] Batch [5250/6375] Loss: 0.2234
Epoch [1/4] Batch [5300/6375] Loss: 0.0454
Epoch [1/4] Batch [5350/6375] Loss: 0.0312
Epoch [1/4] Batch [5400/6375] Loss: 0.4548
Epoch [1/4] Batch [5450/6375] Loss: 0.5777
```

```
Epoch [1/4] Batch [5500/6375] Loss: 0.0130
Epoch [1/4] Batch [5550/6375] Loss: 0.0563
Epoch [1/4] Batch [5600/6375] Loss: 0.2634
Epoch [1/4] Batch [5650/6375] Loss: 0.6087
Epoch [1/4] Batch [5700/6375] Loss: 0.0156
Epoch [1/4] Batch [5750/6375] Loss: 0.3607
Epoch [1/4] Batch [5800/6375] Loss: 0.3653
Epoch [1/4] Batch [5850/6375] Loss: 0.2755
Epoch [1/4] Batch [5900/6375] Loss: 0.0247
Epoch [1/4] Batch [5950/6375] Loss: 0.0408
Epoch [1/4] Batch [6000/6375] Loss: 0.3991
Epoch [1/4] Batch [6050/6375] Loss: 0.0443
Epoch [1/4] Batch [6100/6375] Loss: 0.1478
Epoch [1/4] Batch [6150/6375] Loss: 0.5148
Epoch [1/4] Batch [6200/6375] Loss: 0.4406
Epoch [1/4] Batch [6250/6375] Loss: 0.0132
Epoch [1/4] Batch [6300/6375] Loss: 0.0190
Epoch [1/4] Batch [6350/6375] Loss: 0.2283
Trial 7: Epoch 1/4 | Val F1: 0.9389 | Val Loss: 0.1942

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.

Epoch [1/4] Batch [50/3188] Loss: 1.3831
Epoch [1/4] Batch [100/3188] Loss: 1.2611
Epoch [1/4] Batch [150/3188] Loss: 0.8910
Epoch [1/4] Batch [200/3188] Loss: 0.7109
Epoch [1/4] Batch [250/3188] Loss: 0.3691
Epoch [1/4] Batch [300/3188] Loss: 0.3024
Epoch [1/4] Batch [350/3188] Loss: 0.3970
Epoch [1/4] Batch [400/3188] Loss: 0.3972
Epoch [1/4] Batch [450/3188] Loss: 0.5582
Epoch [1/4] Batch [500/3188] Loss: 0.3379
Epoch [1/4] Batch [550/3188] Loss: 0.2694
Epoch [1/4] Batch [600/3188] Loss: 0.3704
Epoch [1/4] Batch [650/3188] Loss: 0.3146
Epoch [1/4] Batch [700/3188] Loss: 0.1192
Epoch [1/4] Batch [750/3188] Loss: 0.2633
Epoch [1/4] Batch [800/3188] Loss: 0.0613
Epoch [1/4] Batch [850/3188] Loss: 0.2091
Epoch [1/4] Batch [900/3188] Loss: 0.1936
Epoch [1/4] Batch [950/3188] Loss: 0.2863
Epoch [1/4] Batch [1000/3188] Loss: 0.1805
Epoch [1/4] Batch [1050/3188] Loss: 0.1216
Epoch [1/4] Batch [1100/3188] Loss: 0.1627
```

```
Epoch [1/4] Batch [1150/3188] Loss: 0.3233
Epoch [1/4] Batch [1200/3188] Loss: 0.1319
Epoch [1/4] Batch [1250/3188] Loss: 0.3129
Epoch [1/4] Batch [1300/3188] Loss: 0.3613
Epoch [1/4] Batch [1350/3188] Loss: 0.2219
Epoch [1/4] Batch [1400/3188] Loss: 0.3872
Epoch [1/4] Batch [1450/3188] Loss: 0.3283
Epoch [1/4] Batch [1500/3188] Loss: 0.5229
Epoch [1/4] Batch [1550/3188] Loss: 0.0761
Epoch [1/4] Batch [1600/3188] Loss: 0.1121
Epoch [1/4] Batch [1650/3188] Loss: 0.2237
Epoch [1/4] Batch [1700/3188] Loss: 0.5295
Epoch [1/4] Batch [1750/3188] Loss: 0.6716
Epoch [1/4] Batch [1800/3188] Loss: 0.2807
Epoch [1/4] Batch [1850/3188] Loss: 0.3140
Epoch [1/4] Batch [1900/3188] Loss: 0.2622
Epoch [1/4] Batch [1950/3188] Loss: 0.3621
Epoch [1/4] Batch [2000/3188] Loss: 0.1760
Epoch [1/4] Batch [2050/3188] Loss: 0.2514
Epoch [1/4] Batch [2100/3188] Loss: 0.1523
Epoch [1/4] Batch [2150/3188] Loss: 0.2622
Epoch [1/4] Batch [2200/3188] Loss: 0.1358
Epoch [1/4] Batch [2250/3188] Loss: 0.0507
Epoch [1/4] Batch [2300/3188] Loss: 0.1593
Epoch [1/4] Batch [2350/3188] Loss: 0.4924
Epoch [1/4] Batch [2400/3188] Loss: 0.0697
Epoch [1/4] Batch [2450/3188] Loss: 0.2993
Epoch [1/4] Batch [2500/3188] Loss: 0.2468
Epoch [1/4] Batch [2550/3188] Loss: 0.1364
Epoch [1/4] Batch [2600/3188] Loss: 0.3873
Epoch [1/4] Batch [2650/3188] Loss: 0.1122
Epoch [1/4] Batch [2700/3188] Loss: 0.1412
Epoch [1/4] Batch [2750/3188] Loss: 0.4023
Epoch [1/4] Batch [2800/3188] Loss: 0.1900
Epoch [1/4] Batch [2850/3188] Loss: 0.1989
Epoch [1/4] Batch [2900/3188] Loss: 0.3738
Epoch [1/4] Batch [2950/3188] Loss: 0.1754
Epoch [1/4] Batch [3000/3188] Loss: 0.0719
Epoch [1/4] Batch [3050/3188] Loss: 0.1831
Epoch [1/4] Batch [3100/3188] Loss: 0.1175
Epoch [1/4] Batch [3150/3188] Loss: 0.3137
Trial 8: Epoch 1/4 | Val F1: 0.9387 | Val Loss: 0.1838

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.

```
Epoch [1/4] Batch [50/6375] Loss: 1.3717
Epoch [1/4] Batch [100/6375] Loss: 1.3756
Epoch [1/4] Batch [150/6375] Loss: 1.3537
Epoch [1/4] Batch [200/6375] Loss: 1.3336
Epoch [1/4] Batch [250/6375] Loss: 1.2231
Epoch [1/4] Batch [300/6375] Loss: 1.1441
Epoch [1/4] Batch [350/6375] Loss: 0.9259
Epoch [1/4] Batch [400/6375] Loss: 0.6979
Epoch [1/4] Batch [450/6375] Loss: 0.3857
Epoch [1/4] Batch [500/6375] Loss: 0.4256
Epoch [1/4] Batch [550/6375] Loss: 0.3369
Epoch [1/4] Batch [600/6375] Loss: 0.4666
Epoch [1/4] Batch [650/6375] Loss: 0.6317
Epoch [1/4] Batch [700/6375] Loss: 0.2567
Epoch [1/4] Batch [750/6375] Loss: 0.4283
Epoch [1/4] Batch [800/6375] Loss: 0.3467
Epoch [1/4] Batch [850/6375] Loss: 0.4104
Epoch [1/4] Batch [900/6375] Loss: 0.3019
Epoch [1/4] Batch [950/6375] Loss: 0.9248
Epoch [1/4] Batch [1000/6375] Loss: 0.4136
Epoch [1/4] Batch [1050/6375] Loss: 0.8139
Epoch [1/4] Batch [1100/6375] Loss: 0.2301
Epoch [1/4] Batch [1150/6375] Loss: 0.4543
Epoch [1/4] Batch [1200/6375] Loss: 0.3863
Epoch [1/4] Batch [1250/6375] Loss: 0.3095
Epoch [1/4] Batch [1300/6375] Loss: 0.0408
Epoch [1/4] Batch [1350/6375] Loss: 0.4934
Epoch [1/4] Batch [1400/6375] Loss: 0.0452
Epoch [1/4] Batch [1450/6375] Loss: 0.2429
Epoch [1/4] Batch [1500/6375] Loss: 0.1094
Epoch [1/4] Batch [1550/6375] Loss: 0.3981
Epoch [1/4] Batch [1600/6375] Loss: 0.2637
Epoch [1/4] Batch [1650/6375] Loss: 0.5822
Epoch [1/4] Batch [1700/6375] Loss: 0.2257
Epoch [1/4] Batch [1750/6375] Loss: 0.3256
Epoch [1/4] Batch [1800/6375] Loss: 0.5965
Epoch [1/4] Batch [1850/6375] Loss: 0.2633
Epoch [1/4] Batch [1900/6375] Loss: 0.2193
Epoch [1/4] Batch [1950/6375] Loss: 0.0482
Epoch [1/4] Batch [2000/6375] Loss: 0.8502
Epoch [1/4] Batch [2050/6375] Loss: 0.0325
Epoch [1/4] Batch [2100/6375] Loss: 0.1001
Epoch [1/4] Batch [2150/6375] Loss: 0.1204
Epoch [1/4] Batch [2200/6375] Loss: 0.2349
Epoch [1/4] Batch [2250/6375] Loss: 0.2462
Epoch [1/4] Batch [2300/6375] Loss: 0.2886
```

```
Epoch [1/4] Batch [2350/6375] Loss: 0.0295
Epoch [1/4] Batch [2400/6375] Loss: 0.2167
Epoch [1/4] Batch [2450/6375] Loss: 0.3407
Epoch [1/4] Batch [2500/6375] Loss: 0.1470
Epoch [1/4] Batch [2550/6375] Loss: 0.1914
Epoch [1/4] Batch [2600/6375] Loss: 0.0410
Epoch [1/4] Batch [2650/6375] Loss: 0.2090
Epoch [1/4] Batch [2700/6375] Loss: 0.0495
Epoch [1/4] Batch [2750/6375] Loss: 0.4246
Epoch [1/4] Batch [2800/6375] Loss: 0.0235
Epoch [1/4] Batch [2850/6375] Loss: 0.0299
Epoch [1/4] Batch [2900/6375] Loss: 0.4028
Epoch [1/4] Batch [2950/6375] Loss: 0.6261
Epoch [1/4] Batch [3000/6375] Loss: 0.4167
Epoch [1/4] Batch [3050/6375] Loss: 0.0248
Epoch [1/4] Batch [3100/6375] Loss: 0.0275
Epoch [1/4] Batch [3150/6375] Loss: 0.2009
Epoch [1/4] Batch [3200/6375] Loss: 0.0756
Epoch [1/4] Batch [3250/6375] Loss: 0.2532
Epoch [1/4] Batch [3300/6375] Loss: 0.4330
Epoch [1/4] Batch [3350/6375] Loss: 0.2319
Epoch [1/4] Batch [3400/6375] Loss: 0.0778
Epoch [1/4] Batch [3450/6375] Loss: 0.2983
Epoch [1/4] Batch [3500/6375] Loss: 0.0252
Epoch [1/4] Batch [3550/6375] Loss: 0.0341
Epoch [1/4] Batch [3600/6375] Loss: 0.1523
Epoch [1/4] Batch [3650/6375] Loss: 0.3583
Epoch [1/4] Batch [3700/6375] Loss: 0.2903
Epoch [1/4] Batch [3750/6375] Loss: 0.4203
Epoch [1/4] Batch [3800/6375] Loss: 0.1941
Epoch [1/4] Batch [3850/6375] Loss: 0.5489
Epoch [1/4] Batch [3900/6375] Loss: 0.7591
Epoch [1/4] Batch [3950/6375] Loss: 0.2510
Epoch [1/4] Batch [4000/6375] Loss: 0.3526
Epoch [1/4] Batch [4050/6375] Loss: 0.4104
Epoch [1/4] Batch [4100/6375] Loss: 0.2273
Epoch [1/4] Batch [4150/6375] Loss: 0.0654
Epoch [1/4] Batch [4200/6375] Loss: 0.1381
Epoch [1/4] Batch [4250/6375] Loss: 0.2874
Epoch [1/4] Batch [4300/6375] Loss: 0.6002
Epoch [1/4] Batch [4350/6375] Loss: 0.0285
Epoch [1/4] Batch [4400/6375] Loss: 0.5301
Epoch [1/4] Batch [4450/6375] Loss: 0.1115
Epoch [1/4] Batch [4500/6375] Loss: 0.6443
Epoch [1/4] Batch [4550/6375] Loss: 0.0543
Epoch [1/4] Batch [4600/6375] Loss: 0.2257
Epoch [1/4] Batch [4650/6375] Loss: 0.0109
Epoch [1/4] Batch [4700/6375] Loss: 0.3929
```

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Epoch [1/4] Batch [4750/6375] Loss: 0.0589
Epoch [1/4] Batch [4800/6375] Loss: 0.3517
Epoch [1/4] Batch [4850/6375] Loss: 0.3543
Epoch [1/4] Batch [4900/6375] Loss: 0.0251
Epoch [1/4] Batch [4950/6375] Loss: 0.0395
Epoch [1/4] Batch [5000/6375] Loss: 0.1565
Epoch [1/4] Batch [5050/6375] Loss: 0.0241
Epoch [1/4] Batch [5100/6375] Loss: 0.1983
Epoch [1/4] Batch [5150/6375] Loss: 0.0562
Epoch [1/4] Batch [5200/6375] Loss: 0.0652
Epoch [1/4] Batch [5250/6375] Loss: 0.1357
Epoch [1/4] Batch [5300/6375] Loss: 0.0350
Epoch [1/4] Batch [5350/6375] Loss: 0.0220
Epoch [1/4] Batch [5400/6375] Loss: 0.1026
Epoch [1/4] Batch [5450/6375] Loss: 0.0244
Epoch [1/4] Batch [5500/6375] Loss: 0.1727
Epoch [1/4] Batch [5550/6375] Loss: 0.2124
Epoch [1/4] Batch [5600/6375] Loss: 0.4109
Epoch [1/4] Batch [5650/6375] Loss: 0.0593
Epoch [1/4] Batch [5700/6375] Loss: 0.0314
Epoch [1/4] Batch [5750/6375] Loss: 0.1237
Epoch [1/4] Batch [5800/6375] Loss: 0.0564
Epoch [1/4] Batch [5850/6375] Loss: 0.0713
Epoch [1/4] Batch [5900/6375] Loss: 0.1908
Epoch [1/4] Batch [5950/6375] Loss: 0.1008
Epoch [1/4] Batch [6000/6375] Loss: 0.0757
Epoch [1/4] Batch [6050/6375] Loss: 0.1313
Epoch [1/4] Batch [6100/6375] Loss: 0.1386
Epoch [1/4] Batch [6150/6375] Loss: 0.0218
Epoch [1/4] Batch [6200/6375] Loss: 0.0489
Epoch [1/4] Batch [6250/6375] Loss: 0.0423
Epoch [1/4] Batch [6300/6375] Loss: 0.4949
Epoch [1/4] Batch [6350/6375] Loss: 0.0389
Trial 9: Epoch 1/4 | Val F1: 0.9409 | Val Loss: 0.1921
Epoch [2/4] Batch [50/6375] Loss: 0.0098
Epoch [2/4] Batch [100/6375] Loss: 0.5822
Epoch [2/4] Batch [150/6375] Loss: 0.1561
Epoch [2/4] Batch [200/6375] Loss: 0.1646
Epoch [2/4] Batch [250/6375] Loss: 0.0576
Epoch [2/4] Batch [300/6375] Loss: 0.5053
Epoch [2/4] Batch [350/6375] Loss: 0.3020
Epoch [2/4] Batch [400/6375] Loss: 0.0191
Epoch [2/4] Batch [450/6375] Loss: 0.3293
Epoch [2/4] Batch [500/6375] Loss: 0.0279
Epoch [2/4] Batch [550/6375] Loss: 0.0481
Epoch [2/4] Batch [600/6375] Loss: 0.0199
Epoch [2/4] Batch [650/6375] Loss: 0.0399
Epoch [2/4] Batch [700/6375] Loss: 0.0222
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Epoch [2/4] Batch [750/6375] Loss: 0.0332
Epoch [2/4] Batch [800/6375] Loss: 0.4523
Epoch [2/4] Batch [850/6375] Loss: 0.0426
Epoch [2/4] Batch [900/6375] Loss: 0.0537
Epoch [2/4] Batch [950/6375] Loss: 0.1274
Epoch [2/4] Batch [1000/6375] Loss: 0.1208
Epoch [2/4] Batch [1050/6375] Loss: 0.0459
Epoch [2/4] Batch [1100/6375] Loss: 0.2591
Epoch [2/4] Batch [1150/6375] Loss: 0.0083
Epoch [2/4] Batch [1200/6375] Loss: 0.0106
Epoch [2/4] Batch [1250/6375] Loss: 0.2877
Epoch [2/4] Batch [1300/6375] Loss: 0.0767
Epoch [2/4] Batch [1350/6375] Loss: 0.2478
Epoch [2/4] Batch [1400/6375] Loss: 0.1429
Epoch [2/4] Batch [1450/6375] Loss: 0.0429
Epoch [2/4] Batch [1500/6375] Loss: 0.0369
Epoch [2/4] Batch [1550/6375] Loss: 0.0062
Epoch [2/4] Batch [1600/6375] Loss: 0.0368
Epoch [2/4] Batch [1650/6375] Loss: 0.4235
Epoch [2/4] Batch [1700/6375] Loss: 0.1713
Epoch [2/4] Batch [1750/6375] Loss: 0.0742
Epoch [2/4] Batch [1800/6375] Loss: 0.0502
Epoch [2/4] Batch [1850/6375] Loss: 0.0172
Epoch [2/4] Batch [1900/6375] Loss: 0.0579
Epoch [2/4] Batch [1950/6375] Loss: 0.1385
Epoch [2/4] Batch [2000/6375] Loss: 0.2714
Epoch [2/4] Batch [2050/6375] Loss: 0.1973
Epoch [2/4] Batch [2100/6375] Loss: 0.0083
Epoch [2/4] Batch [2150/6375] Loss: 0.0909
Epoch [2/4] Batch [2200/6375] Loss: 0.0262
Epoch [2/4] Batch [2250/6375] Loss: 0.1650
Epoch [2/4] Batch [2300/6375] Loss: 0.0183
Epoch [2/4] Batch [2350/6375] Loss: 0.0430
Epoch [2/4] Batch [2400/6375] Loss: 0.0772
Epoch [2/4] Batch [2450/6375] Loss: 0.0044
Epoch [2/4] Batch [2500/6375] Loss: 0.0119
Epoch [2/4] Batch [2550/6375] Loss: 0.0308
Epoch [2/4] Batch [2600/6375] Loss: 0.2012
Epoch [2/4] Batch [2650/6375] Loss: 0.0109
Epoch [2/4] Batch [2700/6375] Loss: 0.3499
Epoch [2/4] Batch [2750/6375] Loss: 0.2133
Epoch [2/4] Batch [2800/6375] Loss: 0.4559
Epoch [2/4] Batch [2850/6375] Loss: 0.0070
Epoch [2/4] Batch [2900/6375] Loss: 0.0037
Epoch [2/4] Batch [2950/6375] Loss: 0.0113
Epoch [2/4] Batch [3000/6375] Loss: 0.0171
Epoch [2/4] Batch [3050/6375] Loss: 0.0175
Epoch [2/4] Batch [3100/6375] Loss: 0.0196
```

```
Epoch [2/4] Batch [3150/6375] Loss: 0.3371
Epoch [2/4] Batch [3200/6375] Loss: 0.1243
Epoch [2/4] Batch [3250/6375] Loss: 0.1150
Epoch [2/4] Batch [3300/6375] Loss: 0.1453
Epoch [2/4] Batch [3350/6375] Loss: 0.0829
Epoch [2/4] Batch [3400/6375] Loss: 0.4240
Epoch [2/4] Batch [3450/6375] Loss: 0.0158
Epoch [2/4] Batch [3500/6375] Loss: 0.0679
Epoch [2/4] Batch [3550/6375] Loss: 0.0689
Epoch [2/4] Batch [3600/6375] Loss: 0.2735
Epoch [2/4] Batch [3650/6375] Loss: 0.0591
Epoch [2/4] Batch [3700/6375] Loss: 0.2127
Epoch [2/4] Batch [3750/6375] Loss: 0.2823
Epoch [2/4] Batch [3800/6375] Loss: 0.1063
Epoch [2/4] Batch [3850/6375] Loss: 0.0154
Epoch [2/4] Batch [3900/6375] Loss: 0.2065
Epoch [2/4] Batch [3950/6375] Loss: 0.0159
Epoch [2/4] Batch [4000/6375] Loss: 0.3720
Epoch [2/4] Batch [4050/6375] Loss: 0.0093
Epoch [2/4] Batch [4100/6375] Loss: 0.3127
Epoch [2/4] Batch [4150/6375] Loss: 0.0826
Epoch [2/4] Batch [4200/6375] Loss: 0.1106
Epoch [2/4] Batch [4250/6375] Loss: 0.0054
Epoch [2/4] Batch [4300/6375] Loss: 0.0086
Epoch [2/4] Batch [4350/6375] Loss: 0.0204
Epoch [2/4] Batch [4400/6375] Loss: 0.1850
Epoch [2/4] Batch [4450/6375] Loss: 0.6410
Epoch [2/4] Batch [4500/6375] Loss: 0.1370
Epoch [2/4] Batch [4550/6375] Loss: 0.0112
Epoch [2/4] Batch [4600/6375] Loss: 0.4952
Epoch [2/4] Batch [4650/6375] Loss: 0.0618
Epoch [2/4] Batch [4700/6375] Loss: 0.0042
Epoch [2/4] Batch [4750/6375] Loss: 0.2445
Epoch [2/4] Batch [4800/6375] Loss: 0.0159
Epoch [2/4] Batch [4850/6375] Loss: 0.0041
Epoch [2/4] Batch [4900/6375] Loss: 0.0917
Epoch [2/4] Batch [4950/6375] Loss: 0.3334
Epoch [2/4] Batch [5000/6375] Loss: 0.0218
Epoch [2/4] Batch [5050/6375] Loss: 0.0276
Epoch [2/4] Batch [5100/6375] Loss: 0.0618
Epoch [2/4] Batch [5150/6375] Loss: 0.0848
Epoch [2/4] Batch [5200/6375] Loss: 0.0161
Epoch [2/4] Batch [5250/6375] Loss: 0.0055
Epoch [2/4] Batch [5300/6375] Loss: 0.4476
Epoch [2/4] Batch [5350/6375] Loss: 0.4817
Epoch [2/4] Batch [5400/6375] Loss: 0.1177
Epoch [2/4] Batch [5450/6375] Loss: 0.4593
Epoch [2/4] Batch [5500/6375] Loss: 0.2476
```

```
Epoch [2/4] Batch [5550/6375] Loss: 0.5316
Epoch [2/4] Batch [5600/6375] Loss: 0.2605
Epoch [2/4] Batch [5650/6375] Loss: 0.0059
Epoch [2/4] Batch [5700/6375] Loss: 0.4194
Epoch [2/4] Batch [5750/6375] Loss: 0.0054
Epoch [2/4] Batch [5800/6375] Loss: 0.0221
Epoch [2/4] Batch [5850/6375] Loss: 0.0048
Epoch [2/4] Batch [5900/6375] Loss: 0.0382
Epoch [2/4] Batch [5950/6375] Loss: 0.0220
Epoch [2/4] Batch [6000/6375] Loss: 0.0331
Epoch [2/4] Batch [6050/6375] Loss: 0.1440
Epoch [2/4] Batch [6100/6375] Loss: 0.0181
Epoch [2/4] Batch [6150/6375] Loss: 0.0254
Epoch [2/4] Batch [6200/6375] Loss: 0.0042
Epoch [2/4] Batch [6250/6375] Loss: 0.2424
Epoch [2/4] Batch [6300/6375] Loss: 0.0105
Epoch [2/4] Batch [6350/6375] Loss: 0.0532
Trial 9: Epoch 2/4 | Val F1: 0.9472 | Val Loss: 0.1844
Epoch [3/4] Batch [50/6375] Loss: 0.0114
Epoch [3/4] Batch [100/6375] Loss: 0.0721
Epoch [3/4] Batch [150/6375] Loss: 0.2603
Epoch [3/4] Batch [200/6375] Loss: 0.0272
Epoch [3/4] Batch [250/6375] Loss: 0.0086
Epoch [3/4] Batch [300/6375] Loss: 0.2920
Epoch [3/4] Batch [350/6375] Loss: 0.0395
Epoch [3/4] Batch [400/6375] Loss: 0.0064
Epoch [3/4] Batch [450/6375] Loss: 0.3192
Epoch [3/4] Batch [500/6375] Loss: 0.1218
Epoch [3/4] Batch [550/6375] Loss: 0.0084
Epoch [3/4] Batch [600/6375] Loss: 0.0027
Epoch [3/4] Batch [650/6375] Loss: 0.0258
Epoch [3/4] Batch [700/6375] Loss: 0.3741
Epoch [3/4] Batch [750/6375] Loss: 0.0041
Epoch [3/4] Batch [800/6375] Loss: 0.0233
Epoch [3/4] Batch [850/6375] Loss: 0.0190
Epoch [3/4] Batch [900/6375] Loss: 0.0186
Epoch [3/4] Batch [950/6375] Loss: 0.3827
Epoch [3/4] Batch [1000/6375] Loss: 0.0130
Epoch [3/4] Batch [1050/6375] Loss: 0.1256
Epoch [3/4] Batch [1100/6375] Loss: 0.3003
Epoch [3/4] Batch [1150/6375] Loss: 0.0183
Epoch [3/4] Batch [1200/6375] Loss: 0.3468
Epoch [3/4] Batch [1250/6375] Loss: 0.0022
Epoch [3/4] Batch [1300/6375] Loss: 0.2580
Epoch [3/4] Batch [1350/6375] Loss: 0.0112
Epoch [3/4] Batch [1400/6375] Loss: 0.3064
Epoch [3/4] Batch [1450/6375] Loss: 0.0017
Epoch [3/4] Batch [1500/6375] Loss: 0.0153
```

```
Epoch [3/4] Batch [1550/6375] Loss: 0.0101
Epoch [3/4] Batch [1600/6375] Loss: 0.0024
Epoch [3/4] Batch [1650/6375] Loss: 0.0416
Epoch [3/4] Batch [1700/6375] Loss: 0.6377
Epoch [3/4] Batch [1750/6375] Loss: 0.0088
Epoch [3/4] Batch [1800/6375] Loss: 0.1570
Epoch [3/4] Batch [1850/6375] Loss: 0.0490
Epoch [3/4] Batch [1900/6375] Loss: 0.0026
Epoch [3/4] Batch [1950/6375] Loss: 0.1801
Epoch [3/4] Batch [2000/6375] Loss: 0.2848
Epoch [3/4] Batch [2050/6375] Loss: 0.1442
Epoch [3/4] Batch [2100/6375] Loss: 0.0018
Epoch [3/4] Batch [2150/6375] Loss: 0.0073
Epoch [3/4] Batch [2200/6375] Loss: 0.0287
Epoch [3/4] Batch [2250/6375] Loss: 0.1989
Epoch [3/4] Batch [2300/6375] Loss: 0.3450
Epoch [3/4] Batch [2350/6375] Loss: 0.1205
Epoch [3/4] Batch [2400/6375] Loss: 0.1036
Epoch [3/4] Batch [2450/6375] Loss: 0.0098
Epoch [3/4] Batch [2500/6375] Loss: 0.3156
Epoch [3/4] Batch [2550/6375] Loss: 0.2523
Epoch [3/4] Batch [2600/6375] Loss: 0.0056
Epoch [3/4] Batch [2650/6375] Loss: 0.6491
Epoch [3/4] Batch [2700/6375] Loss: 0.3349
Epoch [3/4] Batch [2750/6375] Loss: 0.2410
Epoch [3/4] Batch [2800/6375] Loss: 0.0032
Epoch [3/4] Batch [2850/6375] Loss: 0.0117
Epoch [3/4] Batch [2900/6375] Loss: 0.0015
Epoch [3/4] Batch [2950/6375] Loss: 0.0136
Epoch [3/4] Batch [3000/6375] Loss: 0.0033
Epoch [3/4] Batch [3050/6375] Loss: 0.0661
Epoch [3/4] Batch [3100/6375] Loss: 0.0588
Epoch [3/4] Batch [3150/6375] Loss: 0.0142
Epoch [3/4] Batch [3200/6375] Loss: 0.2102
Epoch [3/4] Batch [3250/6375] Loss: 0.0081
Epoch [3/4] Batch [3300/6375] Loss: 0.0051
Epoch [3/4] Batch [3350/6375] Loss: 0.0070
Epoch [3/4] Batch [3400/6375] Loss: 0.0195
Epoch [3/4] Batch [3450/6375] Loss: 0.0030
Epoch [3/4] Batch [3500/6375] Loss: 0.3401
Epoch [3/4] Batch [3550/6375] Loss: 0.0205
Epoch [3/4] Batch [3600/6375] Loss: 0.1802
Epoch [3/4] Batch [3650/6375] Loss: 0.2952
Epoch [3/4] Batch [3700/6375] Loss: 0.0035
Epoch [3/4] Batch [3750/6375] Loss: 0.0080
Epoch [3/4] Batch [3800/6375] Loss: 0.0068
Epoch [3/4] Batch [3850/6375] Loss: 0.0047
Epoch [3/4] Batch [3900/6375] Loss: 0.0068
```

```
Epoch [3/4] Batch [3950/6375] Loss: 0.0071
Epoch [3/4] Batch [4000/6375] Loss: 0.0109
Epoch [3/4] Batch [4050/6375] Loss: 0.3071
Epoch [3/4] Batch [4100/6375] Loss: 0.1608
Epoch [3/4] Batch [4150/6375] Loss: 0.0034
Epoch [3/4] Batch [4200/6375] Loss: 0.0072
Epoch [3/4] Batch [4250/6375] Loss: 0.1295
Epoch [3/4] Batch [4300/6375] Loss: 0.3354
Epoch [3/4] Batch [4350/6375] Loss: 0.0047
Epoch [3/4] Batch [4400/6375] Loss: 0.2579
Epoch [3/4] Batch [4450/6375] Loss: 0.0479
Epoch [3/4] Batch [4500/6375] Loss: 0.0134
Epoch [3/4] Batch [4550/6375] Loss: 0.0160
Epoch [3/4] Batch [4600/6375] Loss: 0.0045
Epoch [3/4] Batch [4650/6375] Loss: 0.0056
Epoch [3/4] Batch [4700/6375] Loss: 0.2092
Epoch [3/4] Batch [4750/6375] Loss: 0.0049
Epoch [3/4] Batch [4800/6375] Loss: 0.0056
Epoch [3/4] Batch [4850/6375] Loss: 0.1729
Epoch [3/4] Batch [4900/6375] Loss: 0.1244
Epoch [3/4] Batch [4950/6375] Loss: 0.0232
Epoch [3/4] Batch [5000/6375] Loss: 0.0345
Epoch [3/4] Batch [5050/6375] Loss: 0.0045
Epoch [3/4] Batch [5100/6375] Loss: 0.0059
Epoch [3/4] Batch [5150/6375] Loss: 0.3268
Epoch [3/4] Batch [5200/6375] Loss: 0.0216
Epoch [3/4] Batch [5250/6375] Loss: 0.0042
Epoch [3/4] Batch [5300/6375] Loss: 0.0063
Epoch [3/4] Batch [5350/6375] Loss: 0.1615
Epoch [3/4] Batch [5400/6375] Loss: 0.0042
Epoch [3/4] Batch [5450/6375] Loss: 0.0162
Epoch [3/4] Batch [5500/6375] Loss: 0.2063
Epoch [3/4] Batch [5550/6375] Loss: 0.0142
Epoch [3/4] Batch [5600/6375] Loss: 0.0730
Epoch [3/4] Batch [5650/6375] Loss: 0.0028
Epoch [3/4] Batch [5700/6375] Loss: 0.0131
Epoch [3/4] Batch [5750/6375] Loss: 0.2884
Epoch [3/4] Batch [5800/6375] Loss: 0.1529
Epoch [3/4] Batch [5850/6375] Loss: 0.0050
Epoch [3/4] Batch [5900/6375] Loss: 0.1955
Epoch [3/4] Batch [5950/6375] Loss: 0.0035
Epoch [3/4] Batch [6000/6375] Loss: 0.1312
Epoch [3/4] Batch [6050/6375] Loss: 0.0207
Epoch [3/4] Batch [6100/6375] Loss: 0.0020
Epoch [3/4] Batch [6150/6375] Loss: 0.0012
Epoch [3/4] Batch [6200/6375] Loss: 0.0278
Epoch [3/4] Batch [6250/6375] Loss: 0.3310
Epoch [3/4] Batch [6300/6375] Loss: 0.0046
```

```
Epoch [3/4] Batch [6350/6375] Loss: 0.0023
Trial 9: Epoch 3/4 | Val F1: 0.9449 | Val Loss: 0.2144

Best trial: 6
Best F1: 0.9487
Best params: {'learning_rate': 2.8219443464878743e-05, 'batch_size': 64,
'weight_decay': 0.021537846530908268, 'warmup_ratio': 0.04481839946966742}
```

[12]:

```
['results/step6_best_params.pkl']
```

[13]:

```
# 6.6 Train Final Model with Best Hyperparameters



# Load best hyperparameters
best_params = joblib.load(RESULTS_DIR / 'step6_best_params.pkl')

learning_rate = best_params['learning_rate']
batch_size = best_params['batch_size']
weight_decay = best_params['weight_decay']
warmup_ratio = best_params['warmup_ratio']

print(f"Learning Rate: {learning_rate}")
print(f"Batch Size: {batch_size}")
print(f"Weight Decay: {weight_decay}")
print(f"Warmup Ratio: {warmup_ratio}")

# Create model
model = AutoModelForSequenceClassification.from_pretrained(
    MODEL_NAME,
    num_labels=4,
    problem_type='single_label_classification'
).to(DEVICE)

# Create dataloaders with best batch size
final_train_loader = DataLoader(train_dataset, batch_size=batch_size,␣
 ↪shuffle=True)
final_val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)

# Optimizer & Scheduler
optimizer = AdamW(model.parameters(), lr=learning_rate,␣
 ↪weight_decay=weight_decay)

num_training_steps = len(final_train_loader) * 4
num_warmup_steps = int(num_training_steps * warmup_ratio)
scheduler = get_linear_schedule_with_warmup(
    optimizer,
    num_warmup_steps=num_warmup_steps,
```

```
    num_training_steps=num_training_steps
)

scaler = GradScaler(device='cuda')

# Training loop with checkpointing
best_val_f1 = 0.0
training_history = defaultdict(list)

for epoch in range(4):
    train_loss = train_epoch(model, final_train_loader, optimizer, scheduler,␣
↪scaler, DEVICE, epoch, 4)
    val_loss, val_f1, val_acc, _, _ = evaluate(model, final_val_loader, DEVICE)

    training_history['epoch'].append(epoch + 1)
    training_history['train_loss'].append(train_loss)
    training_history['val_loss'].append(val_loss)
    training_history['val_f1'].append(val_f1)
    training_history['val_acc'].append(val_acc)

    print(f"Epoch {epoch+1}/4 | Train Loss: {train_loss:.4f} | Val Loss:␣
↪{val_loss:.4f} | Val F1: {val_f1:.4f} | Val Acc: {val_acc:.4f}")

    # Save checkpoint if best
    if val_f1 > best_val_f1:
        best_val_f1 = val_f1
        model.save_pretrained(MODELS_DIR / 'step6_distilbert_best')
        tokenizer.save_pretrained(MODELS_DIR / 'step6_distilbert_best')
        print(f"Checkpoint saved (F1: {val_f1:.4f})")

print("\nTraining Complete!")
print(f"Best Validation F1: {best_val_f1:.4f}")

# Save training history
history_df = pd.DataFrame(training_history)
history_df.to_csv(RESULTS_DIR / 'step6_training_history.csv', index=False)
```

```
Learning Rate: 2.8219443464878743e-05
Batch Size: 64
Weight Decay: 0.021537846530908268
Warmup Ratio: 0.04481839946966742
```

```
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.
```

```
Epoch [1/4] Batch [50/1594] Loss: 1.3004
Epoch [1/4] Batch [100/1594] Loss: 0.6091
Epoch [1/4] Batch [150/1594] Loss: 0.3182
Epoch [1/4] Batch [200/1594] Loss: 0.3761
Epoch [1/4] Batch [250/1594] Loss: 0.3023
Epoch [1/4] Batch [300/1594] Loss: 0.5146
Epoch [1/4] Batch [350/1594] Loss: 0.2114
Epoch [1/4] Batch [400/1594] Loss: 0.2020
Epoch [1/4] Batch [450/1594] Loss: 0.1664
Epoch [1/4] Batch [500/1594] Loss: 0.1133
Epoch [1/4] Batch [550/1594] Loss: 0.2074
Epoch [1/4] Batch [600/1594] Loss: 0.1607
Epoch [1/4] Batch [650/1594] Loss: 0.2288
Epoch [1/4] Batch [700/1594] Loss: 0.2200
Epoch [1/4] Batch [750/1594] Loss: 0.1388
Epoch [1/4] Batch [800/1594] Loss: 0.3588
Epoch [1/4] Batch [850/1594] Loss: 0.1437
Epoch [1/4] Batch [900/1594] Loss: 0.1700
Epoch [1/4] Batch [950/1594] Loss: 0.1307
Epoch [1/4] Batch [1000/1594] Loss: 0.2112
Epoch [1/4] Batch [1050/1594] Loss: 0.1784
Epoch [1/4] Batch [1100/1594] Loss: 0.1487
Epoch [1/4] Batch [1150/1594] Loss: 0.0426
Epoch [1/4] Batch [1200/1594] Loss: 0.2239
Epoch [1/4] Batch [1250/1594] Loss: 0.1571
Epoch [1/4] Batch [1300/1594] Loss: 0.1950
Epoch [1/4] Batch [1350/1594] Loss: 0.1396
Epoch [1/4] Batch [1400/1594] Loss: 0.1226
Epoch [1/4] Batch [1450/1594] Loss: 0.3669
Epoch [1/4] Batch [1500/1594] Loss: 0.1326
Epoch [1/4] Batch [1550/1594] Loss: 0.2780
Epoch 1/4 | Train Loss: 0.2960 | Val Loss: 0.1689 | Val F1: 0.9427 | Val Acc:
0.9428
Checkpoint saved (F1: 0.9427)
Epoch [2/4] Batch [50/1594] Loss: 0.1877
Epoch [2/4] Batch [100/1594] Loss: 0.1391
Epoch [2/4] Batch [150/1594] Loss: 0.0688
Epoch [2/4] Batch [200/1594] Loss: 0.1403
Epoch [2/4] Batch [250/1594] Loss: 0.1008
Epoch [2/4] Batch [300/1594] Loss: 0.0740
Epoch [2/4] Batch [350/1594] Loss: 0.0447
Epoch [2/4] Batch [400/1594] Loss: 0.1619
Epoch [2/4] Batch [450/1594] Loss: 0.1910
Epoch [2/4] Batch [500/1594] Loss: 0.1439
Epoch [2/4] Batch [550/1594] Loss: 0.2596
Epoch [2/4] Batch [600/1594] Loss: 0.0833
Epoch [2/4] Batch [650/1594] Loss: 0.0586
Epoch [2/4] Batch [700/1594] Loss: 0.0404
```

```
Epoch [2/4] Batch [750/1594] Loss: 0.0976
Epoch [2/4] Batch [800/1594] Loss: 0.1076
Epoch [2/4] Batch [850/1594] Loss: 0.0756
Epoch [2/4] Batch [900/1594] Loss: 0.1044
Epoch [2/4] Batch [950/1594] Loss: 0.1394
Epoch [2/4] Batch [1000/1594] Loss: 0.2146
Epoch [2/4] Batch [1050/1594] Loss: 0.1695
Epoch [2/4] Batch [1100/1594] Loss: 0.1202
Epoch [2/4] Batch [1150/1594] Loss: 0.0786
Epoch [2/4] Batch [1200/1594] Loss: 0.1172
Epoch [2/4] Batch [1250/1594] Loss: 0.1787
Epoch [2/4] Batch [1300/1594] Loss: 0.1086
Epoch [2/4] Batch [1350/1594] Loss: 0.0950
Epoch [2/4] Batch [1400/1594] Loss: 0.0737
Epoch [2/4] Batch [1450/1594] Loss: 0.1904
Epoch [2/4] Batch [1500/1594] Loss: 0.1056
Epoch [2/4] Batch [1550/1594] Loss: 0.1269
Epoch 2/4 | Train Loss: 0.1393 | Val Loss: 0.1617 | Val F1: 0.9459 | Val Acc:
0.9460
Checkpoint saved (F1: 0.9459)
Epoch [3/4] Batch [50/1594] Loss: 0.1034
Epoch [3/4] Batch [100/1594] Loss: 0.0825
Epoch [3/4] Batch [150/1594] Loss: 0.2026
Epoch [3/4] Batch [200/1594] Loss: 0.0526
Epoch [3/4] Batch [250/1594] Loss: 0.0910
Epoch [3/4] Batch [300/1594] Loss: 0.0231
Epoch [3/4] Batch [350/1594] Loss: 0.0389
Epoch [3/4] Batch [400/1594] Loss: 0.0844
Epoch [3/4] Batch [450/1594] Loss: 0.0807
Epoch [3/4] Batch [500/1594] Loss: 0.0776
Epoch [3/4] Batch [550/1594] Loss: 0.0329
Epoch [3/4] Batch [600/1594] Loss: 0.0792
Epoch [3/4] Batch [650/1594] Loss: 0.0935
Epoch [3/4] Batch [700/1594] Loss: 0.0934
Epoch [3/4] Batch [750/1594] Loss: 0.0116
Epoch [3/4] Batch [800/1594] Loss: 0.0467
Epoch [3/4] Batch [850/1594] Loss: 0.1445
Epoch [3/4] Batch [900/1594] Loss: 0.0813
Epoch [3/4] Batch [950/1594] Loss: 0.0579
Epoch [3/4] Batch [1000/1594] Loss: 0.1004
Epoch [3/4] Batch [1050/1594] Loss: 0.0703
Epoch [3/4] Batch [1100/1594] Loss: 0.0301
Epoch [3/4] Batch [1150/1594] Loss: 0.0814
Epoch [3/4] Batch [1200/1594] Loss: 0.0891
Epoch [3/4] Batch [1250/1594] Loss: 0.1023
Epoch [3/4] Batch [1300/1594] Loss: 0.1878
Epoch [3/4] Batch [1350/1594] Loss: 0.1266
Epoch [3/4] Batch [1400/1594] Loss: 0.0238
```

```
Epoch [3/4] Batch [1450/1594] Loss: 0.0319
Epoch [3/4] Batch [1500/1594] Loss: 0.0357
Epoch [3/4] Batch [1550/1594] Loss: 0.1383
Epoch 3/4 | Train Loss: 0.0941 | Val Loss: 0.1717 | Val F1: 0.9471 | Val Acc:
0.9471
Checkpoint saved (F1: 0.9471)
Epoch [4/4] Batch [50/1594] Loss: 0.0210
Epoch [4/4] Batch [100/1594] Loss: 0.0113
Epoch [4/4] Batch [150/1594] Loss: 0.0115
Epoch [4/4] Batch [200/1594] Loss: 0.0411
Epoch [4/4] Batch [250/1594] Loss: 0.0578
Epoch [4/4] Batch [300/1594] Loss: 0.0784
Epoch [4/4] Batch [350/1594] Loss: 0.0765
Epoch [4/4] Batch [400/1594] Loss: 0.0641
Epoch [4/4] Batch [450/1594] Loss: 0.0359
Epoch [4/4] Batch [500/1594] Loss: 0.0615
Epoch [4/4] Batch [550/1594] Loss: 0.0406
Epoch [4/4] Batch [600/1594] Loss: 0.0257
Epoch [4/4] Batch [650/1594] Loss: 0.1328
Epoch [4/4] Batch [700/1594] Loss: 0.0654
Epoch [4/4] Batch [750/1594] Loss: 0.0323
Epoch [4/4] Batch [800/1594] Loss: 0.0252
Epoch [4/4] Batch [850/1594] Loss: 0.0260
Epoch [4/4] Batch [900/1594] Loss: 0.0753
Epoch [4/4] Batch [950/1594] Loss: 0.1595
Epoch [4/4] Batch [1000/1594] Loss: 0.0993
Epoch [4/4] Batch [1050/1594] Loss: 0.1591
Epoch [4/4] Batch [1100/1594] Loss: 0.0724
Epoch [4/4] Batch [1150/1594] Loss: 0.0344
Epoch [4/4] Batch [1200/1594] Loss: 0.0882
Epoch [4/4] Batch [1250/1594] Loss: 0.0102
Epoch [4/4] Batch [1300/1594] Loss: 0.0461
Epoch [4/4] Batch [1350/1594] Loss: 0.1418
Epoch [4/4] Batch [1400/1594] Loss: 0.2867
Epoch [4/4] Batch [1450/1594] Loss: 0.0213
Epoch [4/4] Batch [1500/1594] Loss: 0.0907
Epoch [4/4] Batch [1550/1594] Loss: 0.0064
Epoch 4/4 | Train Loss: 0.0635 | Val Loss: 0.1894 | Val F1: 0.9466 | Val Acc:
0.9467

Training Complete!
Best Validation F1: 0.9471
```

[14]:
```python
# 6.7 Final Test Set Evaluation



# Load best model
```

```
best_model = AutoModelForSequenceClassification.from_pretrained(
    MODELS_DIR / 'step6_distilbert_best'
).to(DEVICE)

# Evaluate on test set
test_loss, test_f1, test_acc, test_preds, test_labels = evaluate(best_model,␣
↪test_loader, DEVICE)

print(f"Test Loss: {test_loss:.4f}")
print(f"Test Macro-F1: {test_f1:.4f}")
print(f"Test Accuracy: {test_acc:.4f}")

# Classification report
print("\nClassification Report:")
class_names = ['World', 'Sports', 'Business', 'Sci/Tech']
print(classification_report(test_labels, test_preds, target_names=class_names,␣
↪digits=4))

# Confusion matrix
conf_matrix = confusion_matrix(test_labels, test_preds)
print("\nConfusion Matrix:")
print(conf_matrix)

# Save results
results = {
    'test_loss': test_loss,
    'test_macro_f1': test_f1,
    'test_accuracy': test_acc,
    'test_predictions': test_preds,
    'test_labels': test_labels,
    'confusion_matrix': conf_matrix
}

joblib.dump(results, RESULTS_DIR / 'step6_test_results.pkl')
print("\nResults saved.")
```

```
Test Loss: 0.1818
Test Macro-F1: 0.9423
Test Accuracy: 0.9422

Classification Report:
              precision    recall  f1-score   support

       World     0.9606    0.9489    0.9547      1900
      Sports     0.9853    0.9879    0.9866      1900
    Business     0.9064    0.9179    0.9121      1900
    Sci/Tech     0.9171    0.9142    0.9157      1900
```

```
    accuracy                         0.9422      7600
   macro avg     0.9424    0.9422    0.9423      7600
weighted avg     0.9424    0.9422    0.9423      7600


Confusion Matrix:
[[1803   14   47   36]
 [  10 1877    7    6]
 [  36    5 1744  115]
 [  28    9  126 1737]]

Results saved.
```

[15]:

```python
# 6.8 Ablation 1: Frozen Embeddings vs. Full Fine-Tuning



ablation_results = {}

# Scenario 1: Freeze all DistilBERT layers, train only classification head
print("\n1. Frozen DistilBERT (only train classification head)...")
model_frozen = AutoModelForSequenceClassification.from_pretrained(MODEL_NAME,␣
 ↪num_labels=4).to(DEVICE)

for param in model_frozen.distilbert.parameters():
    param.requires_grad = False

optimizer_frozen = AdamW(model_frozen.parameters(), lr=2e-4, weight_decay=0.01)
scaler_frozen = GradScaler(device='cuda')

best_frozen_f1 = 0.0
for epoch in range(2):  # Fewer epochs for frozen
    train_loss = train_epoch(model_frozen, final_train_loader,␣
 ↪optimizer_frozen, scheduler, scaler_frozen, DEVICE, epoch, 2)
    val_loss, val_f1, val_acc, _, _ = evaluate(model_frozen, final_val_loader,␣
 ↪DEVICE)
    print(f"Epoch {epoch+1}: Val F1: {val_f1:.4f}")
    best_frozen_f1 = max(best_frozen_f1, val_f1)

ablation_results['frozen_f1'] = best_frozen_f1
print(f"Frozen Model Best F1: {best_frozen_f1:.4f}")

# Scenario 2: Full fine-tuning (already done above)
ablation_results['full_tuning_f1'] = best_val_f1
print(f"Full Fine-Tuning Best F1: {best_val_f1:.4f}")

# Comparison
```

```python
gain = best_val_f1 - best_frozen_f1
print(f"\nGain from Full Fine-Tuning: {gain:.4f} ({gain*100:.2f}%)")

joblib.dump(ablation_results, RESULTS_DIR / 'step6_ablation_frozen_vs_tuned.
↪pkl')
```

```
1. Frozen DistilBERT (only train classification head)…
```

```
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.
```

```
Epoch [1/2] Batch [50/1594] Loss: 0.4481
Epoch [1/2] Batch [100/1594] Loss: 0.4780
Epoch [1/2] Batch [150/1594] Loss: 0.2372
Epoch [1/2] Batch [200/1594] Loss: 0.4479
Epoch [1/2] Batch [250/1594] Loss: 0.3457
Epoch [1/2] Batch [300/1594] Loss: 0.3995
Epoch [1/2] Batch [350/1594] Loss: 0.3741
Epoch [1/2] Batch [400/1594] Loss: 0.3730
Epoch [1/2] Batch [450/1594] Loss: 0.4120
Epoch [1/2] Batch [500/1594] Loss: 0.2431
Epoch [1/2] Batch [550/1594] Loss: 0.3817
Epoch [1/2] Batch [600/1594] Loss: 0.3543
Epoch [1/2] Batch [650/1594] Loss: 0.2669
Epoch [1/2] Batch [700/1594] Loss: 0.3007
Epoch [1/2] Batch [750/1594] Loss: 0.1818
Epoch [1/2] Batch [800/1594] Loss: 0.2533
Epoch [1/2] Batch [850/1594] Loss: 0.2527
Epoch [1/2] Batch [900/1594] Loss: 0.2087
Epoch [1/2] Batch [950/1594] Loss: 0.2897
Epoch [1/2] Batch [1000/1594] Loss: 0.2632
Epoch [1/2] Batch [1050/1594] Loss: 0.3365
Epoch [1/2] Batch [1100/1594] Loss: 0.3479
Epoch [1/2] Batch [1150/1594] Loss: 0.1305
Epoch [1/2] Batch [1200/1594] Loss: 0.2014
Epoch [1/2] Batch [1250/1594] Loss: 0.4334
Epoch [1/2] Batch [1300/1594] Loss: 0.2709
Epoch [1/2] Batch [1350/1594] Loss: 0.1480
Epoch [1/2] Batch [1400/1594] Loss: 0.0948
Epoch [1/2] Batch [1450/1594] Loss: 0.1811
Epoch [1/2] Batch [1500/1594] Loss: 0.3636
Epoch [1/2] Batch [1550/1594] Loss: 0.1549
Epoch 1: Val F1: 0.9017
Epoch [2/2] Batch [50/1594] Loss: 0.1858
```

```
Epoch [2/2] Batch [100/1594] Loss: 0.2099
Epoch [2/2] Batch [150/1594] Loss: 0.4180
Epoch [2/2] Batch [200/1594] Loss: 0.2662
Epoch [2/2] Batch [250/1594] Loss: 0.1477
Epoch [2/2] Batch [300/1594] Loss: 0.1566
Epoch [2/2] Batch [350/1594] Loss: 0.2202
Epoch [2/2] Batch [400/1594] Loss: 0.3518
Epoch [2/2] Batch [450/1594] Loss: 0.1670
Epoch [2/2] Batch [500/1594] Loss: 0.2765
Epoch [2/2] Batch [550/1594] Loss: 0.2865
Epoch [2/2] Batch [600/1594] Loss: 0.2529
Epoch [2/2] Batch [650/1594] Loss: 0.1944
Epoch [2/2] Batch [700/1594] Loss: 0.4452
Epoch [2/2] Batch [750/1594] Loss: 0.1447
Epoch [2/2] Batch [800/1594] Loss: 0.2706
Epoch [2/2] Batch [850/1594] Loss: 0.3085
Epoch [2/2] Batch [900/1594] Loss: 0.2601
Epoch [2/2] Batch [950/1594] Loss: 0.1143
Epoch [2/2] Batch [1000/1594] Loss: 0.2633
Epoch [2/2] Batch [1050/1594] Loss: 0.2136
Epoch [2/2] Batch [1100/1594] Loss: 0.1929
Epoch [2/2] Batch [1150/1594] Loss: 0.2972
Epoch [2/2] Batch [1200/1594] Loss: 0.1594
Epoch [2/2] Batch [1250/1594] Loss: 0.1591
Epoch [2/2] Batch [1300/1594] Loss: 0.4004
Epoch [2/2] Batch [1350/1594] Loss: 0.3292
Epoch [2/2] Batch [1400/1594] Loss: 0.3528
Epoch [2/2] Batch [1450/1594] Loss: 0.2574
Epoch [2/2] Batch [1500/1594] Loss: 0.3150
Epoch [2/2] Batch [1550/1594] Loss: 0.3388
Epoch 2: Val F1: 0.9087
Frozen Model Best F1: 0.9087
Full Fine-Tuning Best F1: 0.9471

Gain from Full Fine-Tuning: 0.0383 (3.83%)
```

[15]:

```
['results/step6_ablation_frozen_vs_tuned.pkl']
```

[16]:

```python
# 6.9 Ablation 2: Max Sequence Length Impact



max_lengths = [128, 256, 512]
length_results = {}

for max_len in max_lengths:
    print(f"\nTesting MAX_LENGTH = {max_len}...")
```

```
    # Re-tokenize
    temp_train_enc = tokenizer(
        X_train_text.tolist(),
        truncation=True,
        padding='max_length',
        max_length=max_len,
        return_tensors='pt'
    )

    temp_val_enc = tokenizer(
        X_val_text.tolist(),
        truncation=True,
        padding='max_length',
        max_length=max_len,
        return_tensors='pt'
    )

    temp_train_dataset = NewsDataset(temp_train_enc, y_train)
    temp_val_dataset = NewsDataset(temp_val_enc, y_val)

    temp_train_loader = DataLoader(temp_train_dataset, batch_size=32,␣
↪shuffle=True)
    temp_val_loader = DataLoader(temp_val_dataset, batch_size=32, shuffle=False)

    # Quick 2-epoch training
    model_temp = AutoModelForSequenceClassification.from_pretrained(MODEL_NAME,␣
↪num_labels=4).to(DEVICE)
    optimizer_temp = AdamW(model_temp.parameters(), lr=learning_rate,␣
↪weight_decay=weight_decay)
    scaler_temp = GradScaler(device='cuda')

    best_f1_temp = 0.0
    for epoch in range(2):
        train_loss = train_epoch(model_temp, temp_train_loader, optimizer_temp,␣
↪scheduler, scaler_temp, DEVICE, epoch, 2)
        val_loss, val_f1, val_acc, _, _ = evaluate(model_temp, temp_val_loader,␣
↪DEVICE)
        best_f1_temp = max(best_f1_temp, val_f1)

    length_results[max_len] = best_f1_temp
    print(f"Max Length {max_len}: Best Val F1 = {best_f1_temp:.4f}")

joblib.dump(length_results, RESULTS_DIR / 'step6_ablation_sequence_length.pkl')
print(f"\nSequence Length Results: {length_results}")
```

```
Testing MAX_LENGTH = 128…
```

```
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.

Epoch [1/2] Batch [50/3188] Loss: 0.3548
Epoch [1/2] Batch [100/3188] Loss: 0.4136
Epoch [1/2] Batch [150/3188] Loss: 0.1985
Epoch [1/2] Batch [200/3188] Loss: 0.4134
Epoch [1/2] Batch [250/3188] Loss: 0.3583
Epoch [1/2] Batch [300/3188] Loss: 0.4257
Epoch [1/2] Batch [350/3188] Loss: 0.2784
Epoch [1/2] Batch [400/3188] Loss: 0.3622
Epoch [1/2] Batch [450/3188] Loss: 0.3804
Epoch [1/2] Batch [500/3188] Loss: 0.2374
Epoch [1/2] Batch [550/3188] Loss: 0.6169
Epoch [1/2] Batch [600/3188] Loss: 0.4351
Epoch [1/2] Batch [650/3188] Loss: 0.1685
Epoch [1/2] Batch [700/3188] Loss: 0.1212
Epoch [1/2] Batch [750/3188] Loss: 0.1415
Epoch [1/2] Batch [800/3188] Loss: 0.3537
Epoch [1/2] Batch [850/3188] Loss: 0.1776
Epoch [1/2] Batch [900/3188] Loss: 0.2954
Epoch [1/2] Batch [950/3188] Loss: 0.4112
Epoch [1/2] Batch [1000/3188] Loss: 0.0660
Epoch [1/2] Batch [1050/3188] Loss: 0.5133
Epoch [1/2] Batch [1100/3188] Loss: 0.2524
Epoch [1/2] Batch [1150/3188] Loss: 0.2792
Epoch [1/2] Batch [1200/3188] Loss: 0.2060
Epoch [1/2] Batch [1250/3188] Loss: 0.0305
Epoch [1/2] Batch [1300/3188] Loss: 0.0960
Epoch [1/2] Batch [1350/3188] Loss: 0.4296
Epoch [1/2] Batch [1400/3188] Loss: 0.1250
Epoch [1/2] Batch [1450/3188] Loss: 0.4246
Epoch [1/2] Batch [1500/3188] Loss: 0.1371
Epoch [1/2] Batch [1550/3188] Loss: 0.5034
Epoch [1/2] Batch [1600/3188] Loss: 0.2574
Epoch [1/2] Batch [1650/3188] Loss: 0.3293
Epoch [1/2] Batch [1700/3188] Loss: 0.3346
Epoch [1/2] Batch [1750/3188] Loss: 0.1988
Epoch [1/2] Batch [1800/3188] Loss: 0.0871
Epoch [1/2] Batch [1850/3188] Loss: 0.3175
Epoch [1/2] Batch [1900/3188] Loss: 0.0287
Epoch [1/2] Batch [1950/3188] Loss: 0.0999
Epoch [1/2] Batch [2000/3188] Loss: 0.1278
Epoch [1/2] Batch [2050/3188] Loss: 0.1466
```

```
Epoch [1/2] Batch [2100/3188] Loss: 0.1281
Epoch [1/2] Batch [2150/3188] Loss: 0.3606
Epoch [1/2] Batch [2200/3188] Loss: 0.3599
Epoch [1/2] Batch [2250/3188] Loss: 0.2940
Epoch [1/2] Batch [2300/3188] Loss: 0.2631
Epoch [1/2] Batch [2350/3188] Loss: 0.0803
Epoch [1/2] Batch [2400/3188] Loss: 0.1453
Epoch [1/2] Batch [2450/3188] Loss: 0.0521
Epoch [1/2] Batch [2500/3188] Loss: 0.4489
Epoch [1/2] Batch [2550/3188] Loss: 0.0325
Epoch [1/2] Batch [2600/3188] Loss: 0.0938
Epoch [1/2] Batch [2650/3188] Loss: 0.3716
Epoch [1/2] Batch [2700/3188] Loss: 0.2800
Epoch [1/2] Batch [2750/3188] Loss: 0.3726
Epoch [1/2] Batch [2800/3188] Loss: 0.1692
Epoch [1/2] Batch [2850/3188] Loss: 0.3529
Epoch [1/2] Batch [2900/3188] Loss: 0.1569
Epoch [1/2] Batch [2950/3188] Loss: 0.3958
Epoch [1/2] Batch [3000/3188] Loss: 0.0427
Epoch [1/2] Batch [3050/3188] Loss: 0.2326
Epoch [1/2] Batch [3100/3188] Loss: 0.3109
Epoch [1/2] Batch [3150/3188] Loss: 0.1598
Epoch [2/2] Batch [50/3188] Loss: 0.0646
Epoch [2/2] Batch [100/3188] Loss: 0.2456
Epoch [2/2] Batch [150/3188] Loss: 0.0168
Epoch [2/2] Batch [200/3188] Loss: 0.0708
Epoch [2/2] Batch [250/3188] Loss: 0.0817
Epoch [2/2] Batch [300/3188] Loss: 0.0698
Epoch [2/2] Batch [350/3188] Loss: 0.1043
Epoch [2/2] Batch [400/3188] Loss: 0.1169
Epoch [2/2] Batch [450/3188] Loss: 0.0670
Epoch [2/2] Batch [500/3188] Loss: 0.1727
Epoch [2/2] Batch [550/3188] Loss: 0.2949
Epoch [2/2] Batch [600/3188] Loss: 0.0702
Epoch [2/2] Batch [650/3188] Loss: 0.0295
Epoch [2/2] Batch [700/3188] Loss: 0.2718
Epoch [2/2] Batch [750/3188] Loss: 0.1157
Epoch [2/2] Batch [800/3188] Loss: 0.0980
Epoch [2/2] Batch [850/3188] Loss: 0.0584
Epoch [2/2] Batch [900/3188] Loss: 0.0208
Epoch [2/2] Batch [950/3188] Loss: 0.2047
Epoch [2/2] Batch [1000/3188] Loss: 0.3353
Epoch [2/2] Batch [1050/3188] Loss: 0.0607
Epoch [2/2] Batch [1100/3188] Loss: 0.3917
Epoch [2/2] Batch [1150/3188] Loss: 0.0384
Epoch [2/2] Batch [1200/3188] Loss: 0.5134
Epoch [2/2] Batch [1250/3188] Loss: 0.0891
Epoch [2/2] Batch [1300/3188] Loss: 0.4077
```

```
Epoch [2/2] Batch [1350/3188] Loss: 0.0274
Epoch [2/2] Batch [1400/3188] Loss: 0.0810
Epoch [2/2] Batch [1450/3188] Loss: 0.1719
Epoch [2/2] Batch [1500/3188] Loss: 0.1134
Epoch [2/2] Batch [1550/3188] Loss: 0.1232
Epoch [2/2] Batch [1600/3188] Loss: 0.1613
Epoch [2/2] Batch [1650/3188] Loss: 0.0936
Epoch [2/2] Batch [1700/3188] Loss: 0.1155
Epoch [2/2] Batch [1750/3188] Loss: 0.1202
Epoch [2/2] Batch [1800/3188] Loss: 0.3837
Epoch [2/2] Batch [1850/3188] Loss: 0.1182
Epoch [2/2] Batch [1900/3188] Loss: 0.0836
Epoch [2/2] Batch [1950/3188] Loss: 0.1808
Epoch [2/2] Batch [2000/3188] Loss: 0.2526
Epoch [2/2] Batch [2050/3188] Loss: 0.1875
Epoch [2/2] Batch [2100/3188] Loss: 0.1460
Epoch [2/2] Batch [2150/3188] Loss: 0.1575
Epoch [2/2] Batch [2200/3188] Loss: 0.1726
Epoch [2/2] Batch [2250/3188] Loss: 0.1718
Epoch [2/2] Batch [2300/3188] Loss: 0.3352
Epoch [2/2] Batch [2350/3188] Loss: 0.4135
Epoch [2/2] Batch [2400/3188] Loss: 0.2274
Epoch [2/2] Batch [2450/3188] Loss: 0.1742
Epoch [2/2] Batch [2500/3188] Loss: 0.1429
Epoch [2/2] Batch [2550/3188] Loss: 0.0587
Epoch [2/2] Batch [2600/3188] Loss: 0.1656
Epoch [2/2] Batch [2650/3188] Loss: 0.1064
Epoch [2/2] Batch [2700/3188] Loss: 0.0047
Epoch [2/2] Batch [2750/3188] Loss: 0.1351
Epoch [2/2] Batch [2800/3188] Loss: 0.3279
Epoch [2/2] Batch [2850/3188] Loss: 0.1855
Epoch [2/2] Batch [2900/3188] Loss: 0.0422
Epoch [2/2] Batch [2950/3188] Loss: 0.1324
Epoch [2/2] Batch [3000/3188] Loss: 0.1070
Epoch [2/2] Batch [3050/3188] Loss: 0.0380
Epoch [2/2] Batch [3100/3188] Loss: 0.1180
Epoch [2/2] Batch [3150/3188] Loss: 0.0724
Max Length 128: Best Val F1 = 0.9420

Testing MAX_LENGTH = 256…

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.

Epoch [1/2] Batch [50/3188] Loss: 0.5544
```

```
Epoch [1/2] Batch [100/3188] Loss: 0.2415
Epoch [1/2] Batch [150/3188] Loss: 0.3941
Epoch [1/2] Batch [200/3188] Loss: 0.4168
Epoch [1/2] Batch [250/3188] Loss: 0.2073
Epoch [1/2] Batch [300/3188] Loss: 0.6041
Epoch [1/2] Batch [350/3188] Loss: 0.3664
Epoch [1/2] Batch [400/3188] Loss: 0.1065
Epoch [1/2] Batch [450/3188] Loss: 0.0584
Epoch [1/2] Batch [500/3188] Loss: 0.0737
Epoch [1/2] Batch [550/3188] Loss: 0.6780
Epoch [1/2] Batch [600/3188] Loss: 0.2507
Epoch [1/2] Batch [650/3188] Loss: 0.3120
Epoch [1/2] Batch [700/3188] Loss: 0.5305
Epoch [1/2] Batch [750/3188] Loss: 0.0719
Epoch [1/2] Batch [800/3188] Loss: 0.3655
Epoch [1/2] Batch [850/3188] Loss: 0.1167
Epoch [1/2] Batch [900/3188] Loss: 0.2603
Epoch [1/2] Batch [950/3188] Loss: 0.1351
Epoch [1/2] Batch [1000/3188] Loss: 0.1779
Epoch [1/2] Batch [1050/3188] Loss: 0.2989
Epoch [1/2] Batch [1100/3188] Loss: 0.1538
Epoch [1/2] Batch [1150/3188] Loss: 0.1468
Epoch [1/2] Batch [1200/3188] Loss: 0.0984
Epoch [1/2] Batch [1250/3188] Loss: 0.1679
Epoch [1/2] Batch [1300/3188] Loss: 0.1126
Epoch [1/2] Batch [1350/3188] Loss: 0.3024
Epoch [1/2] Batch [1400/3188] Loss: 0.3858
Epoch [1/2] Batch [1450/3188] Loss: 0.2435
Epoch [1/2] Batch [1500/3188] Loss: 0.1104
Epoch [1/2] Batch [1550/3188] Loss: 0.1687
Epoch [1/2] Batch [1600/3188] Loss: 0.1770
Epoch [1/2] Batch [1650/3188] Loss: 0.1622
Epoch [1/2] Batch [1700/3188] Loss: 0.1719
Epoch [1/2] Batch [1750/3188] Loss: 0.0587
Epoch [1/2] Batch [1800/3188] Loss: 0.0955
Epoch [1/2] Batch [1850/3188] Loss: 0.1116
Epoch [1/2] Batch [1900/3188] Loss: 0.2692
Epoch [1/2] Batch [1950/3188] Loss: 0.1844
Epoch [1/2] Batch [2000/3188] Loss: 0.2152
Epoch [1/2] Batch [2050/3188] Loss: 0.1964
Epoch [1/2] Batch [2100/3188] Loss: 0.0747
Epoch [1/2] Batch [2150/3188] Loss: 0.2815
Epoch [1/2] Batch [2200/3188] Loss: 0.5011
Epoch [1/2] Batch [2250/3188] Loss: 0.1919
Epoch [1/2] Batch [2300/3188] Loss: 0.2414
Epoch [1/2] Batch [2350/3188] Loss: 0.0978
Epoch [1/2] Batch [2400/3188] Loss: 0.1735
Epoch [1/2] Batch [2450/3188] Loss: 0.3043
```

```
Epoch [1/2] Batch [2500/3188] Loss: 0.1868
Epoch [1/2] Batch [2550/3188] Loss: 0.4983
Epoch [1/2] Batch [2600/3188] Loss: 0.2445
Epoch [1/2] Batch [2650/3188] Loss: 0.1048
Epoch [1/2] Batch [2700/3188] Loss: 0.1956
Epoch [1/2] Batch [2750/3188] Loss: 0.0938
Epoch [1/2] Batch [2800/3188] Loss: 0.2265
Epoch [1/2] Batch [2850/3188] Loss: 0.1633
Epoch [1/2] Batch [2900/3188] Loss: 0.2983
Epoch [1/2] Batch [2950/3188] Loss: 0.0714
Epoch [1/2] Batch [3000/3188] Loss: 0.0925
Epoch [1/2] Batch [3050/3188] Loss: 0.2269
Epoch [1/2] Batch [3100/3188] Loss: 0.1486
Epoch [1/2] Batch [3150/3188] Loss: 0.2309
Epoch [2/2] Batch [50/3188] Loss: 0.0869
Epoch [2/2] Batch [100/3188] Loss: 0.0270
Epoch [2/2] Batch [150/3188] Loss: 0.5019
Epoch [2/2] Batch [200/3188] Loss: 0.0160
Epoch [2/2] Batch [250/3188] Loss: 0.1050
Epoch [2/2] Batch [300/3188] Loss: 0.0759
Epoch [2/2] Batch [350/3188] Loss: 0.3716
Epoch [2/2] Batch [400/3188] Loss: 0.1767
Epoch [2/2] Batch [450/3188] Loss: 0.1991
Epoch [2/2] Batch [500/3188] Loss: 0.2103
Epoch [2/2] Batch [550/3188] Loss: 0.3328
Epoch [2/2] Batch [600/3188] Loss: 0.3625
Epoch [2/2] Batch [650/3188] Loss: 0.1950
Epoch [2/2] Batch [700/3188] Loss: 0.0738
Epoch [2/2] Batch [750/3188] Loss: 0.1999
Epoch [2/2] Batch [800/3188] Loss: 0.0119
Epoch [2/2] Batch [850/3188] Loss: 0.1340
Epoch [2/2] Batch [900/3188] Loss: 0.1559
Epoch [2/2] Batch [950/3188] Loss: 0.0232
Epoch [2/2] Batch [1000/3188] Loss: 0.3417
Epoch [2/2] Batch [1050/3188] Loss: 0.1610
Epoch [2/2] Batch [1100/3188] Loss: 0.0280
Epoch [2/2] Batch [1150/3188] Loss: 0.2547
Epoch [2/2] Batch [1200/3188] Loss: 0.2907
Epoch [2/2] Batch [1250/3188] Loss: 0.0560
Epoch [2/2] Batch [1300/3188] Loss: 0.2890
Epoch [2/2] Batch [1350/3188] Loss: 0.0827
Epoch [2/2] Batch [1400/3188] Loss: 0.0117
Epoch [2/2] Batch [1450/3188] Loss: 0.1839
Epoch [2/2] Batch [1500/3188] Loss: 0.0494
Epoch [2/2] Batch [1550/3188] Loss: 0.0723
Epoch [2/2] Batch [1600/3188] Loss: 0.0820
Epoch [2/2] Batch [1650/3188] Loss: 0.0552
Epoch [2/2] Batch [1700/3188] Loss: 0.2367
```

```
Epoch [2/2] Batch [1750/3188] Loss: 0.0819
Epoch [2/2] Batch [1800/3188] Loss: 0.1984
Epoch [2/2] Batch [1850/3188] Loss: 0.0715
Epoch [2/2] Batch [1900/3188] Loss: 0.0812
Epoch [2/2] Batch [1950/3188] Loss: 0.0165
Epoch [2/2] Batch [2000/3188] Loss: 0.3168
Epoch [2/2] Batch [2050/3188] Loss: 0.2568
Epoch [2/2] Batch [2100/3188] Loss: 0.2468
Epoch [2/2] Batch [2150/3188] Loss: 0.2911
Epoch [2/2] Batch [2200/3188] Loss: 0.2122
Epoch [2/2] Batch [2250/3188] Loss: 0.0276
Epoch [2/2] Batch [2300/3188] Loss: 0.1562
Epoch [2/2] Batch [2350/3188] Loss: 0.2705
Epoch [2/2] Batch [2400/3188] Loss: 0.3083
Epoch [2/2] Batch [2450/3188] Loss: 0.0721
Epoch [2/2] Batch [2500/3188] Loss: 0.1288
Epoch [2/2] Batch [2550/3188] Loss: 0.2573
Epoch [2/2] Batch [2600/3188] Loss: 0.0902
Epoch [2/2] Batch [2650/3188] Loss: 0.0846
Epoch [2/2] Batch [2700/3188] Loss: 0.0617
Epoch [2/2] Batch [2750/3188] Loss: 0.0065
Epoch [2/2] Batch [2800/3188] Loss: 0.1505
Epoch [2/2] Batch [2850/3188] Loss: 0.0916
Epoch [2/2] Batch [2900/3188] Loss: 0.1727
Epoch [2/2] Batch [2950/3188] Loss: 0.2530
Epoch [2/2] Batch [3000/3188] Loss: 0.0639
Epoch [2/2] Batch [3050/3188] Loss: 0.1753
Epoch [2/2] Batch [3100/3188] Loss: 0.0828
Epoch [2/2] Batch [3150/3188] Loss: 0.1226
Max Length 256: Best Val F1 = 0.9465

Testing MAX_LENGTH = 512…

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.

Epoch [1/2] Batch [50/3188] Loss: 0.5616
Epoch [1/2] Batch [100/3188] Loss: 0.2703
Epoch [1/2] Batch [150/3188] Loss: 0.7215
Epoch [1/2] Batch [200/3188] Loss: 0.3663
Epoch [1/2] Batch [250/3188] Loss: 0.4736
Epoch [1/2] Batch [300/3188] Loss: 0.0952
Epoch [1/2] Batch [350/3188] Loss: 0.1000
Epoch [1/2] Batch [400/3188] Loss: 0.2248
Epoch [1/2] Batch [450/3188] Loss: 0.1906
```

```
Epoch [1/2] Batch [500/3188] Loss: 0.0929
Epoch [1/2] Batch [550/3188] Loss: 0.1641
Epoch [1/2] Batch [600/3188] Loss: 0.1670
Epoch [1/2] Batch [650/3188] Loss: 0.3587
Epoch [1/2] Batch [700/3188] Loss: 0.1807
Epoch [1/2] Batch [750/3188] Loss: 0.2298
Epoch [1/2] Batch [800/3188] Loss: 0.2432
Epoch [1/2] Batch [850/3188] Loss: 0.0831
Epoch [1/2] Batch [900/3188] Loss: 0.2770
Epoch [1/2] Batch [950/3188] Loss: 0.1582
Epoch [1/2] Batch [1000/3188] Loss: 0.1818
Epoch [1/2] Batch [1050/3188] Loss: 0.2704
Epoch [1/2] Batch [1100/3188] Loss: 0.2807
Epoch [1/2] Batch [1150/3188] Loss: 0.2244
Epoch [1/2] Batch [1200/3188] Loss: 0.3325
Epoch [1/2] Batch [1250/3188] Loss: 0.2628
Epoch [1/2] Batch [1300/3188] Loss: 0.3970
Epoch [1/2] Batch [1350/3188] Loss: 0.1266
Epoch [1/2] Batch [1400/3188] Loss: 0.4354
Epoch [1/2] Batch [1450/3188] Loss: 0.4370
Epoch [1/2] Batch [1500/3188] Loss: 0.2084
Epoch [1/2] Batch [1550/3188] Loss: 0.3239
Epoch [1/2] Batch [1600/3188] Loss: 0.1383
Epoch [1/2] Batch [1650/3188] Loss: 0.0789
Epoch [1/2] Batch [1700/3188] Loss: 0.2213
Epoch [1/2] Batch [1750/3188] Loss: 0.6380
Epoch [1/2] Batch [1800/3188] Loss: 0.1570
Epoch [1/2] Batch [1850/3188] Loss: 0.4698
Epoch [1/2] Batch [1900/3188] Loss: 0.3199
Epoch [1/2] Batch [1950/3188] Loss: 0.2411
Epoch [1/2] Batch [2000/3188] Loss: 0.3240
Epoch [1/2] Batch [2050/3188] Loss: 0.0718
Epoch [1/2] Batch [2100/3188] Loss: 0.1337
Epoch [1/2] Batch [2150/3188] Loss: 0.1717
Epoch [1/2] Batch [2200/3188] Loss: 0.3796
Epoch [1/2] Batch [2250/3188] Loss: 0.0576
Epoch [1/2] Batch [2300/3188] Loss: 0.1070
Epoch [1/2] Batch [2350/3188] Loss: 0.1936
Epoch [1/2] Batch [2400/3188] Loss: 0.2224
Epoch [1/2] Batch [2450/3188] Loss: 0.5176
Epoch [1/2] Batch [2500/3188] Loss: 0.2008
Epoch [1/2] Batch [2550/3188] Loss: 0.2319
Epoch [1/2] Batch [2600/3188] Loss: 0.1158
Epoch [1/2] Batch [2650/3188] Loss: 0.2484
Epoch [1/2] Batch [2700/3188] Loss: 0.1563
Epoch [1/2] Batch [2750/3188] Loss: 0.0969
Epoch [1/2] Batch [2800/3188] Loss: 0.3402
Epoch [1/2] Batch [2850/3188] Loss: 0.1000
```

```
Epoch [1/2] Batch [2900/3188] Loss: 0.1949
Epoch [1/2] Batch [2950/3188] Loss: 0.2209
Epoch [1/2] Batch [3000/3188] Loss: 0.0546
Epoch [1/2] Batch [3050/3188] Loss: 0.1655
Epoch [1/2] Batch [3100/3188] Loss: 0.0879
Epoch [1/2] Batch [3150/3188] Loss: 0.1878
Epoch [2/2] Batch [50/3188] Loss: 0.0636
Epoch [2/2] Batch [100/3188] Loss: 0.1926
Epoch [2/2] Batch [150/3188] Loss: 0.0332
Epoch [2/2] Batch [200/3188] Loss: 0.3132
Epoch [2/2] Batch [250/3188] Loss: 0.1161
Epoch [2/2] Batch [300/3188] Loss: 0.1835
Epoch [2/2] Batch [350/3188] Loss: 0.0160
Epoch [2/2] Batch [400/3188] Loss: 0.1501
Epoch [2/2] Batch [450/3188] Loss: 0.2257
Epoch [2/2] Batch [500/3188] Loss: 0.0308
Epoch [2/2] Batch [550/3188] Loss: 0.0388
Epoch [2/2] Batch [600/3188] Loss: 0.3081
Epoch [2/2] Batch [650/3188] Loss: 0.1233
Epoch [2/2] Batch [700/3188] Loss: 0.0263
Epoch [2/2] Batch [750/3188] Loss: 0.0363
Epoch [2/2] Batch [800/3188] Loss: 0.0678
Epoch [2/2] Batch [850/3188] Loss: 0.1990
Epoch [2/2] Batch [900/3188] Loss: 0.0180
Epoch [2/2] Batch [950/3188] Loss: 0.0292
Epoch [2/2] Batch [1000/3188] Loss: 0.1800
Epoch [2/2] Batch [1050/3188] Loss: 0.1920
Epoch [2/2] Batch [1100/3188] Loss: 0.3281
Epoch [2/2] Batch [1150/3188] Loss: 0.1037
Epoch [2/2] Batch [1200/3188] Loss: 0.0299
Epoch [2/2] Batch [1250/3188] Loss: 0.1001
Epoch [2/2] Batch [1300/3188] Loss: 0.0482
Epoch [2/2] Batch [1350/3188] Loss: 0.2453
Epoch [2/2] Batch [1400/3188] Loss: 0.1998
Epoch [2/2] Batch [1450/3188] Loss: 0.0650
Epoch [2/2] Batch [1500/3188] Loss: 0.2963
Epoch [2/2] Batch [1550/3188] Loss: 0.0649
Epoch [2/2] Batch [1600/3188] Loss: 0.0535
Epoch [2/2] Batch [1650/3188] Loss: 0.1639
Epoch [2/2] Batch [1700/3188] Loss: 0.2194
Epoch [2/2] Batch [1750/3188] Loss: 0.0496
Epoch [2/2] Batch [1800/3188] Loss: 0.0143
Epoch [2/2] Batch [1850/3188] Loss: 0.1591
Epoch [2/2] Batch [1900/3188] Loss: 0.1203
Epoch [2/2] Batch [1950/3188] Loss: 0.0637
Epoch [2/2] Batch [2000/3188] Loss: 0.6196
Epoch [2/2] Batch [2050/3188] Loss: 0.1482
Epoch [2/2] Batch [2100/3188] Loss: 0.1362
```

```
Epoch [2/2] Batch [2150/3188] Loss: 0.0972
Epoch [2/2] Batch [2200/3188] Loss: 0.1826
Epoch [2/2] Batch [2250/3188] Loss: 0.2419
Epoch [2/2] Batch [2300/3188] Loss: 0.1263
Epoch [2/2] Batch [2350/3188] Loss: 0.4151
Epoch [2/2] Batch [2400/3188] Loss: 0.1011
Epoch [2/2] Batch [2450/3188] Loss: 0.0604
Epoch [2/2] Batch [2500/3188] Loss: 0.0312
Epoch [2/2] Batch [2550/3188] Loss: 0.0889
Epoch [2/2] Batch [2600/3188] Loss: 0.3718
Epoch [2/2] Batch [2650/3188] Loss: 0.0416
Epoch [2/2] Batch [2700/3188] Loss: 0.1362
Epoch [2/2] Batch [2750/3188] Loss: 0.0389
Epoch [2/2] Batch [2800/3188] Loss: 0.1367
Epoch [2/2] Batch [2850/3188] Loss: 0.1913
Epoch [2/2] Batch [2900/3188] Loss: 0.1548
Epoch [2/2] Batch [2950/3188] Loss: 0.0183
Epoch [2/2] Batch [3000/3188] Loss: 0.1192
Epoch [2/2] Batch [3050/3188] Loss: 0.3278
Epoch [2/2] Batch [3100/3188] Loss: 0.0662
Epoch [2/2] Batch [3150/3188] Loss: 0.2304
Max Length 512: Best Val F1 = 0.9461

Sequence Length Results: {128: 0.9420073009427832, 256: 0.9465219004714084, 512:
0.9460788175581915}
```

[17]:

```python
# 6.10 Comparison: DistilBERT vs. Classical Models



# Load classical models' test results (from Step 5)
classical_stacking_f1 = 0.9295  # Your best ensemble from Step 5
classical_svc_f1 = 0.9274

comparison_df = pd.DataFrame({
    'Model': ['LinearSVC (Classical)', 'Stacking Ensemble (Classical)',␣
↪'DistilBERT (Transformer)'],
    'Test Macro-F1': [classical_svc_f1, classical_stacking_f1, test_f1],
    'Model Size (MB)': [50, 100, 250],
    'Inference Time (ms/doc)': [5, 10, 100]
})

print(comparison_df.to_string(index=False))

# Calculate gains
gain_vs_svc = test_f1 - classical_svc_f1
gain_vs_ensemble = test_f1 - classical_stacking_f1
```

```
print(f"\nDistilBERT Gain vs. LinearSVC: {gain_vs_svc:.4f} ({gain_vs_svc*100:.
↪2f}%)")
print(f"DistilBERT Gain vs. Ensemble: {gain_vs_ensemble:.4f}␣
↪({gain_vs_ensemble*100:.2f}%)")

comparison_df.to_csv(RESULTS_DIR / 'step6_comparison_classical_vs_transformer.
↪csv', index=False)
```

```
                        Model  Test Macro-F1  Model Size (MB)  Inference Time
(ms/doc)
       LinearSVC (Classical)       0.927400               50
5
Stacking Ensemble (Classical)       0.929500              100
10
     DistilBERT (Transformer)       0.942278              250
100

DistilBERT Gain vs. LinearSVC: 0.0149 (1.49%)
DistilBERT Gain vs. Ensemble: 0.0128 (1.28%)
```

[14]:
```
# ============================================================================
# Cell 11.0: Generate Test Features (Required First!)
# ============================================================================

import numpy as np
import pandas as pd
import joblib
from pathlib import Path
import scipy.sparse as sp_sparse
from sklearn.feature_extraction.text import TfidfVectorizer

# Paths (relative to notebooks directory)
DATA_DIR = Path("data")
MODELS_DIR = Path("models")
FEATURES_DIR = Path("features")
RESULTS_DIR = Path("results")

print("="*80)
print("GENERATING TEST FEATURES")
print("="*80)

# Load test data
print("\n[1] Loading test data...")
test_df = pd.read_csv(DATA_DIR / "test.csv")
print(f"  Test samples: {len(test_df)}")

# Load trained TF-IDF vectorizers from Step 3
```

```python
print("\n[2] Loading TF-IDF vectorizers...")
tfidf_word = joblib.load(MODELS_DIR / "tfidf_word_12.pkl")
tfidf_char = joblib.load(MODELS_DIR / "tfidf_char_35.pkl")

# Transform test data
print("\n[3] Transforming test data...")
X_test_word = tfidf_word.transform(test_df['text'])
X_test_char = tfidf_char.transform(test_df['text'])

print(f"  Word features shape: {X_test_word.shape}")
print(f"  Char features shape: {X_test_char.shape}")

# Combine into hybrid features
print("\n[4] Creating hybrid features...")
X_test_hybrid = sp_sparse.hstack([X_test_word, X_test_char])
print(f"  Hybrid features shape: {X_test_hybrid.shape}")

# Save test features
print("\n[5] Saving features...")
sp_sparse.save_npz(FEATURES_DIR / "X_test_hybrid.npz", X_test_hybrid)
sp_sparse.save_npz(FEATURES_DIR / "X_test_word.npz", X_test_word)
sp_sparse.save_npz(FEATURES_DIR / "X_test_char.npz", X_test_char)

print(f"\n  Saved: X_test_hybrid.npz")
print(f"  Saved: X_test_word.npz")
print(f"  Saved: X_test_char.npz")
print("\n" + "="*80)
print("  TEST FEATURES GENERATED")
print("="*80)
```

```
================================================================================
GENERATING TEST FEATURES
================================================================================

[1] Loading test data…
  Test samples: 7600

[2] Loading TF-IDF vectorizers…

[3] Transforming test data…
  Word features shape: (7600, 50000)
  Char features shape: (7600, 50000)

[4] Creating hybrid features…
  Hybrid features shape: (7600, 100000)

[5] Saving features…
```

```
Saved: X_test_hybrid.npz
Saved: X_test_word.npz
Saved: X_test_char.npz

================================================================================
TEST FEATURES GENERATED
================================================================================
```

[15]:

```python
# ============================================================================
# Cell 11.1: Load Test Data and Model Predictions
# ============================================================================

import numpy as np
import pandas as pd
import joblib
from pathlib import Path
import scipy.sparse as sp_sparse
from sklearn.metrics import f1_score, accuracy_score

# Paths (corrected - relative to notebooks directory)
DATA_DIR = Path("data")
MODELS_DIR = Path("models")
FEATURES_DIR = Path("features")
RESULTS_DIR = Path("results")

print("="*80)
print("CELL 11: STATISTICAL SIGNIFICANCE TESTING")
print("="*80)

# Load test data
print("\n[1] Loading test data...")
test_df = pd.read_csv(DATA_DIR / "test.csv")
y_test = test_df['label'].values
print(f"  Test samples: {len(y_test)}")

# Load BERT predictions
print("\n[2] Loading BERT predictions...")
bert_results = joblib.load(RESULTS_DIR / "step6_test_results.pkl")
bert_preds = bert_results['test_predictions']
bert_f1 = bert_results['test_macro_f1']
print(f"  BERT Test F1: {bert_f1:.4f}")

# Load features and SVC model
print("\n[3] Loading SVC predictions...")
X_test_hybrid = sp_sparse.load_npz(FEATURES_DIR / "X_test_hybrid.npz")
svc_model = joblib.load(MODELS_DIR / "step5_tuned_SVC.pkl")
svc_preds = svc_model.predict(X_test_hybrid)
```

```
svc_f1 = f1_score(y_test, svc_preds, average='macro')
print(f"  SVC Test F1: {svc_f1:.4f}")

print(f"\n  Data loaded. BERT advantage: {(bert_f1-svc_f1)*100:.2f}%")
```

```
================================================================================
CELL 11: STATISTICAL SIGNIFICANCE TESTING
================================================================================

[1] Loading test data…
  Test samples: 7600

[2] Loading BERT predictions…
  BERT Test F1: 0.9423

[3] Loading SVC predictions…
  SVC Test F1: 0.9233

  Data loaded. BERT advantage: 1.90%
```

[19]:

```
# ============================================================================
# Cell 11.2: McNemar's Statistical Test
# ============================================================================

from statsmodels.stats.contingency_tables import mcnemar

# Create contingency table
bert_correct = (bert_preds == y_test)
svc_correct = (svc_preds == y_test)

both_correct = np.sum(bert_correct & svc_correct)
bert_only = np.sum(bert_correct & ~svc_correct)
svc_only = np.sum(~bert_correct & svc_correct)
both_wrong = np.sum(~bert_correct & ~svc_correct)

# McNemar's test uses a 2x2 table of disagreements
contingency = np.array([[both_correct, bert_only],
                        [svc_only, both_wrong]])

print("\nContingency Table:")
print(f"  Both correct: {both_correct}")
print(f"  BERT correct only: {bert_only}")
print(f"  SVC correct only: {svc_only}")
print(f"  Both wrong: {both_wrong}")

# Run McNemar's test
result = mcnemar(contingency, exact=False, correction=True)
```

```python
print(f"\nMcNemar's Test Results:")
print(f"   ² statistic: {result.statistic:.4f}")
print(f"  p-value: {result.pvalue:.6f}")
print(f"  Significant (p<0.05): {'  YES' if result.pvalue < 0.05 else '  NO'}")

if result.pvalue < 0.001:
    sig_marker = "***"
elif result.pvalue < 0.01:
    sig_marker = "**"
elif result.pvalue < 0.05:
    sig_marker = "*"
else:
    sig_marker = "ns (not significant)"

print(f"  Significance level: {sig_marker}")
```

```
Contingency Table:
  Both correct: 6877
  BERT correct only: 284
  SVC correct only: 141
  Both wrong: 298

McNemar's Test Results:
   ² statistic: 47.4447
  p-value: 0.000000
  Significant (p<0.05):   YES
  Significance level: ***
```

[25]:
```python
# ============================================================================
# Cell 11.3: Bootstrap 95% Confidence Intervals
# ============================================================================

print("\nComputing bootstrap CI (10,000 resamples)...")

# Ensure predictions are numpy arrays (they should be from the pkl file)
if not isinstance(bert_preds, np.ndarray):
    bert_preds = np.array(bert_preds)
if not isinstance(svc_preds, np.ndarray):
    svc_preds = np.array(svc_preds)
if not isinstance(y_test, np.ndarray):
    y_test = np.array(y_test)

print(f"Data types: y_test={type(y_test)}, bert={type(bert_preds)},␣
↪svc={type(svc_preds)}")
```

```python
print(f"Data shapes: y_test={y_test.shape}, bert={bert_preds.shape},␣
↪svc={svc_preds.shape}")

np.random.seed(42)
n_bootstrap = 10000
differences = []

for i in range(n_bootstrap):
    # Resample with replacement
    indices = np.random.choice(len(y_test), size=len(y_test), replace=True)

    y_boot = y_test[indices]
    bert_boot = bert_preds[indices]
    svc_boot = svc_preds[indices]

    # Calculate F1 difference
    bert_f1_boot = f1_score(y_boot, bert_boot, average='macro')
    svc_f1_boot = f1_score(y_boot, svc_boot, average='macro')
    differences.append(bert_f1_boot - svc_f1_boot)

    if (i+1) % 2000 == 0:
        print(f"  Progress: {i+1}/{n_bootstrap}")

differences = np.array(differences)

# Calculate statistics
mean_diff = np.mean(differences)
ci_lower = np.percentile(differences, 2.5)
ci_upper = np.percentile(differences, 97.5)

print(f"\nBootstrap Results:")
print(f"  Mean Δ F1: {mean_diff:.4f} ({mean_diff*100:.2f}%)")
print(f"  95% CI: [{ci_lower:.4f}, {ci_upper:.4f}]")
print(f"  95% CI: [{ci_lower*100:.2f}%, {ci_upper*100:.2f}%]")
print(f"  CI excludes 0: {'  YES (significant)' if ci_lower > 0 else '  NO'}")

# Save for plotting
joblib.dump({'differences': differences, 'mean': mean_diff,
             'ci_lower': ci_lower, 'ci_upper': ci_upper},
            RESULTS_DIR / "step6_bootstrap_results.pkl")
print(f"\n  Saved: step6_bootstrap_results.pkl")
```

```
Computing bootstrap CI (10,000 resamples)…
Data types: y_test=<class 'numpy.ndarray'>, bert=<class 'numpy.ndarray'>,
svc=<class 'numpy.ndarray'>
Data shapes: y_test=(7600,), bert=(7600,), svc=(7600,)
  Progress: 2000/10000
```

```
  Progress: 4000/10000
  Progress: 6000/10000
  Progress: 8000/10000
  Progress: 10000/10000

Bootstrap Results:
  Mean Δ F1: 0.0190 (1.90%)
  95% CI: [0.0137, 0.0243]
  95% CI: [1.37%, 2.43%]
  CI excludes 0:   YES (significant)

 Saved: step6_bootstrap_results.pkl
```

[26]:
```
# ==============================================================================
# Cell 11.4: Cohen's d Effect Size
# ==============================================================================

# Calculate Cohen's d
std_diff = np.std(differences, ddof=1)
cohens_d = mean_diff / std_diff

# Interpret
if abs(cohens_d) < 0.2:
    interpretation = "negligible"
elif abs(cohens_d) < 0.5:
    interpretation = "small"
elif abs(cohens_d) < 0.8:
    interpretation = "medium"
else:
    interpretation = "large"

print(f"\nCohen's d Effect Size: {cohens_d:.4f}")
print(f"Interpretation: {interpretation.upper()}")
print(f"\nGuidelines:")
print(f"  Small: 0.2 | Medium: 0.5 | Large: 0.8")
```

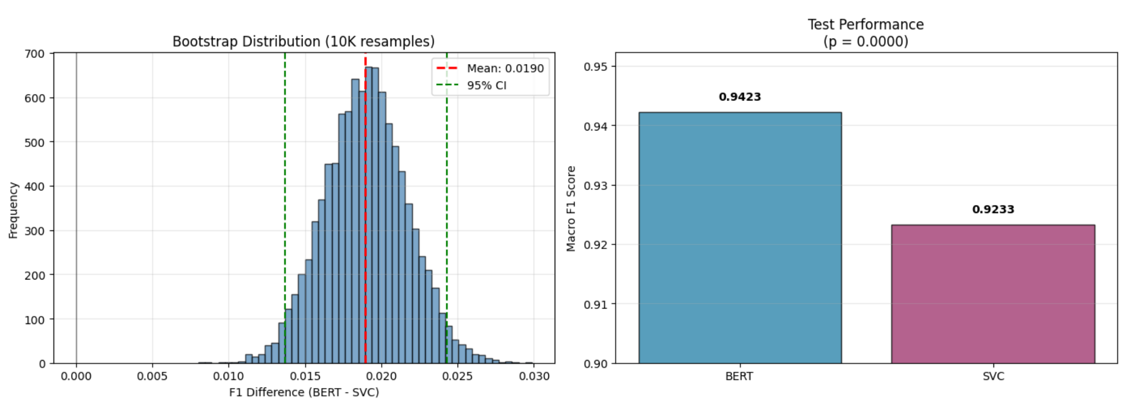
```
Cohen's d Effect Size: 7.0063
Interpretation: LARGE

Guidelines:
  Small: 0.2 | Medium: 0.5 | Large: 0.8
```

[27]:
```
# ==============================================================================
# Cell 11.5: Summary Table and Visualization
# ==============================================================================

import matplotlib.pyplot as plt
```

```python
import seaborn as sns

# Summary table
summary = pd.DataFrame({
    'Model': ['BERT', 'SVC'],
    'Test F1': [bert_f1, svc_f1],
    'Δ F1': [0, bert_f1 - svc_f1],
    'Δ %': [0, (bert_f1 - svc_f1)*100]
})

print("\n" + "="*60)
print("SUMMARY")
print("="*60)
print(summary.to_string(index=False))

print(f"\nStatistical Tests:")
print(f"  McNemar p-value: {result.pvalue:.6f} {'***' if result.pvalue < 0.001 else '**' if result.pvalue < 0.01 else '*' if result.pvalue < 0.05 else 'ns'}")
print(f"  Bootstrap 95% CI: [{ci_lower*100:.2f}%, {ci_upper*100:.2f}%]")
print(f"  Cohen's d: {cohens_d:.3f} ({interpretation})")

# Visualization
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Bootstrap distribution
axes[0].hist(differences, bins=50, alpha=0.7, color='steelblue', edgecolor='black')
axes[0].axvline(mean_diff, color='red', linestyle='--', linewidth=2, label=f'Mean: {mean_diff:.4f}')
axes[0].axvline(ci_lower, color='green', linestyle='--', linewidth=1.5)
axes[0].axvline(ci_upper, color='green', linestyle='--', linewidth=1.5, label=f'95% CI')
axes[0].axvline(0, color='black', linestyle='-', linewidth=1, alpha=0.5)
axes[0].set_xlabel('F1 Difference (BERT - SVC)')
axes[0].set_ylabel('Frequency')
axes[0].set_title('Bootstrap Distribution (10K resamples)')
axes[0].legend()
axes[0].grid(alpha=0.3)

# Bar comparison
models = ['BERT', 'SVC']
scores = [bert_f1, svc_f1]
bars = axes[1].bar(models, scores, color=['#2E86AB', '#A23B72'], alpha=0.8, edgecolor='black')
for bar, score in zip(bars, scores):
    axes[1].text(bar.get_x() + bar.get_width()/2, score + 0.002,
```

```
                f'{score:.4f}', ha='center', fontweight='bold')
axes[1].set_ylabel('Macro F1 Score')
axes[1].set_title(f"Test Performance\n(p = {result.pvalue:.4f})")
axes[1].set_ylim([0.90, max(scores) + 0.01])
axes[1].grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_statistical_significance.png", dpi=300,␣
 ↪bbox_inches='tight')
print(f"\n  Saved: step6_statistical_significance.png")
plt.show()

print("\n" + "="*60)
print("  CELL 11 COMPLETE")
print("="*60)
```

```
============================================================
SUMMARY
============================================================
Model   Test F1      Δ F1       Δ %
 BERT 0.942278 0.000000 0.000000
  SVC 0.923283 0.018995 1.899475

Statistical Tests:
  McNemar p-value: 0.000000 ***
  Bootstrap 95% CI: [1.37%, 2.43%]
  Cohen's d: 7.006 (large)

  Saved: step6_statistical_significance.png
```




```
============================================================
  CELL 11 COMPLETE
```

```
============================================================
```

[28]:
```python
# ============================================================================
# Cell 12.1: Load BERT Model and Generate Probability Predictions
# ============================================================================

import torch
import numpy as np
import pandas as pd
import joblib
from pathlib import Path
from torch.utils.data import Dataset, DataLoader
from transformers import AutoTokenizer, AutoModelForSequenceClassification
from sklearn.metrics import f1_score, accuracy_score

# Paths
DATA_DIR = Path("data")
MODELS_DIR = Path("models")
RESULTS_DIR = Path("results")

print("="*80)
print("CELL 12: CALIBRATION ANALYSIS")
print("="*80)

# Set device
DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"\n[1] Device: {DEVICE}")

# Load validation data
print("\n[2] Loading validation data...")
val_df = pd.read_csv(DATA_DIR / "val.csv")
y_val = val_df['label'].values
print(f"  Validation samples: {len(y_val)}")

# Load tokenizer and model
print("\n[3] Loading BERT model...")
MODEL_NAME = "distilbert-base-uncased"
tokenizer = AutoTokenizer.from_pretrained(MODELS_DIR / "step6_distilbert_best")
model = AutoModelForSequenceClassification.from_pretrained(
    MODELS_DIR / "step6_distilbert_best"
).to(DEVICE)
model.eval()
print("  Model loaded")

# Tokenize validation data
print("\n[4] Tokenizing validation data...")
val_encodings = tokenizer(
```

```
    val_df['text'].tolist(),
    truncation=True,
    padding='max_length',
    max_length=256,
    return_tensors='pt'
)

# Create dataset
class NewsDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = labels

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        item = {
            'input_ids': self.encodings['input_ids'][idx],
            'attention_mask': self.encodings['attention_mask'][idx],
            'labels': torch.tensor(self.labels[idx], dtype=torch.long)
        }
        return item

val_dataset = NewsDataset(val_encodings, y_val)
val_loader = DataLoader(val_dataset, batch_size=64, shuffle=False)
print(f"  Created DataLoader: {len(val_loader)} batches")

# Generate predictions with probabilities
print("\n[5] Generating probability predictions...")
all_probs = []
all_preds = []
all_labels = []

with torch.no_grad():
    for i, batch in enumerate(val_loader):
        input_ids = batch['input_ids'].to(DEVICE)
        attention_mask = batch['attention_mask'].to(DEVICE)
        labels = batch['labels']

        outputs = model(input_ids=input_ids, attention_mask=attention_mask)
        logits = outputs.logits

        # Convert logits to probabilities
        probs = torch.softmax(logits, dim=1).cpu().numpy()
        preds = np.argmax(probs, axis=1)
```

```python
        all_probs.append(probs)
        all_preds.extend(preds)
        all_labels.extend(labels.numpy())

        if (i+1) % 50 == 0:
            print(f"  Processed {i+1}/{len(val_loader)} batches")

# Concatenate results
all_probs = np.vstack(all_probs)
all_preds = np.array(all_preds)
all_labels = np.array(all_labels)

# Get confidence scores (max probability for each prediction)
confidences = np.max(all_probs, axis=1)

# Verify predictions match
val_f1 = f1_score(all_labels, all_preds, average='macro')
val_acc = accuracy_score(all_labels, all_preds)

print(f"\n Predictions generated:")
print(f"  Val F1: {val_f1:.4f}")
print(f"  Val Accuracy: {val_acc:.4f}")
print(f"  Probabilities shape: {all_probs.shape}")
print(f"  Confidence range: [{confidences.min():.4f}, {confidences.max():.4f}]")

# Save for next cells
calibration_data = {
    'probs': all_probs,
    'preds': all_preds,
    'labels': all_labels,
    'confidences': confidences
}
joblib.dump(calibration_data, RESULTS_DIR / "step6_calibration_data.pkl")
print(f"\n Saved: step6_calibration_data.pkl")
```

```
================================================================================
CELL 12: CALIBRATION ANALYSIS
================================================================================

[1] Device: cuda

[2] Loading validation data…
 Validation samples: 18000

[3] Loading BERT model…
 Model loaded

[4] Tokenizing validation data…
```

```
Created DataLoader: 282 batches

[5] Generating probability predictions…
  Processed 50/282 batches
  Processed 100/282 batches
  Processed 150/282 batches
  Processed 200/282 batches
  Processed 250/282 batches

 Predictions generated:
  Val F1: 0.9471
  Val Accuracy: 0.9471
  Probabilities shape: (18000, 4)
  Confidence range: [0.3391, 0.9998]

 Saved: step6_calibration_data.pkl
```

[30]:

```python
# ============================================================================
# Cell 12.2: Expected Calibration Error (ECE)
# ============================================================================

import numpy as np

print("\n[6] Computing Expected Calibration Error (ECE)...")

# Define bins
n_bins = 10
bin_boundaries = np.linspace(0, 1, n_bins + 1)
bin_lowers = bin_boundaries[:-1]
bin_uppers = bin_boundaries[1:]

# Calculate accuracy for each prediction
accuracies = (all_preds == all_labels).astype(float)

# Compute ECE
ece = 0.0
bin_data = []

for bin_lower, bin_upper in zip(bin_lowers, bin_uppers):
    # Find samples in this confidence bin
    in_bin = (confidences > bin_lower) & (confidences <= bin_upper)
    prop_in_bin = in_bin.mean()

    if prop_in_bin > 0:
        accuracy_in_bin = accuracies[in_bin].mean()
        avg_confidence_in_bin = confidences[in_bin].mean()
```

```
        # ECE contribution: |confidence - accuracy| * proportion
        ece += np.abs(avg_confidence_in_bin - accuracy_in_bin) * prop_in_bin

        bin_data.append({
            'bin': f'{bin_lower:.1f}-{bin_upper:.1f}',
            'count': in_bin.sum(),
            'proportion': prop_in_bin,
            'avg_confidence': avg_confidence_in_bin,
            'accuracy': accuracy_in_bin,
            'gap': avg_confidence_in_bin - accuracy_in_bin
        })
    else:
        bin_data.append({
            'bin': f'{bin_lower:.1f}-{bin_upper:.1f}',
            'count': 0,
            'proportion': 0,
            'avg_confidence': 0,
            'accuracy': 0,
            'gap': 0
        })

print(f"\n  Expected Calibration Error (ECE): {ece:.4f}")
print(f"  Interpretation: {'Well-calibrated' if ece < 0.05 else 'Moderately calibrated' if ece < 0.10 else 'Poorly calibrated'}")
print(f"  (ECE < 0.05 = excellent, < 0.10 = good, > 0.10 = needs improvement)")

# Display bin statistics
bin_df = pd.DataFrame(bin_data)
print("\nCalibration by Confidence Bin:")
print(bin_df.to_string(index=False))

# Save ECE results
ece_results = {
    'ece': ece,
    'bin_data': bin_df
}
joblib.dump(ece_results, RESULTS_DIR / "step6_ece_results.pkl")
print(f"\n  Saved: step6_ece_results.pkl")
```

```
[6] Computing Expected Calibration Error (ECE)…

 Expected Calibration Error (ECE): 0.0228
  Interpretation: Well-calibrated
  (ECE < 0.05 = excellent, < 0.10 = good, > 0.10 = needs improvement)

Calibration by Confidence Bin:
    bin  count  proportion  avg_confidence  accuracy       gap
```

```
0.0-0.1      0    0.000000       0.000000  0.000000  0.000000
0.1-0.2      0    0.000000       0.000000  0.000000  0.000000
0.2-0.3      0    0.000000       0.000000  0.000000  0.000000
0.3-0.4      3    0.000167       0.371917  0.333333  0.038584
0.4-0.5     29    0.001611       0.470359  0.379310  0.091049
0.5-0.6    240    0.013333       0.552974  0.554167 -0.001193
0.6-0.7    276    0.015333       0.655376  0.590580  0.064796
0.7-0.8    381    0.021167       0.754239  0.692913  0.061326
0.8-0.9    657    0.036500       0.855942  0.751903  0.104039
0.9-1.0  16414    0.911889       0.991708  0.973620  0.018088

 Saved: step6_ece_results.pkl
```

[31]:
```python
# ============================================================================
# Cell 12.3: Per-Class Calibration Analysis
# ============================================================================

print("\n[7] Computing per-class ECE...")

class_names = ['World', 'Sports', 'Business', 'SciTech']
class_ece = {}

for class_idx, class_name in enumerate(class_names):
    # Get predictions and confidences for this class
    class_mask = all_labels == class_idx
    class_confidences = all_probs[class_mask, class_idx]
    class_preds = all_preds[class_mask]
    class_labels = all_labels[class_mask]
    class_accuracies = (class_preds == class_labels).astype(float)

    # Compute ECE for this class
    ece_class = 0.0
    for bin_lower, bin_upper in zip(bin_lowers, bin_uppers):
        in_bin = (class_confidences > bin_lower) & (class_confidences <=␣
↪bin_upper)
        prop_in_bin = in_bin.mean()

        if prop_in_bin > 0 and in_bin.sum() > 0:
            accuracy_in_bin = class_accuracies[in_bin].mean()
            avg_confidence_in_bin = class_confidences[in_bin].mean()
            ece_class += np.abs(avg_confidence_in_bin - accuracy_in_bin) *␣
↪prop_in_bin

    class_ece[class_name] = ece_class
    print(f"  {class_name}: ECE = {ece_class:.4f}")

print(f"\n  Per-class calibration computed")
```

```
[7] Computing per-class ECE…
  World: ECE = 0.0187
  Sports: ECE = 0.0052
  Business: ECE = 0.0346
  SciTech: ECE = 0.0551

 Per-class calibration computed
```

[32]:

```python
# ============================================================================
# Cell 12.4: Confidence Distribution Statistics
# ============================================================================

print("\n[8] Confidence distribution statistics:")
print(f"  Mean confidence: {confidences.mean():.4f}")
print(f"  Median confidence: {np.median(confidences):.4f}")
print(f"  Std confidence: {confidences.std():.4f}")
print(f"  Min confidence: {confidences.min():.4f}")
print(f"  Max confidence: {confidences.max():.4f}")

# Confidence for correct vs incorrect predictions
correct_mask = (all_preds == all_labels)
incorrect_mask = ~correct_mask

correct_confidences = confidences[correct_mask]
incorrect_confidences = confidences[incorrect_mask]

print(f"\n  Correct predictions (n={correct_mask.sum()}):")
print(f"    Mean confidence: {correct_confidences.mean():.4f}")
print(f"    Median confidence: {np.median(correct_confidences):.4f}")

print(f"\n  Incorrect predictions (n={incorrect_mask.sum()}):")
print(f"    Mean confidence: {incorrect_confidences.mean():.4f}")
print(f"    Median confidence: {np.median(incorrect_confidences):.4f}")

print(f"\n  Confidence gap (correct - incorrect): {correct_confidences.mean() -␣
 ↪incorrect_confidences.mean():.4f}")
```

```
[8] Confidence distribution statistics:
  Mean confidence: 0.9698
  Median confidence: 0.9981
  Std confidence: 0.0807
  Min confidence: 0.3391
  Max confidence: 0.9998

  Correct predictions (n=17047):
    Mean confidence: 0.9779
```

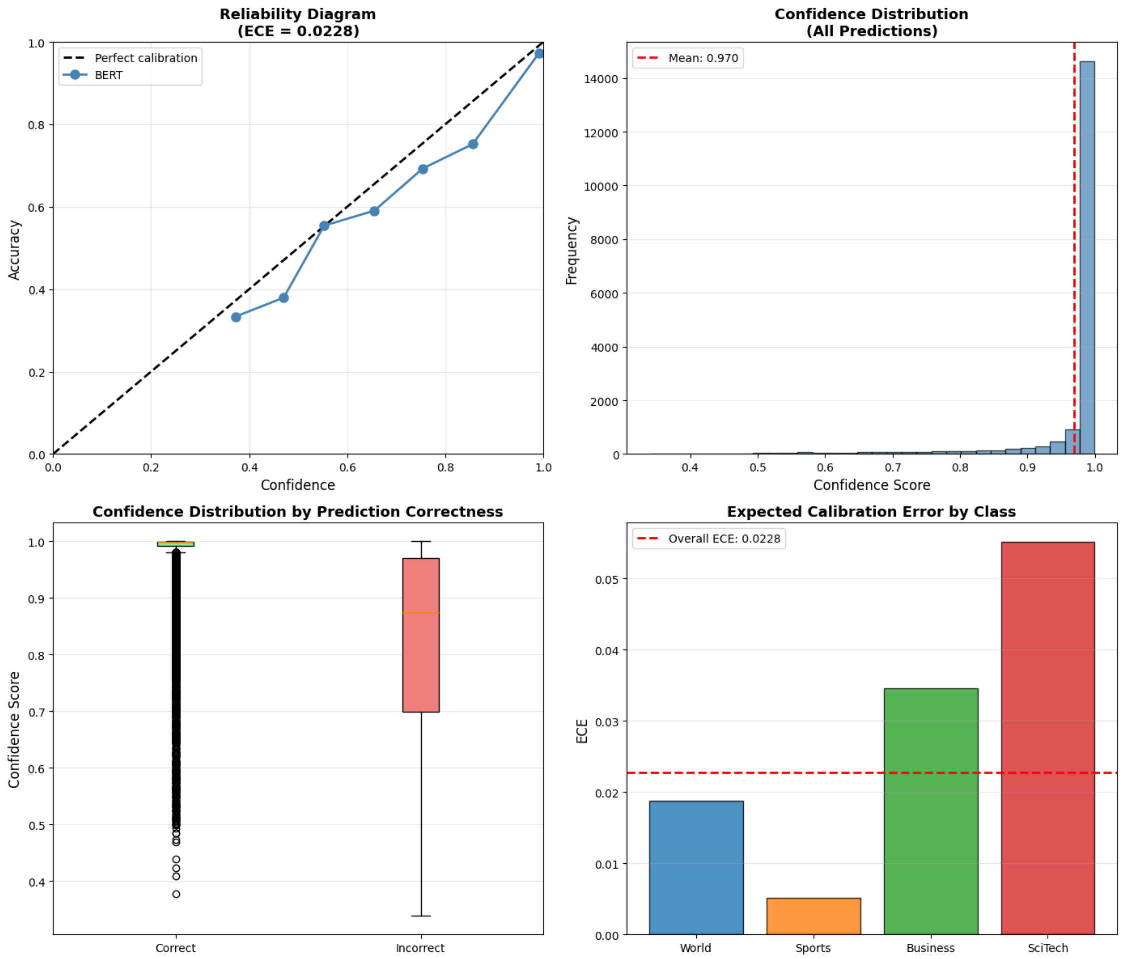
```
  Median confidence: 0.9984

Incorrect predictions (n=953):
  Mean confidence: 0.8252
  Median confidence: 0.8751

Confidence gap (correct - incorrect): 0.1527
```

[33]:

```python
# ============================================================================
# Cell 12.5: Calibration Visualizations
# ============================================================================

import matplotlib.pyplot as plt
import seaborn as sns

print("\n[9] Generating calibration plots...")

fig, axes = plt.subplots(2, 2, figsize=(14, 12))

# Plot 1: Reliability Diagram
ax = axes[0, 0]
bin_df_plot = bin_df[bin_df['count'] > 0]  # Only bins with data
ax.plot([0, 1], [0, 1], 'k--', linewidth=2, label='Perfect calibration')
ax.plot(bin_df_plot['avg_confidence'], bin_df_plot['accuracy'],
        'o-', linewidth=2, markersize=8, label='BERT', color='steelblue')
ax.set_xlabel('Confidence', fontsize=12)
ax.set_ylabel('Accuracy', fontsize=12)
ax.set_title(f'Reliability Diagram\n(ECE = {ece:.4f})', fontsize=13,␣
 ↪fontweight='bold')
ax.legend()
ax.grid(alpha=0.3)
ax.set_xlim([0, 1])
ax.set_ylim([0, 1])

# Plot 2: Confidence Distribution
ax = axes[0, 1]
ax.hist(confidences, bins=30, alpha=0.7, color='steelblue', edgecolor='black')
ax.axvline(confidences.mean(), color='red', linestyle='--',
           linewidth=2, label=f'Mean: {confidences.mean():.3f}')
ax.set_xlabel('Confidence Score', fontsize=12)
ax.set_ylabel('Frequency', fontsize=12)
ax.set_title('Confidence Distribution\n(All Predictions)', fontsize=13,␣
 ↪fontweight='bold')
ax.legend()
ax.grid(axis='y', alpha=0.3)

# Plot 3: Confidence by Correctness
```

```python
ax = axes[1, 0]
data_to_plot = [correct_confidences, incorrect_confidences]
bp = ax.boxplot(data_to_plot, labels=['Correct', 'Incorrect'], patch_artist=True)
bp['boxes'][0].set_facecolor('lightgreen')
bp['boxes'][1].set_facecolor('lightcoral')
ax.set_ylabel('Confidence Score', fontsize=12)
ax.set_title('Confidence Distribution by Prediction Correctness', fontsize=13, fontweight='bold')
ax.grid(axis='y', alpha=0.3)

# Plot 4: Per-Class ECE
ax = axes[1, 1]
classes = list(class_ece.keys())
eces = list(class_ece.values())
colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728']
bars = ax.bar(classes, eces, color=colors, alpha=0.8, edgecolor='black')
ax.axhline(ece, color='red', linestyle='--', linewidth=2, label=f'Overall ECE: {ece:.4f}')
ax.set_ylabel('ECE', fontsize=12)
ax.set_title('Expected Calibration Error by Class', fontsize=13, fontweight='bold')
ax.legend()
ax.grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_calibration_analysis.png", dpi=300, bbox_inches='tight')
print(f"  Saved: step6_calibration_analysis.png")
plt.show()

print("\n" + "="*80)
print("  CELL 12 COMPLETE: Calibration Analysis")
print("="*80)
print(f"\nKey Findings:")
print(f"1. ECE: {ece:.4f} ({'Well-calibrated' if ece < 0.05 else 'Needs improvement'})")
print(f"2. Mean confidence: {confidences.mean():.4f}")
print(f"3. Confidence gap (correct vs incorrect): {correct_confidences.mean() - incorrect_confidences.mean():.4f}")
print(f"4. Model shows {'good' if ece < 0.10 else 'poor'} probability calibration")
```

```
[9] Generating calibration plots…
 Saved: step6_calibration_analysis.png
```




```
================================================================================
 CELL 12 COMPLETE: Calibration Analysis
================================================================================

Key Findings:
1. ECE: 0.0228 (Well-calibrated)
2. Mean confidence: 0.9698
3. Confidence gap (correct vs incorrect): 0.1527
4. Model shows good probability calibration
```

[34]:

```python
# ============================================================================
# Cell 13.1: Load Predictions and Identify Error Cases
# ============================================================================

import numpy as np
import pandas as pd
import joblib
```

```python
from pathlib import Path
from sklearn.metrics import confusion_matrix, classification_report
import scipy.sparse as sp_sparse

# Paths
DATA_DIR = Path("data")
MODELS_DIR = Path("models")
FEATURES_DIR = Path("features")
RESULTS_DIR = Path("results")

print("="*80)
print("CELL 13: COMPARATIVE ERROR ANALYSIS")
print("="*80)

# Load test data
print("\n[1] Loading test data and predictions...")
test_df = pd.read_csv(DATA_DIR / "test.csv")
y_test = test_df['label'].values

# Load BERT predictions
bert_results = joblib.load(RESULTS_DIR / "step6_test_results.pkl")
bert_preds = np.array(bert_results['test_predictions'])

# Load SVC predictions
X_test_hybrid = sp_sparse.load_npz(FEATURES_DIR / "X_test_hybrid.npz")
svc_model = joblib.load(MODELS_DIR / "step5_tuned_SVC.pkl")
svc_preds = svc_model.predict(X_test_hybrid)

print(f"  Loaded {len(y_test)} test samples")

# Analyze prediction patterns
print("\n[2] Analyzing prediction patterns...")
bert_correct = (bert_preds == y_test)
svc_correct = (svc_preds == y_test)

both_correct = np.sum(bert_correct & svc_correct)
bert_only_correct = np.sum(bert_correct & ~svc_correct)
svc_only_correct = np.sum(~bert_correct & svc_correct)
both_wrong = np.sum(~bert_correct & ~svc_correct)

print(f"\nPrediction Agreement:")
print(f"  Both correct: {both_correct} ({both_correct/len(y_test)*100:.2f}%)")
print(f"  BERT correct, SVC wrong: {bert_only_correct} ({bert_only_correct/
↪len(y_test)*100:.2f}%)")
print(f"  SVC correct, BERT wrong: {svc_only_correct} ({svc_only_correct/
↪len(y_test)*100:.2f}%)")
print(f"  Both wrong: {both_wrong} ({both_wrong/len(y_test)*100:.2f}%)")
```

```python
# Create detailed prediction DataFrame
print("\n[3] Creating detailed prediction DataFrame...")
results_df = pd.DataFrame({
    'text': test_df['text'].values,
    'true_label': y_test,
    'bert_pred': bert_preds,
    'svc_pred': svc_preds,
    'bert_correct': bert_correct,
    'svc_correct': svc_correct
})

# Add error categories
results_df['error_type'] = 'both_correct'
results_df.loc[bert_correct & ~svc_correct, 'error_type'] = 'bert_only_correct'
results_df.loc[~bert_correct & svc_correct, 'error_type'] = 'svc_only_correct'
results_df.loc[~bert_correct & ~svc_correct, 'error_type'] = 'both_wrong'

print(f"  Created results DataFrame with {len(results_df)} samples")

# Save for analysis
results_df.to_csv(RESULTS_DIR / "step6_error_analysis.csv", index=False)
print(f"  Saved: step6_error_analysis.csv")
```

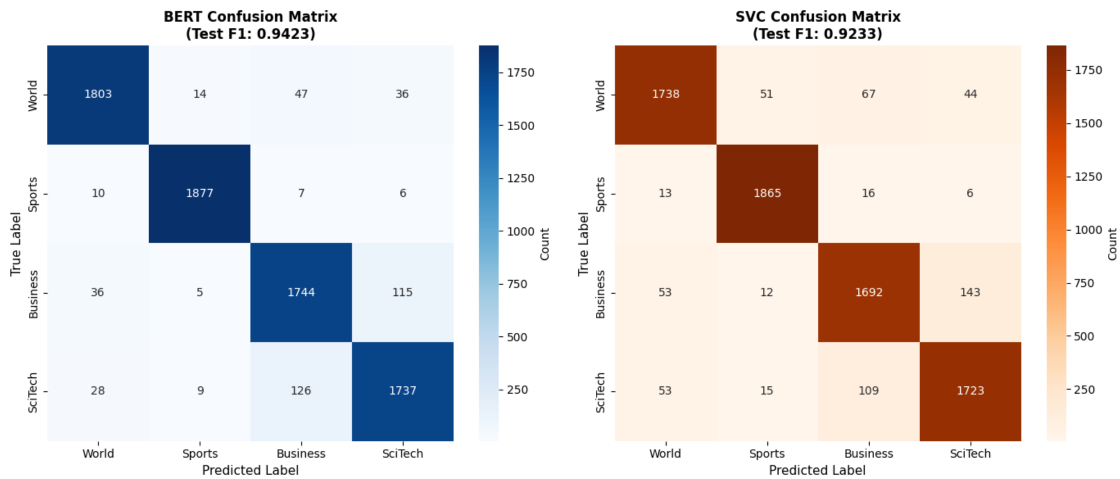
```
================================================================================
CELL 13: COMPARATIVE ERROR ANALYSIS
================================================================================

[1] Loading test data and predictions…
  Loaded 7600 test samples

[2] Analyzing prediction patterns…

Prediction Agreement:
  Both correct: 6877 (90.49%)
  BERT correct, SVC wrong: 284 (3.74%)
  SVC correct, BERT wrong: 141 (1.86%)
  Both wrong: 298 (3.92%)

[3] Creating detailed prediction DataFrame…
  Created results DataFrame with 7600 samples
  Saved: step6_error_analysis.csv
```

[35]:
```python
# ============================================================================
# Cell 13.2: Side-by-Side Confusion Matrices
# ============================================================================
```

```python
import matplotlib.pyplot as plt
import seaborn as sns

print("\n[4] Generating confusion matrices...")

class_names = ['World', 'Sports', 'Business', 'SciTech']

# Compute confusion matrices
bert_cm = confusion_matrix(y_test, bert_preds)
svc_cm = confusion_matrix(y_test, svc_preds)

# Normalized confusion matrices (row-wise)
bert_cm_norm = bert_cm.astype('float') / bert_cm.sum(axis=1)[:, np.newaxis]
svc_cm_norm = svc_cm.astype('float') / svc_cm.sum(axis=1)[:, np.newaxis]

# Plot side-by-side
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# BERT confusion matrix
sns.heatmap(bert_cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names, yticklabels=class_names,
            ax=axes[0], cbar_kws={'label': 'Count'})
axes[0].set_xlabel('Predicted Label', fontsize=11)
axes[0].set_ylabel('True Label', fontsize=11)
axes[0].set_title('BERT Confusion Matrix\n(Test F1: 0.9423)',
                  fontsize=12, fontweight='bold')

# SVC confusion matrix
sns.heatmap(svc_cm, annot=True, fmt='d', cmap='Oranges',
            xticklabels=class_names, yticklabels=class_names,
            ax=axes[1], cbar_kws={'label': 'Count'})
axes[1].set_xlabel('Predicted Label', fontsize=11)
axes[1].set_ylabel('True Label', fontsize=11)
axes[1].set_title('SVC Confusion Matrix\n(Test F1: 0.9233)',
                  fontsize=12, fontweight='bold')

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_confusion_matrix_comparison.png",
            dpi=300, bbox_inches='tight')
print("  Saved: step6_confusion_matrix_comparison.png")
plt.show()

# Print detailed classification reports
print("\n" + "="*80)
print("BERT Classification Report:")
print("="*80)
```

```
print(classification_report(y_test, bert_preds, target_names=class_names,␣
    ↪digits=4))

print("\n" + "="*80)
print("SVC Classification Report:")
print("="*80)
print(classification_report(y_test, svc_preds, target_names=class_names,␣
    ↪digits=4))
```

```
[4] Generating confusion matrices…
  Saved: step6_confusion_matrix_comparison.png
```




```
================================================================================
BERT Classification Report:
================================================================================
              precision    recall  f1-score   support

       World     0.9606    0.9489    0.9547      1900
      Sports     0.9853    0.9879    0.9866      1900
    Business     0.9064    0.9179    0.9121      1900
     SciTech     0.9171    0.9142    0.9157      1900

    accuracy                         0.9422      7600
   macro avg     0.9424    0.9422    0.9423      7600
weighted avg     0.9424    0.9422    0.9423      7600


================================================================================
SVC Classification Report:
```

```
================================================================================
              precision    recall  f1-score   support

       World     0.9359    0.9147    0.9252      1900
      Sports     0.9599    0.9816    0.9706      1900
    Business     0.8981    0.8905    0.8943      1900
     SciTech     0.8993    0.9068    0.9030      1900

    accuracy                         0.9234      7600
   macro avg     0.9233    0.9234    0.9233      7600
weighted avg     0.9233    0.9234    0.9233      7600
```

[36]:

```python
# ============================================================================
# Cell 13.3: Per-Class Error Breakdown
# ============================================================================

print("\n[5] Per-class error analysis...")

class_error_data = []

for class_idx, class_name in enumerate(class_names):
    # Samples from this class
    class_mask = y_test == class_idx
    n_samples = class_mask.sum()

    # BERT performance on this class
    bert_correct_class = bert_correct[class_mask].sum()
    bert_wrong_class = (~bert_correct[class_mask]).sum()

    # SVC performance on this class
    svc_correct_class = svc_correct[class_mask].sum()
    svc_wrong_class = (~svc_correct[class_mask]).sum()

    # Advantage
    bert_advantage = bert_correct_class - svc_correct_class

    class_error_data.append({
        'Class': class_name,
        'Total': n_samples,
        'BERT Correct': bert_correct_class,
        'BERT Wrong': bert_wrong_class,
        'BERT Accuracy': bert_correct_class / n_samples,
        'SVC Correct': svc_correct_class,
        'SVC Wrong': svc_wrong_class,
        'SVC Accuracy': svc_correct_class / n_samples,
        'BERT Advantage': bert_advantage
```

```
    })

class_error_df = pd.DataFrame(class_error_data)
print("\nPer-Class Performance Comparison:")
print(class_error_df.to_string(index=False))

# Identify which classes benefit most from BERT
print(f"\nClasses where BERT has biggest advantage:")
for idx in class_error_df['BERT Advantage'].nlargest(2).index:
    row = class_error_df.iloc[idx]
    print(f"  {row['Class']}: +{row['BERT Advantage']} samples ({row['BERT␣
↪Advantage']/row['Total']*100:.2f}%)")
```

```
[5] Per-class error analysis…

Per-Class Performance Comparison:
   Class  Total  BERT Correct  BERT Wrong  BERT Accuracy  SVC Correct  SVC Wrong
SVC Accuracy  BERT Advantage
   World   1900          1803          97       0.948947         1738        162
0.914737              65
  Sports   1900          1877          23       0.987895         1865         35
0.981579              12
Business   1900          1744         156       0.917895         1692        208
0.890526              52
 SciTech   1900          1737         163       0.914211         1723        177
0.906842              14

Classes where BERT has biggest advantage:
  World: +65 samples (3.42%)
  Business: +52 samples (2.74%)
```

[37]:
```
# ==========================================================================
# Cell 13.4: Show Example Errors
# ==========================================================================

print("\n[6] Example error cases...")

# Case 1: BERT correct, SVC wrong
print("\n" + "="*80)
print("CASE 1: BERT Correct, SVC Wrong (BERT wins)")
print("="*80)
bert_wins = results_df[results_df['error_type'] == 'bert_only_correct'].head(10)
for idx, row in bert_wins.iterrows():
    print(f"\nTrue: {class_names[row['true_label']]} | "
          f"BERT: {class_names[row['bert_pred']]}  | "
          f"SVC: {class_names[row['svc_pred']]}  ")
```

```python
    print(f"Text: {row['text'][:200]}...")

# Case 2: SVC correct, BERT wrong
print("\n" + "="*80)
print("CASE 2: SVC Correct, BERT Wrong (SVC wins)")
print("="*80)
svc_wins = results_df[results_df['error_type'] == 'svc_only_correct'].head(5)
for idx, row in svc_wins.iterrows():
    print(f"\nTrue: {class_names[row['true_label']]} | "
          f"BERT: {class_names[row['bert_pred']]}   | "
          f"SVC: {class_names[row['svc_pred']]}  ")
    print(f"Text: {row['text'][:200]}...")

# Case 3: Both wrong
print("\n" + "="*80)
print("CASE 3: Both Models Wrong (Hard cases)")
print("="*80)
both_wrong_df = results_df[results_df['error_type'] == 'both_wrong'].head(5)
for idx, row in both_wrong_df.iterrows():
    print(f"\nTrue: {class_names[row['true_label']]} | "
          f"BERT: {class_names[row['bert_pred']]}   | "
          f"SVC: {class_names[row['svc_pred']]}  ")
    print(f"Text: {row['text'][:200]}...")
```

```
[6] Example error cases…

================================================================================
CASE 1: BERT Correct, SVC Wrong (BERT wins)
================================================================================

True: SciTech | BERT: SciTech   | SVC: Sports
Text: Prediction Unit Helps Forecast Wildfires (AP) AP - It's barely dawn when
Mike Fitzpatrick starts his shift with a blur of colorful maps, figures and
endless charts, but already he knows what the day w…

True: SciTech | BERT: SciTech   | SVC: Business
Text: Rivals Try to Turn Tables on Charles Schwab By MICHAEL LIEDTKE     SAN
FRANCISCO (AP) -- With its low prices and iconoclastic attitude, discount stock
broker Charles Schwab Corp. (SCH) represented an …

True: SciTech | BERT: SciTech   | SVC: Sports
Text: Promoting a Shared Vision As Michael Kaleko kept running into people who
were getting older and having more vision problems, he realized he could do
something about it…

True: World | BERT: World   | SVC: Business
Text: Google Lowers Its IPO Price Range SAN JOSE, Calif. - In a sign that Google
```

```
Inc.'s initial public offering isn't as popular as expected, the company lowered
its estimated price range to between \$85 an…

True: World | BERT: World  | SVC: SciTech
Text: Future Doctors, Crossing Borders Students at the Mount Sinai School of
Medicine learn that diet and culture shape health in East Harlem…

True: Business | BERT: Business  | SVC: SciTech
Text: Ross Stores Profit Plummets 40 Percent (AP) AP - Discount retailer Ross
Stores Inc. Wednesday said its profit fell about 40 percent in the latest
quarter due to problems with a new computer system tha…

True: World | BERT: World  | SVC: Business
Text: Stock Prices Climb Ahead of Google IPO NEW YORK - Investors shrugged off
rising crude futures Wednesday to capture well-priced shares, sending the Nasdaq
composite index up 1.6 percent ahead of Google…

True: SciTech | BERT: SciTech  | SVC: Business
Text: Ecuadorean Lawsuit Vs Texaco Boils Down to Science (Reuters) Reuters -
After a decade\of court battles, lawyers on Wednesday took a lawsuit
by\Ecuadorean Indians accusing U.S. oil firm ChevronTexaco C…

True: SciTech | BERT: SciTech  | SVC: World
Text: Atlantis "Evidence" Found in Spain, Ireland In 360 B.C. the Greek
philosopher Plato described an island he called Atlantis. Now contradicting new
evidence claims the fabled city-state was based on a r…

True: Business | BERT: Business  | SVC: SciTech
Text: Ohio Sues Best Buy, Alleging Used Sales (AP) AP - Ohio authorities sued
Best Buy Co. Inc. on Thursday, alleging the electronics retailer engaged in
unfair and deceptive business practices…

================================================================================
CASE 2: SVC Correct, BERT Wrong (SVC wins)
================================================================================

True: SciTech | BERT: Business  | SVC: SciTech
Text: Dell Exits Low-End China Consumer PC Market  HONG KONG (Reuters) - Dell
Inc. &lt;DELL.O&gt;, the world's  largest PC maker, said on Monday it has left
the low-end  consumer PC market in China and cut …

True: SciTech | BERT: Business  | SVC: SciTech
Text: IBM Buys Two Danish Services Firms IBM said Tuesday it has acquired a pair
of Danish IT services firms as part of its effort to broaden its presence in
Scandinavia. As a result of the moves, IBM will …

True: World | BERT: SciTech  | SVC: World
Text: Bush Promotes His Plan for Missile Defense System President Bush, in
```

```
Pennsylvania, said that opponents of a missile defense system were putting the
nation's security at risk…

True: SciTech | BERT: World   | SVC: SciTech
Text: Stunt pilots to save sun dust IT PROMISES to be a scene worthy of a
science fiction spectacular. A space probe carrying primordial material scooped
from outer space starts to plunge towards our planet…

True: Sports | BERT: World   | SVC: Sports
Text: Ali gives Iraq fighting chance The back of his shirt told the story last
night at the Peristeri Olympic Boxing Hall…

================================================================================
CASE 3: Both Models Wrong (Hard cases)
================================================================================

True: SciTech | BERT: Business   | SVC: Business
Text: IBM to hire even more new workers By the end of the year, the computing
giant plans to have its biggest headcount since 1991…

True: SciTech | BERT: Business   | SVC: Business
Text: Some People Not Eligible to Get in on Google IPO Google has billed its IPO
as a way for everyday people to get in on the process, denying Wall Street the
usual stranglehold it's had on IPOs. Public bi…

True: World | BERT: Business   | SVC: Business
Text: Venezuela Prepares for Chavez Recall Vote Supporters and rivals warn of
possible fraud; government says Chavez's defeat could produce turmoil in world
oil market…

True: World | BERT: Sports   | SVC: Sports
Text: Live: Olympics day four Richard Faulds and Stephen Parry are going for
gold for Great Britain on day four in Athens…

True: Business | BERT: SciTech   | SVC: SciTech
Text: Intel to delay product aimed for high-definition TVs SAN FRANCISCO -- In
the latest of a series of product delays, Intel Corp. has postponed the launch
of a video display chip it had previously planne…
```

[38]:
```python
# ============================================================================
# Cell 13.5: Categorize Common Error Patterns
# ============================================================================

print("\n[7] Analyzing common error patterns...")

# Most common confusion pairs for BERT
print("\nBERT Most Common Confusions:")
```

```
bert_errors = results_df[~results_df['bert_correct']]
bert_confusion_pairs = bert_errors.groupby(['true_label', 'bert_pred']).size().
↪sort_values(ascending=False).head(5)
for (true_label, pred_label), count in bert_confusion_pairs.items():
    print(f"  {class_names[true_label]} → {class_names[pred_label]}: {count}␣
↪errors")

# Most common confusion pairs for SVC
print("\nSVC Most Common Confusions:")
svc_errors = results_df[~results_df['svc_correct']]
svc_confusion_pairs = svc_errors.groupby(['true_label', 'svc_pred']).size().
↪sort_values(ascending=False).head(5)
for (true_label, pred_label), count in svc_confusion_pairs.items():
    print(f"  {class_names[true_label]} → {class_names[pred_label]}: {count}␣
↪errors")

# Analyze text length for errors
print("\n[8] Error analysis by text length...")
results_df['text_length'] = results_df['text'].str.len()

avg_length_all = results_df['text_length'].mean()
avg_length_bert_correct = results_df[results_df['bert_correct']]['text_length'].
↪mean()
avg_length_bert_wrong = results_df[~results_df['bert_correct']]['text_length'].
↪mean()

print(f"\nAverage text length:")
print(f"  All samples: {avg_length_all:.1f} chars")
print(f"  BERT correct: {avg_length_bert_correct:.1f} chars")
print(f"  BERT wrong: {avg_length_bert_wrong:.1f} chars")
print(f"  Difference: {avg_length_bert_wrong - avg_length_bert_correct:.1f}␣
↪chars")
```

```
[7] Analyzing common error patterns…

BERT Most Common Confusions:
  SciTech → Business: 126 errors
  Business → SciTech: 115 errors
  World → Business: 47 errors
  World → SciTech: 36 errors
  Business → World: 36 errors

SVC Most Common Confusions:
  Business → SciTech: 143 errors
  SciTech → Business: 109 errors
  World → Business: 67 errors
```

```
  Business → World: 53 errors
  SciTech → World: 53 errors

[8] Error analysis by text length…

Average text length:
  All samples: 235.3 chars
  BERT correct: 235.8 chars
  BERT wrong: 227.9 chars
  Difference: -7.8 chars
```

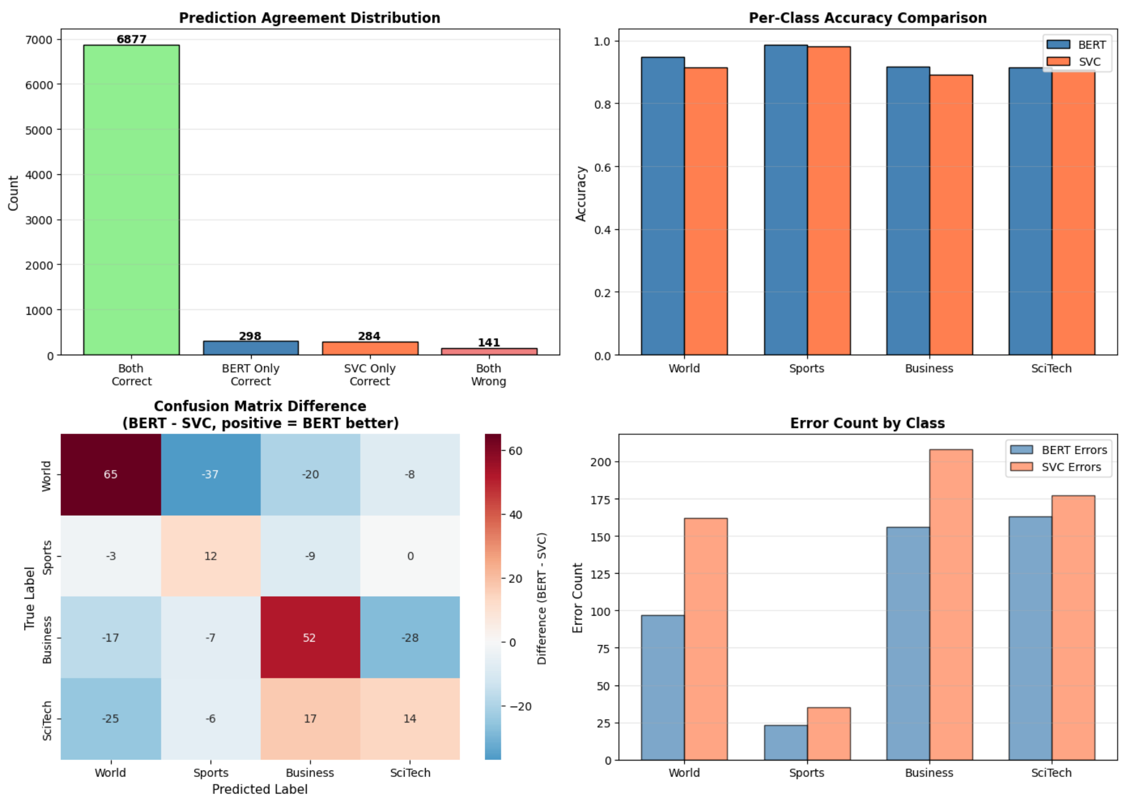
[39]:

```python
# ============================================================================
# Cell 13.6: Error Category Visualization
# ============================================================================

print("\n[9] Creating error analysis visualizations...")

fig, axes = plt.subplots(2, 2, figsize=(14, 10))

# Plot 1: Error type distribution
ax = axes[0, 0]
error_counts = results_df['error_type'].value_counts()
colors = ['lightgreen', 'steelblue', 'coral', 'lightcoral']
ax.bar(range(len(error_counts)), error_counts.values, color=colors,␣
 ↪edgecolor='black')
ax.set_xticks(range(len(error_counts)))
ax.set_xticklabels(['Both\nCorrect', 'BERT Only\nCorrect', 'SVC Only\nCorrect',␣
 ↪'Both\nWrong'], fontsize=10)
ax.set_ylabel('Count', fontsize=11)
ax.set_title('Prediction Agreement Distribution', fontsize=12,␣
 ↪fontweight='bold')
ax.grid(axis='y', alpha=0.3)
for i, v in enumerate(error_counts.values):
    ax.text(i, v + 50, str(v), ha='center', fontweight='bold')

# Plot 2: Per-class accuracy comparison
ax = axes[0, 1]
x = np.arange(len(class_names))
width = 0.35
bert_accs = class_error_df['BERT Accuracy'].values
svc_accs = class_error_df['SVC Accuracy'].values
ax.bar(x - width/2, bert_accs, width, label='BERT', color='steelblue',␣
 ↪edgecolor='black')
ax.bar(x + width/2, svc_accs, width, label='SVC', color='coral',␣
 ↪edgecolor='black')
ax.set_ylabel('Accuracy', fontsize=11)
ax.set_title('Per-Class Accuracy Comparison', fontsize=12, fontweight='bold')
```

```
ax.set_xticks(x)
ax.set_xticklabels(class_names)
ax.legend()
ax.grid(axis='y', alpha=0.3)

# Plot 3: Confusion matrix difference (BERT - SVC)
ax = axes[1, 0]
cm_diff = bert_cm - svc_cm
sns.heatmap(cm_diff, annot=True, fmt='d', cmap='RdBu_r', center=0,
            xticklabels=class_names, yticklabels=class_names, ax=ax,
            cbar_kws={'label': 'Difference (BERT - SVC)'})
ax.set_xlabel('Predicted Label', fontsize=11)
ax.set_ylabel('True Label', fontsize=11)
ax.set_title('Confusion Matrix Difference\n(BERT - SVC, positive = BERT better)',
             fontsize=12, fontweight='bold')

# Plot 4: Error distribution by class
ax = axes[1, 1]
bert_errors_by_class = [np.sum((y_test == i) & ~bert_correct) for i in range(4)]
svc_errors_by_class = [np.sum((y_test == i) & ~svc_correct) for i in range(4)]
x = np.arange(len(class_names))
ax.bar(x - width/2, bert_errors_by_class, width, label='BERT Errors',
       color='steelblue', edgecolor='black', alpha=0.7)
ax.bar(x + width/2, svc_errors_by_class, width, label='SVC Errors',
       color='coral', edgecolor='black', alpha=0.7)
ax.set_ylabel('Error Count', fontsize=11)
ax.set_title('Error Count by Class', fontsize=12, fontweight='bold')
ax.set_xticks(x)
ax.set_xticklabels(class_names)
ax.legend()
ax.grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_error_analysis_detailed.png",
            dpi=300, bbox_inches='tight')
print("  Saved: step6_error_analysis_detailed.png")
plt.show()

print("\n" + "="*80)
print("  CELL 13 COMPLETE: Comparative Error Analysis")
print("="*80)
print(f"\nKey Findings:")
print(f"1. BERT wins on {bert_only_correct} samples, SVC wins on {svc_only_correct}")
print(f"2. Both wrong on {both_wrong} hard cases ({both_wrong/len(y_test)*100:.2f}%)")
```

```
print(f"3. BERT shows biggest improvement on: {class_error_df.
    ↪iloc[class_error_df['BERT Advantage'].idxmax()]['Class']}")
print(f"4. Detailed examples saved to: step6_error_analysis.csv")
```

```
[9] Creating error analysis visualizations…
 Saved: step6_error_analysis_detailed.png
```




```
================================================================================
 CELL 13 COMPLETE: Comparative Error Analysis
================================================================================

Key Findings:
1. BERT wins on 284 samples, SVC wins on 141
2. Both wrong on 298 hard cases (3.92%)
3. BERT shows biggest improvement on: World
4. Detailed examples saved to: step6_error_analysis.csv
```

[1]:
```
# ============================================================================
# Cell 15.1: Load All Results for Visualization
# ============================================================================
```

```python
import numpy as np
import pandas as pd
import joblib
import matplotlib.pyplot as plt
import seaborn as sns
from pathlib import Path

# Paths
RESULTS_DIR = Path("results")

# Set style
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")

print("="*80)
print("CELL 15: PUBLICATION VISUALIZATION SUITE")
print("="*80)

# Load training history
print("\n[1] Loading training history...")
history_df = pd.read_csv(RESULTS_DIR / "step6_training_history.csv")
print(f"  Loaded {len(history_df)} epochs")

# Load test results
print("\n[2] Loading test results...")
test_results = joblib.load(RESULTS_DIR / "step6_test_results.pkl")
bert_cm = test_results['confusion_matrix']
print("  Loaded BERT confusion matrix")

# Load comparison data
print("\n[3] Loading model comparison...")
comparison_df = pd.read_csv(RESULTS_DIR /␣
↪"step6_comparison_classical_vs_transformer.csv")
print(comparison_df)

# Load ablation results
print("\n[4] Loading ablation results...")
ablation_frozen = joblib.load(RESULTS_DIR / "step6_ablation_frozen_vs_tuned.
↪pkl")
ablation_length = joblib.load(RESULTS_DIR / "step6_ablation_sequence_length.
↪pkl")
print(f"  Frozen F1: {ablation_frozen['frozen_f1']:.4f}")
print(f"  Full tuning F1: {ablation_frozen['full_tuning_f1']:.4f}")
print(f"  Sequence lengths tested: {list(ablation_length.keys())}")

# Load bootstrap results
```

```python
print("\n[5] Loading bootstrap results...")
bootstrap_data = joblib.load(RESULTS_DIR / "step6_bootstrap_results.pkl")
print(f"  Mean difference: {bootstrap_data['mean']:.4f}")

print("\n  All data loaded successfully!")
```

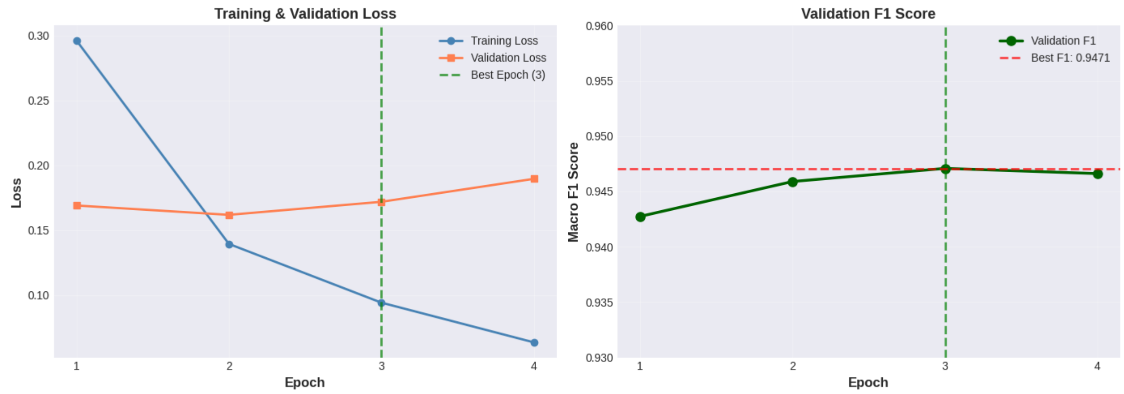
```
================================================================================
CELL 15: PUBLICATION VISUALIZATION SUITE
================================================================================

[1] Loading training history…
  Loaded 4 epochs

[2] Loading test results…
  Loaded BERT confusion matrix

[3] Loading model comparison…
                           Model  Test Macro-F1  Model Size (MB)  \
0          LinearSVC (Classical)       0.927400               50
1  Stacking Ensemble (Classical)       0.929500              100
2       DistilBERT (Transformer)       0.942278              250

   Inference Time (ms/doc)
0                        5
1                       10
2                      100

[4] Loading ablation results…
  Frozen F1: 0.9087
  Full tuning F1: 0.9471
  Sequence lengths tested: [128, 256, 512]

[5] Loading bootstrap results…
  Mean difference: 0.0190

  All data loaded successfully!
```

[2]:

```python
# ==============================================================================
# Cell 15.2: Figure 1 - Training Curves (Loss & F1)
# ==============================================================================

print("\n[6] Creating Figure 1: Training Curves...")

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Plot 1: Loss curves
ax = axes[0]
```

```
epochs = history_df['epoch']
ax.plot(epochs, history_df['train_loss'], 'o-', linewidth=2, markersize=6,
        label='Training Loss', color='steelblue')
ax.plot(epochs, history_df['val_loss'], 's-', linewidth=2, markersize=6,
        label='Validation Loss', color='coral')

# Mark best epoch
best_epoch = history_df['val_f1'].idxmax() + 1
ax.axvline(best_epoch, color='green', linestyle='--', linewidth=2,
           alpha=0.7, label=f'Best Epoch ({best_epoch})')

ax.set_xlabel('Epoch', fontsize=12, fontweight='bold')
ax.set_ylabel('Loss', fontsize=12, fontweight='bold')
ax.set_title('Training & Validation Loss', fontsize=13, fontweight='bold')
ax.legend(fontsize=10)
ax.grid(True, alpha=0.3)
ax.set_xticks(epochs)

# Plot 2: F1 score
ax = axes[1]
ax.plot(epochs, history_df['val_f1'], 'o-', linewidth=2.5, markersize=8,
        color='darkgreen', label='Validation F1')

# Mark best F1
best_f1 = history_df['val_f1'].max()
ax.axhline(best_f1, color='red', linestyle='--', linewidth=2,
           alpha=0.7, label=f'Best F1: {best_f1:.4f}')
ax.axvline(best_epoch, color='green', linestyle='--', linewidth=2, alpha=0.7)

ax.set_xlabel('Epoch', fontsize=12, fontweight='bold')
ax.set_ylabel('Macro F1 Score', fontsize=12, fontweight='bold')
ax.set_title('Validation F1 Score', fontsize=13, fontweight='bold')
ax.legend(fontsize=10)
ax.grid(True, alpha=0.3)
ax.set_xticks(epochs)
ax.set_ylim([0.93, 0.96])

plt.tight_layout()
plt.savefig(RESULTS_DIR / "figure1_training_curves.png", dpi=300,␣
 ↪bbox_inches='tight')
print("  Saved: figure1_training_curves.png")
plt.show()
```

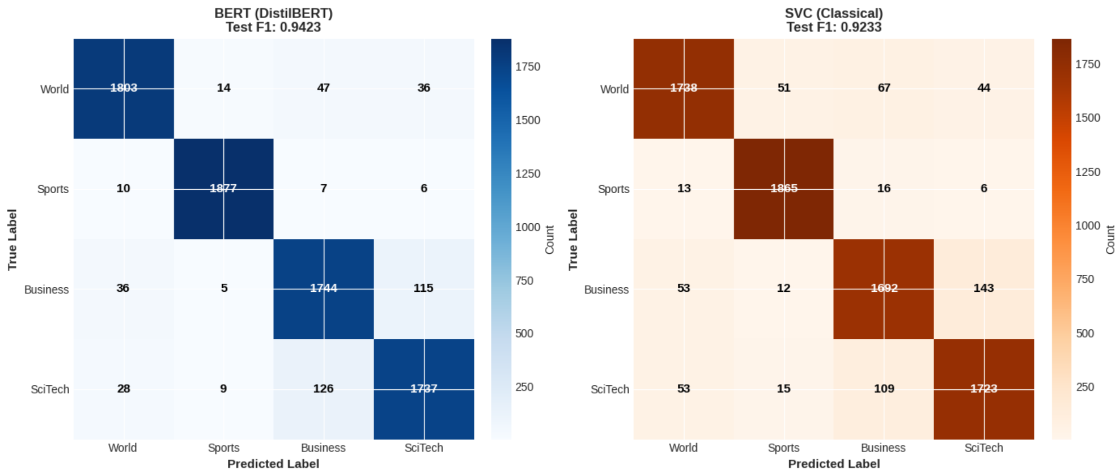
```
[6] Creating Figure 1: Training Curves…
  Saved: figure1_training_curves.png
```



[3]:
```python
# ============================================================================
# Cell 15.3: Figure 2 - Confusion Matrix Comparison
# ============================================================================

print("\n[7] Creating Figure 2: Confusion Matrix Comparison...")

# Load SVC confusion matrix (regenerate from saved predictions)
from sklearn.metrics import confusion_matrix
import scipy.sparse as sp_sparse

# Load data
test_df = pd.read_csv(Path("data") / "test.csv")
y_test = test_df['label'].values

# SVC predictions
X_test = sp_sparse.load_npz(Path("features") / "X_test_hybrid.npz")
svc_model = joblib.load(Path("models") / "step5_tuned_SVC.pkl")
svc_preds = svc_model.predict(X_test)
svc_cm = confusion_matrix(y_test, svc_preds)

# Create figure
class_names = ['World', 'Sports', 'Business', 'SciTech']
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# BERT confusion matrix
im1 = axes[0].imshow(bert_cm, cmap='Blues', aspect='auto')
axes[0].set_xticks(range(4))
axes[0].set_yticks(range(4))
axes[0].set_xticklabels(class_names, fontsize=10)
axes[0].set_yticklabels(class_names, fontsize=10)
axes[0].set_xlabel('Predicted Label', fontsize=11, fontweight='bold')
axes[0].set_ylabel('True Label', fontsize=11, fontweight='bold')
axes[0].set_title('BERT (DistilBERT)\nTest F1: 0.9423',
```

```
                  fontsize=12, fontweight='bold')

# Annotate cells
for i in range(4):
    for j in range(4):
        text_color = 'white' if bert_cm[i, j] > bert_cm.max()/2 else 'black'
        axes[0].text(j, i, str(bert_cm[i, j]), ha='center', va='center',
                    fontsize=11, fontweight='bold', color=text_color)

# Add colorbar
cbar1 = plt.colorbar(im1, ax=axes[0], fraction=0.046, pad=0.04)
cbar1.set_label('Count', fontsize=10)

# SVC confusion matrix
im2 = axes[1].imshow(svc_cm, cmap='Oranges', aspect='auto')
axes[1].set_xticks(range(4))
axes[1].set_yticks(range(4))
axes[1].set_xticklabels(class_names, fontsize=10)
axes[1].set_yticklabels(class_names, fontsize=10)
axes[1].set_xlabel('Predicted Label', fontsize=11, fontweight='bold')
axes[1].set_ylabel('True Label', fontsize=11, fontweight='bold')
axes[1].set_title('SVC (Classical)\nTest F1: 0.9233',
                  fontsize=12, fontweight='bold')

# Annotate cells
for i in range(4):
    for j in range(4):
        text_color = 'white' if svc_cm[i, j] > svc_cm.max()/2 else 'black'
        axes[1].text(j, i, str(svc_cm[i, j]), ha='center', va='center',
                    fontsize=11, fontweight='bold', color=text_color)

# Add colorbar
cbar2 = plt.colorbar(im2, ax=axes[1], fraction=0.046, pad=0.04)
cbar2.set_label('Count', fontsize=10)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "figure2_confusion_matrices.png", dpi=300,␣
 ↪bbox_inches='tight')
print("  Saved: figure2_confusion_matrices.png")
plt.show()
```

```
[7] Creating Figure 2: Confusion Matrix Comparison…
  Saved: figure2_confusion_matrices.png
```

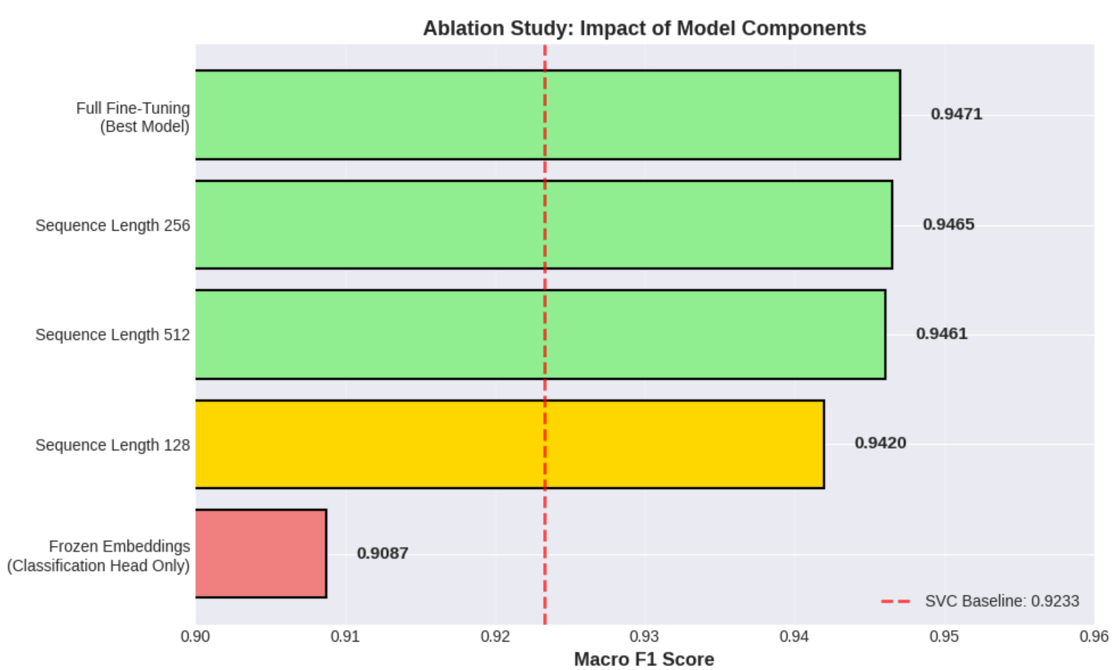


[4]:

```python
# ==========================================================================
# Cell 15.4: Figure 3 - Ablation Study Results
# ==========================================================================

print("\n[8] Creating Figure 3: Ablation Studies...")

# Compile ablation results
ablation_results = {
    'Frozen Embeddings\n(Classification Head Only)': ablation_frozen['frozen_f1'],
    'Sequence Length 128': ablation_length[128],
    'Sequence Length 256': ablation_length[256],
    'Sequence Length 512': ablation_length[512],
    'Full Fine-Tuning\n(Best Model)': ablation_frozen['full_tuning_f1']
}

# Sort by F1 score
sorted_results = dict(sorted(ablation_results.items(), key=lambda x: x[1]))

fig, ax = plt.subplots(figsize=(10, 6))

# Create horizontal bar chart
labels = list(sorted_results.keys())
values = list(sorted_results.values())
colors = ['lightcoral' if v < 0.94 else 'gold' if v < 0.945 else 'lightgreen'
          for v in values]

bars = ax.barh(labels, values, color=colors, edgecolor='black', linewidth=1.5)

# Add value labels
```

```python
for i, (bar, val) in enumerate(zip(bars, values)):
    ax.text(val + 0.002, i, f'{val:.4f}', va='center', fontsize=11, fontweight='bold')

# Add baseline line (SVC performance)
svc_f1 = 0.9233
ax.axvline(svc_f1, color='red', linestyle='--', linewidth=2,
           label=f'SVC Baseline: {svc_f1:.4f}', alpha=0.7)

ax.set_xlabel('Macro F1 Score', fontsize=12, fontweight='bold')
ax.set_title('Ablation Study: Impact of Model Components',
             fontsize=13, fontweight='bold')
ax.set_xlim([0.90, 0.96])
ax.legend(fontsize=10)
ax.grid(axis='x', alpha=0.3)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "figure3_ablation_studies.png", dpi=300, bbox_inches='tight')
print("  Saved: figure3_ablation_studies.png")
plt.show()
```

```
[8] Creating Figure 3: Ablation Studies…
 Saved: figure3_ablation_studies.png
```

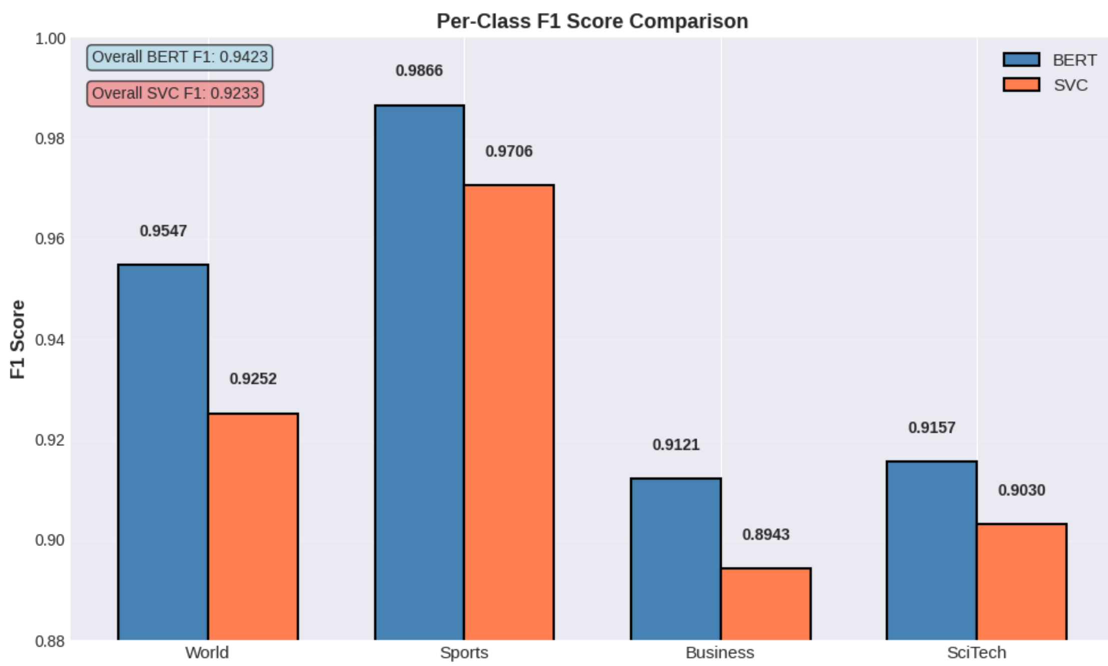


[5]:

```python
# ============================================================================
# Cell 15.5: Figure 4 - Per-Class F1 Comparison
# ============================================================================

print("\n[9] Creating Figure 4: Per-Class F1 Comparison...")

from sklearn.metrics import classification_report

# BERT per-class F1
bert_preds = test_results['test_predictions']
bert_report = classification_report(y_test, bert_preds, output_dict=True)
bert_f1_scores = [bert_report[str(i)]['f1-score'] for i in range(4)]

# SVC per-class F1
svc_report = classification_report(y_test, svc_preds, output_dict=True)
svc_f1_scores = [svc_report[str(i)]['f1-score'] for i in range(4)]

# Create plot
fig, ax = plt.subplots(figsize=(10, 6))

x = np.arange(len(class_names))
width = 0.35

bars1 = ax.bar(x - width/2, bert_f1_scores, width, label='BERT',
               color='steelblue', edgecolor='black', linewidth=1.5)
bars2 = ax.bar(x + width/2, svc_f1_scores, width, label='SVC',
               color='coral', edgecolor='black', linewidth=1.5)

# Add value labels
for bars in [bars1, bars2]:
    for bar in bars:
        height = bar.get_height()
        ax.text(bar.get_x() + bar.get_width()/2., height + 0.005,
                f'{height:.4f}', ha='center', va='bottom',
                fontsize=10, fontweight='bold')

ax.set_ylabel('F1 Score', fontsize=12, fontweight='bold')
ax.set_title('Per-Class F1 Score Comparison', fontsize=13, fontweight='bold')
ax.set_xticks(x)
ax.set_xticklabels(class_names, fontsize=11)
ax.legend(fontsize=11)
ax.set_ylim([0.88, 1.0])
ax.grid(axis='y', alpha=0.3)

# Add overall F1 annotations
ax.text(0.02, 0.98, f'Overall BERT F1: {test_results["test_macro_f1"]:.4f}',
        transform=ax.transAxes, fontsize=10, verticalalignment='top',
```

```
        bbox=dict(boxstyle='round', facecolor='lightblue', alpha=0.7))
ax.text(0.02, 0.92, f'Overall SVC F1: 0.9233',
        transform=ax.transAxes, fontsize=10, verticalalignment='top',
        bbox=dict(boxstyle='round', facecolor='lightcoral', alpha=0.7))

plt.tight_layout()
plt.savefig(RESULTS_DIR / "figure4_perclass_f1.png", dpi=300,
 ↪bbox_inches='tight')
print("  Saved: figure4_perclass_f1.png")
plt.show()
```

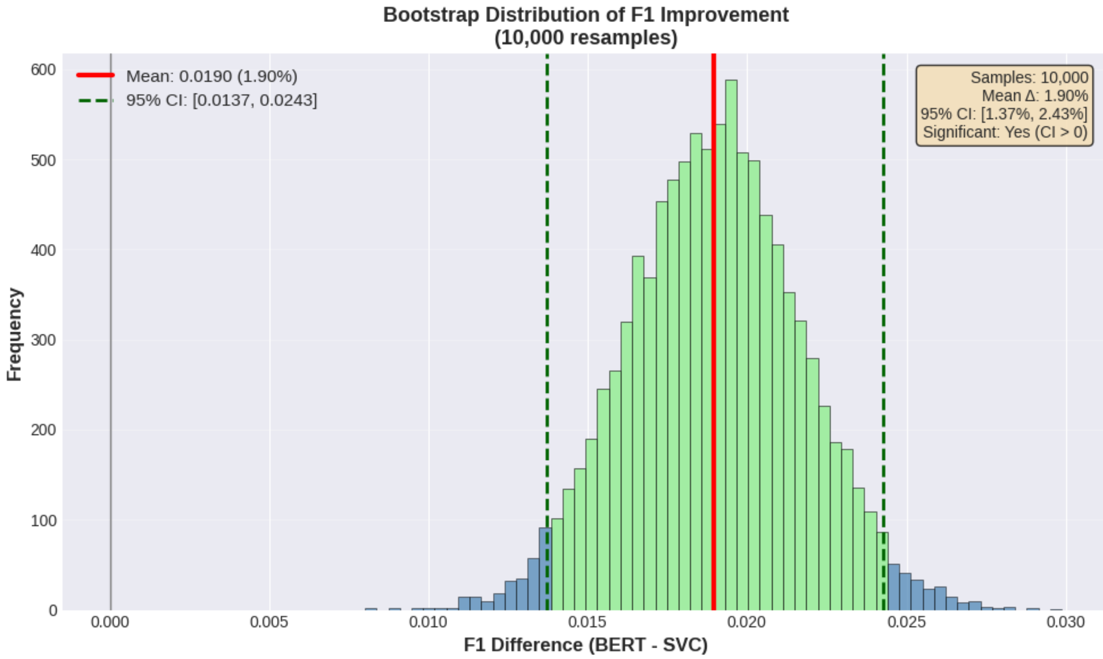
```
[9] Creating Figure 4: Per-Class F1 Comparison…
 Saved: figure4_perclass_f1.png
```



[7]:
```
# ============================================================================
# Cell 15.6: Figure 5 - Bootstrap Distribution with CI
# ============================================================================

print("\n[10] Creating Figure 5: Bootstrap Distribution...")

differences = bootstrap_data['differences']
mean_diff = bootstrap_data['mean']
ci_lower = bootstrap_data['ci_lower']
ci_upper = bootstrap_data['ci_upper']
```

```python
fig, ax = plt.subplots(figsize=(10, 6))

# Histogram
n, bins, patches = ax.hist(differences, bins=60, alpha=0.7, color='steelblue',
                            edgecolor='black', linewidth=0.5)

# Color the CI region
for i, patch in enumerate(patches):
    if ci_lower <= bins[i] <= ci_upper:
        patch.set_facecolor('lightgreen')
        patch.set_alpha(0.8)

# Add vertical lines
ax.axvline(mean_diff, color='red', linestyle='-', linewidth=3,
           label=f'Mean: {mean_diff:.4f} ({mean_diff*100:.2f}%)', zorder=5)
ax.axvline(ci_lower, color='darkgreen', linestyle='--', linewidth=2,
           label=f'95% CI: [{ci_lower:.4f}, {ci_upper:.4f}]', zorder=5)
ax.axvline(ci_upper, color='darkgreen', linestyle='--', linewidth=2, zorder=5)
ax.axvline(0, color='black', linestyle='-', linewidth=1, alpha=0.5, zorder=5)

ax.set_xlabel('F1 Difference (BERT - SVC)', fontsize=12, fontweight='bold')
ax.set_ylabel('Frequency', fontsize=12, fontweight='bold')
ax.set_title('Bootstrap Distribution of F1 Improvement\n(10,000 resamples)',
             fontsize=13, fontweight='bold')
ax.legend(fontsize=11, loc='upper left')
ax.grid(axis='y', alpha=0.3)

# Add text box with statistics
textstr = f'Samples: 10,000\nMean Δ: {mean_diff*100:.2f}%\n95% CI:␣
 ↪[{ci_lower*100:.2f}%, {ci_upper*100:.2f}%]\nSignificant: Yes (CI > 0)'
props = dict(boxstyle='round', facecolor='wheat', alpha=0.8)
ax.text(0.98, 0.97, textstr, transform=ax.transAxes, fontsize=10,
        verticalalignment='top', horizontalalignment='right', bbox=props)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "figure5_bootstrap_distribution.png", dpi=300,␣
 ↪bbox_inches='tight')
print("  Saved: figure5_bootstrap_distribution.png")
plt.show()
```

```
[10] Creating Figure 5: Bootstrap Distribution…
  Saved: figure5_bootstrap_distribution.png
```



[9]:
```
# ==============================================================================
# Cell 16.1: Load BERT Model and Select Examples for Attention Visualization
# ==============================================================================

import torch
import numpy as np
import pandas as pd
import joblib
from pathlib import Path
from transformers import AutoTokenizer, AutoModelForSequenceClassification

# Paths
DATA_DIR = Path("data")
MODELS_DIR = Path("models")
RESULTS_DIR = Path("results")

print("="*80)
print("CELL 16: ATTENTION VISUALIZATION")
print("="*80)

# Set device
DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"\n[1] Device: {DEVICE}")

# Load model and tokenizer
```

```
print("\n[2] Loading BERT model...")
tokenizer = AutoTokenizer.from_pretrained(MODELS_DIR / "step6_distilbert_best")
model = AutoModelForSequenceClassification.from_pretrained(
    MODELS_DIR / "step6_distilbert_best",
    output_attentions=True  # Important: Enable attention outputs
).to(DEVICE)
model.eval()
print("  Model loaded with attention outputs enabled")

# Load error analysis results
print("\n[3] Loading predictions and selecting examples...")
error_df = pd.read_csv(RESULTS_DIR / "step6_error_analysis.csv")
class_names = ['World', 'Sports', 'Business', 'SciTech']

# Select 10 diverse examples:
# - 4 correct predictions (1 per class)
# - 3 BERT correct, SVC wrong
# - 3 BERT wrong (1 both wrong, 2 BERT-only wrong)

examples = []

# 1. One correctly classified example from each class
print("\n  Selecting examples:")
for class_idx in range(4):
    correct_examples = error_df[
        (error_df['true_label'] == class_idx) &
        (error_df['bert_correct'] == True)
    ]
    if len(correct_examples) > 0:
        example = correct_examples.iloc[0]
        examples.append({
            'text': example['text'],
            'true_label': class_idx,
            'bert_pred': example['bert_pred'],
            'category': f'Correct ({class_names[class_idx]})'
        })
        print(f"    Correct {class_names[class_idx]} example")

# 2. BERT correct, SVC wrong (3 examples)
bert_wins = error_df[error_df['error_type'] == 'bert_only_correct']
for i in range(min(3, len(bert_wins))):
    example = bert_wins.iloc[i]
    examples.append({
        'text': example['text'],
        'true_label': int(example['true_label']),
        'bert_pred': int(example['bert_pred']),
        'category': 'BERT Correct, SVC Wrong'
```

```
    })
print(f"    {min(3, len(bert_wins))} BERT-wins examples")

# 3. BERT wrong (3 examples: mix of both-wrong and BERT-only-wrong)
bert_errors = error_df[error_df['bert_correct'] == False]
for i in range(min(3, len(bert_errors))):
    example = bert_errors.iloc[i]
    examples.append({
        'text': example['text'],
        'true_label': int(example['true_label']),
        'bert_pred': int(example['bert_pred']),
        'category': 'BERT Wrong'
    })
print(f"    {min(3, len(bert_errors))} BERT-error examples")

print(f"\n  Selected {len(examples)} examples for visualization")
```

```
================================================================================
CELL 16: ATTENTION VISUALIZATION
================================================================================

[1] Device: cuda

[2] Loading BERT model…
 Model loaded with attention outputs enabled

[3] Loading predictions and selecting examples…

  Selecting examples:
    Correct World example
    Correct Sports example
    Correct Business example
    Correct SciTech example
    3 BERT-wins examples
    3 BERT-error examples

 Selected 10 examples for visualization
```

[10]:
```
# ==============================================================================
# Cell 16.2: Extract Attention Weights from Model
# ==============================================================================

print("\n[4] Extracting attention weights...")

attention_data = []

for idx, example in enumerate(examples):
```

```
    text = example['text']

    # Tokenize
    inputs = tokenizer(
        text,
        return_tensors='pt',
        truncation=True,
        max_length=256,
        padding='max_length'
    )

    input_ids = inputs['input_ids'].to(DEVICE)
    attention_mask = inputs['attention_mask'].to(DEVICE)

    # Get tokens for visualization
    tokens = tokenizer.convert_ids_to_tokens(input_ids[0])

    # Forward pass with attention
    with torch.no_grad():
        outputs = model(
            input_ids=input_ids,
            attention_mask=attention_mask
        )
        attentions = outputs.attentions  # Tuple of (batch, heads, seq_len,␣
↪seq_len)

    # Get prediction
    logits = outputs.logits
    pred = torch.argmax(logits, dim=1).item()
    probs = torch.softmax(logits, dim=1).cpu().numpy()[0]

    # Average attention across all heads and layers
    # attentions: tuple of 6 layers, each (1, 12, seq_len, seq_len)
    # We'll use the last layer's attention
    last_layer_attention = attentions[-1]  # Shape: (1, 12, seq_len, seq_len)

    # Average across heads: (1, 12, seq_len, seq_len) -> (seq_len, seq_len)
    avg_attention = last_layer_attention[0].mean(dim=0).cpu().numpy()

    # Get attention to [CLS] token (first token)
    # This shows which tokens the model focuses on for classification
    cls_attention = avg_attention[0, :]  # Attention from [CLS] to all tokens

    # Only keep non-padding tokens
    seq_len = attention_mask.sum().item()
    tokens = tokens[:seq_len]
    cls_attention = cls_attention[:seq_len]
```

```
    # Store results
    attention_data.append({
        'example_idx': idx,
        'text': text,
        'tokens': tokens,
        'attention': cls_attention,
        'true_label': example['true_label'],
        'pred_label': pred,
        'confidence': probs[pred],
        'category': example['category'],
        'is_correct': pred == example['true_label']
    })

    print(f"  [{idx+1}/{len(examples)}] Processed: {example['category']}")

print(f"\n Extracted attention for {len(attention_data)} examples")
```

```
[4] Extracting attention weights…
  [1/10] Processed: Correct (World)
  [2/10] Processed: Correct (Sports)
  [3/10] Processed: Correct (Business)
  [4/10] Processed: Correct (SciTech)
  [5/10] Processed: BERT Correct, SVC Wrong
  [6/10] Processed: BERT Correct, SVC Wrong
  [7/10] Processed: BERT Correct, SVC Wrong
  [8/10] Processed: BERT Wrong
  [9/10] Processed: BERT Wrong
  [10/10] Processed: BERT Wrong

 Extracted attention for 10 examples
```

[11]:
```
# ============================================================================
# Cell 16.3: Identify Top Attended Tokens
# ============================================================================

print("\n[5] Analyzing top attended tokens...")

for data in attention_data:
    tokens = data['tokens']
    attention = data['attention']

    # Remove special tokens for analysis
    content_tokens = []
    content_attention = []
```

```
    for token, att in zip(tokens, attention):
        if token not in ['[CLS]', '[SEP]', '[PAD]']:
            content_tokens.append(token)
            content_attention.append(att)

    # Get top 5 attended tokens
    if len(content_attention) > 0:
        top_indices = np.argsort(content_attention)[-5:][::-1]
        top_tokens = [content_tokens[i] for i in top_indices]
        top_scores = [content_attention[i] for i in top_indices]

        data['top_tokens'] = top_tokens
        data['top_scores'] = top_scores
    else:
        data['top_tokens'] = []
        data['top_scores'] = []

# Print summary
print("\nTop 5 Attended Tokens per Example:")
print("="*80)
for data in attention_data:
    print(f"\nExample {data['example_idx']+1}: {data['category']}")
    print(f"  True: {class_names[data['true_label']]} | "
          f"Pred: {class_names[data['pred_label']]} "
          f"({' ' if data['is_correct'] else ' '}) | "
          f"Conf: {data['confidence']:.3f}")
    print(f"  Text: {data['text'][:100]}...")
    print(f"  Top tokens:")
    for token, score in zip(data['top_tokens'], data['top_scores']):
        print(f"    {token:20s} → {score:.4f}")
```

```
[5] Analyzing top attended tokens…

Top 5 Attended Tokens per Example:
================================================================================

Example 1: Correct (World)
  True: World | Pred: World ( ) | Conf: 0.999
  Text: Sister of man who died in Vancouver police custody slams chief (Canadian
Press) Canadian Press - VAN…
  Top tokens:
    .                    → 0.2338
    sister               → 0.0466
    -                    → 0.0458
    sister               → 0.0448
    press                → 0.0437
```

```
Example 2: Correct (Sports)
  True: Sports | Pred: Sports ( ) | Conf: 0.929
  Text: Giddy Phelps Touches Gold for First Time Michael Phelps won the gold
medal in the 400 individual med…
  Top tokens:
    .                    → 0.3119
    first                → 0.1473
    time                 → 0.0573
    for                  → 0.0478
    medley               → 0.0300

Example 3: Correct (Business)
  True: Business | Pred: Business ( ) | Conf: 0.989
  Text: Fears for T N pension after talks Unions representing workers at Turner
Newall say they are 'disap…
  Top tokens:
    .                    → 0.2415
    after                → 0.0785
    n                    → 0.0561
    t                    → 0.0541
    pension              → 0.0484

Example 4: Correct (SciTech)
  True: SciTech | Pred: SciTech ( ) | Conf: 0.997
  Text: The Race is On: Second Private Team Sets Launch Date for Human
Spaceflight (SPACE.com) SPACE.com - T…
  Top tokens:
    .                    → 0.1865
    \                    → 0.1061
    ,                    → 0.0888
    \                    → 0.0472
    com                  → 0.0448

Example 5: BERT Correct, SVC Wrong
  True: SciTech | Pred: SciTech ( ) | Conf: 0.992
  Text: Prediction Unit Helps Forecast Wildfires (AP) AP - It's barely dawn when
Mike Fitzpatrick starts his…
  Top tokens:
    .                    → 0.1199
    ap                   → 0.0971
    ap                   → 0.0945
    -                    → 0.0689
    unit                 → 0.0573

Example 6: BERT Correct, SVC Wrong
  True: SciTech | Pred: SciTech ( ) | Conf: 0.597
  Text: Rivals Try to Turn Tables on Charles Schwab By MICHAEL LIEDTKE     SAN
FRANCISCO (AP) -- With its lo…
```

```
  Top tokens:
    ,                      → 0.0856
    )                      → 0.0735
    ap                     → 0.0653
    .                      → 0.0598
    -                      → 0.0396

Example 7: BERT Correct, SVC Wrong
  True: SciTech | Pred: SciTech ( ) | Conf: 0.949
  Text: Promoting a Shared Vision As Michael Kaleko kept running into people who
were getting older and havi…
  Top tokens:
    promoting              → 0.1347
    could                  → 0.0841
    .                      → 0.0649
    realized               → 0.0608
    it                     → 0.0588

Example 8: BERT Wrong
  True: SciTech | Pred: Business ( ) | Conf: 0.585
  Text: IBM to hire even more new workers By the end of the year, the computing
giant plans to have its bigg…
  Top tokens:
    plans                  → 0.1169
    .                      → 0.0728
    since                  → 0.0666
    hire                   → 0.0626
    1991                   → 0.0568

Example 9: BERT Wrong
  True: SciTech | Pred: Business ( ) | Conf: 0.965
  Text: Some People Not Eligible to Get in on Google IPO Google has billed its
IPO as a way for everyday peo…
  Top tokens:
    .                      → 0.1466
    .                      → 0.1128
    isn                    → 0.0732
    t                      → 0.0659
    but                    → 0.0653

Example 10: BERT Wrong
  True: World | Pred: Business ( ) | Conf: 0.917
  Text: Venezuela Prepares for Chavez Recall Vote Supporters and rivals warn of
possible fraud; government s…
  Top tokens:
    .                      → 0.2947
    ;                      → 0.1396
    recall                 → 0.0905
```

```
venezuela            → 0.0457
oil                  → 0.0335
```

[12]:
```python
# ============================================================================
# Cell 16.4: Create Attention Heatmap Visualizations
# ============================================================================

import matplotlib.pyplot as plt
import seaborn as sns

print("\n[6] Creating attention heatmaps...")

# Create a grid of subplots (5 rows x 2 columns for 10 examples)
fig, axes = plt.subplots(5, 2, figsize=(16, 20))
axes = axes.flatten()

for idx, data in enumerate(attention_data):
    ax = axes[idx]

    tokens = data['tokens']
    attention = data['attention']

    # Limit to first 50 tokens for visualization
    max_tokens = min(50, len(tokens))
    tokens_vis = tokens[:max_tokens]
    attention_vis = attention[:max_tokens]

    # Create heatmap
    attention_matrix = attention_vis.reshape(1, -1)

    # Clean tokens (remove ## from subwords)
    clean_tokens = [t.replace('##', '') for t in tokens_vis]

    # Plot
    im = ax.imshow(attention_matrix, cmap='YlOrRd', aspect='auto')

    # Set ticks
    ax.set_yticks([0])
    ax.set_yticklabels(['Attention'])
    ax.set_xticks(range(0, max_tokens, max(1, max_tokens//10)))
    ax.set_xticklabels([clean_tokens[i] for i in range(0, max_tokens, max(1, max_tokens//10))],
                       rotation=45, ha='right', fontsize=8)

    # Title
    pred_marker = ' ' if data['is_correct'] else ' '
    title = f"Ex {idx+1}: {data['category']}\n"
```

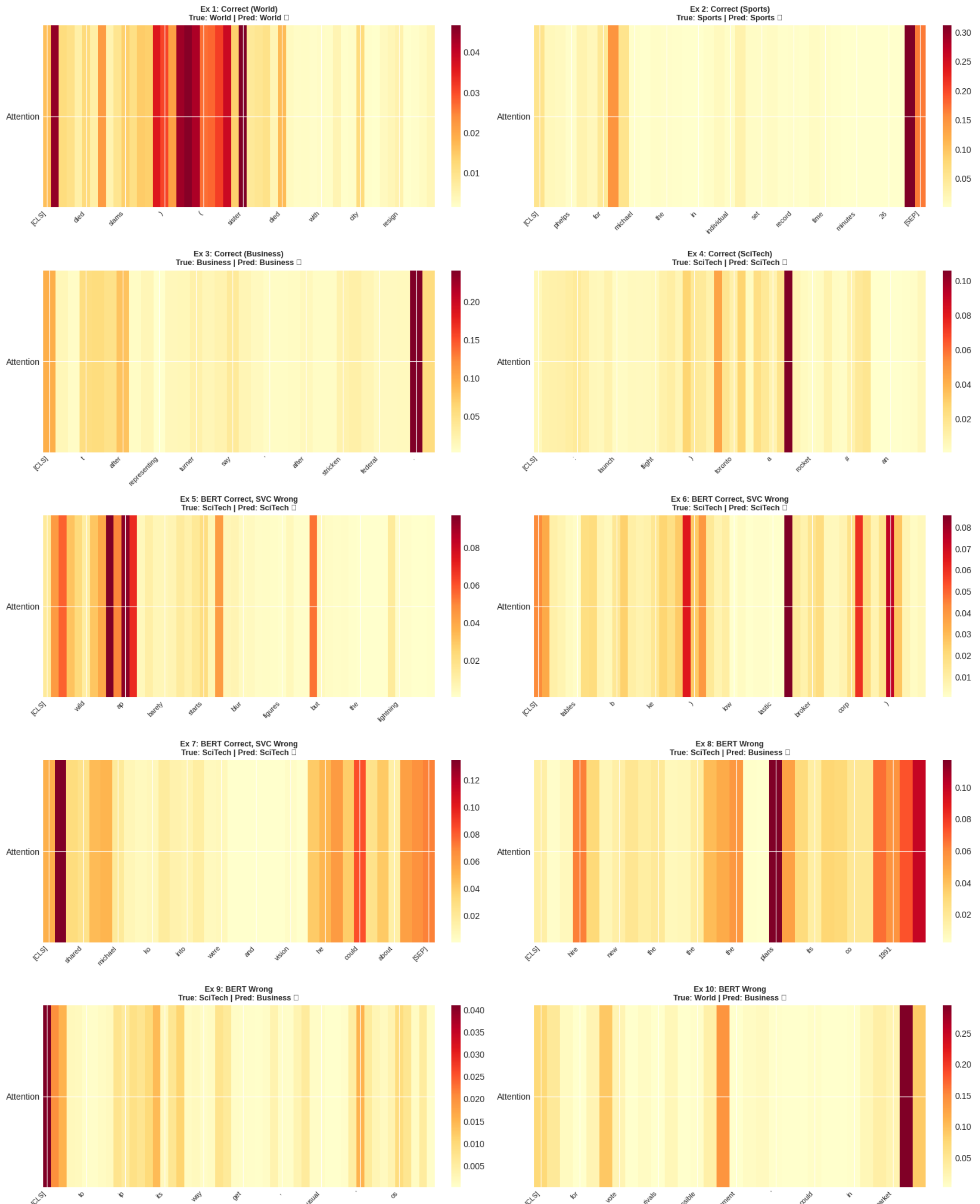
```python
    title += f"True: {class_names[data['true_label']]} | "
    title += f"Pred: {class_names[data['pred_label']]} {pred_marker}"
    ax.set_title(title, fontsize=9, fontweight='bold')

    # Colorbar
    plt.colorbar(im, ax=ax, fraction=0.046, pad=0.04)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_attention_heatmaps.png", dpi=300,␣
↪bbox_inches='tight')
print("  Saved: step6_attention_heatmaps.png")
plt.show()
```

```
[6] Creating attention heatmaps…
```

```
/tmp/ipykernel_6430/907106147.py:51: UserWarning: Glyph 10003 (\N{CHECK MARK})
missing from font(s) Liberation Sans.
  plt.tight_layout()
/tmp/ipykernel_6430/907106147.py:51: UserWarning: Glyph 10007 (\N{BALLOT X})
missing from font(s) Liberation Sans.
  plt.tight_layout()
/tmp/ipykernel_6430/907106147.py:52: UserWarning: Glyph 10003 (\N{CHECK MARK})
missing from font(s) Liberation Sans.
  plt.savefig(RESULTS_DIR / "step6_attention_heatmaps.png", dpi=300,
bbox_inches='tight')
/tmp/ipykernel_6430/907106147.py:52: UserWarning: Glyph 10007 (\N{BALLOT X})
missing from font(s) Liberation Sans.
  plt.savefig(RESULTS_DIR / "step6_attention_heatmaps.png", dpi=300,
bbox_inches='tight')
```

```
  Saved: step6_attention_heatmaps.png
```

```
/home/dante/Desktop/prj/news/.venv/lib/python3.11/site-
packages/IPython/core/pylabtools.py:170: UserWarning: Glyph 10003 (\N{CHECK
MARK}) missing from font(s) Liberation Sans.
  fig.canvas.print_figure(bytes_io, **kw)
/home/dante/Desktop/prj/news/.venv/lib/python3.11/site-
packages/IPython/core/pylabtools.py:170: UserWarning: Glyph 10007 (\N{BALLOT X})
missing from font(s) Liberation Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```



[14]:

```python
# ============================================================================
# Cell 16.5: Create Attention Summary Table
# ============================================================================

print("\n[7] Creating attention summary table...")
```

```python
# Create summary DataFrame
summary_data = []

for data in attention_data:
    summary_data.append({
        'Example': data['example_idx'] + 1,
        'Category': data['category'],
        'True Label': class_names[data['true_label']],
        'Predicted': class_names[data['pred_label']],
        'Correct': ' ' if data['is_correct'] else ' ',
        'Confidence': f"{data['confidence']:.3f}",
        'Top 1 Token': data['top_tokens'][0] if data['top_tokens'] else '',
        'Top 1 Score': f"{data['top_scores'][0]:.4f}" if data['top_scores']␣
 ↪else '',
        'Text Preview': data['text'][:80] + '...'
    })

summary_df = pd.DataFrame(summary_data)

print("\nAttention Analysis Summary:")
print("="*80)
print(summary_df.to_string(index=False))

# Save to CSV
summary_df.to_csv(RESULTS_DIR / "step6_attention_summary.csv", index=False)
print(f"\n Saved: step6_attention_summary.csv")
```

```
[7] Creating attention summary table…

Attention Analysis Summary:
================================================================================
 Example                Category True Label Predicted Correct Confidence Top 1
Token Top 1 Score
Text Preview
       1         Correct (World)      World     World               0.999
.      0.2338 Sister of man who died in Vancouver police custody slams chief
(Canadian Press) …
       2        Correct (Sports)     Sports    Sports               0.929
.      0.3119 Giddy Phelps Touches Gold for First Time Michael Phelps won the
gold medal in th…
       3      Correct (Business)   Business  Business               0.989
.      0.2415 Fears for T N pension after talks Unions representing workers at
Turner   Newall…
       4       Correct (SciTech)    SciTech   SciTech               0.997
.      0.1865 The Race is On: Second Private Team Sets Launch Date for Human
Spaceflight (SPAC…
```

```
       5 BERT Correct, SVC Wrong    SciTech   SciTech              0.992
.      0.1199 Prediction Unit Helps Forecast Wildfires (AP) AP - It's barely
dawn when Mike Fi…
       6 BERT Correct, SVC Wrong    SciTech   SciTech              0.597
,      0.0856 Rivals Try to Turn Tables on Charles Schwab By MICHAEL LIEDTKE
SAN FRANCISCO…
       7 BERT Correct, SVC Wrong    SciTech   SciTech              0.949
promoting      0.1347 Promoting a Shared Vision As Michael Kaleko kept running
into people who were ge…
       8              BERT Wrong    SciTech  Business              0.585
plans      0.1169 IBM to hire even more new workers By the end of the year, the
computing giant pl…
       9              BERT Wrong    SciTech  Business              0.965
.      0.1466 Some People Not Eligible to Get in on Google IPO Google has billed
its IPO as a …
      10              BERT Wrong      World  Business              0.917
.      0.2947 Venezuela Prepares for Chavez Recall Vote Supporters and rivals
warn of possible…

 Saved: step6_attention_summary.csv
```

[16]:
```python
# ============================================================================
# Cell 17.1: Install LIME and Setup
# ============================================================================

# Install LIME if not already installed
# Uncomment the line below if needed:
# !pip install lime

import numpy as np
import pandas as pd
import joblib
import torch
from pathlib import Path
from lime.lime_text import LimeTextExplainer
from transformers import AutoTokenizer, AutoModelForSequenceClassification

print("="*80)
print("CELL 17: LIME EXPLAINABILITY")
print("="*80)

# Paths
DATA_DIR = Path("data")
MODELS_DIR = Path("models")
RESULTS_DIR = Path("results")

# Set device
```

```
DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"\n[1] Device: {DEVICE}")

# Load model and tokenizer
print("\n[2] Loading BERT model...")
tokenizer = AutoTokenizer.from_pretrained(MODELS_DIR / "step6_distilbert_best")
model = AutoModelForSequenceClassification.from_pretrained(
    MODELS_DIR / "step6_distilbert_best"
).to(DEVICE)
model.eval()
print("  Model loaded")

# Class names
class_names = ['World', 'Sports', 'Business', 'SciTech']
```

```
================================================================================
CELL 17: LIME EXPLAINABILITY
================================================================================

[1] Device: cuda

[2] Loading BERT model…
  Model loaded
```

[17]:
```
# ============================================================================
# Cell 17.2: Create Prediction Wrapper for LIME
# ============================================================================

print("\n[3] Creating BERT prediction wrapper for LIME...")

def bert_predict_proba(texts):
    """
    Wrapper function for BERT that LIME can use.
    Takes a list of text strings and returns probability predictions.
    """
    # Tokenize batch
    inputs = tokenizer(
        texts,
        return_tensors='pt',
        truncation=True,
        max_length=256,
        padding=True
    )

    input_ids = inputs['input_ids'].to(DEVICE)
    attention_mask = inputs['attention_mask'].to(DEVICE)
```

```python
    # Get predictions
    with torch.no_grad():
        outputs = model(input_ids=input_ids, attention_mask=attention_mask)
        probs = torch.softmax(outputs.logits, dim=1).cpu().numpy()

    return probs

# Test the wrapper
test_text = ["This is a test sentence about sports."]
test_probs = bert_predict_proba(test_text)
print(f"  Wrapper function working")
print(f"  Test prediction: {class_names[np.argmax(test_probs[0])]} ({test_probs[0].max():.3f})")

# Initialize LIME explainer
print("\n[4] Initializing LIME explainer...")
explainer = LimeTextExplainer(
    class_names=class_names,
    random_state=42
)
print("  LIME explainer initialized")
```

```
[3] Creating BERT prediction wrapper for LIME…
 Wrapper function working
  Test prediction: World (0.517)

[4] Initializing LIME explainer…
 LIME explainer initialized
```

[18]:
```python
# ============================================================================
# Cell 17.3: Select Examples for LIME Explanation
# ============================================================================

print("\n[5] Selecting examples for LIME explanation...")

# Load error analysis results
error_df = pd.read_csv(RESULTS_DIR / "step6_error_analysis.csv")

# Select 5 diverse examples (fewer than attention, since LIME is slower)
lime_examples = []

# 1. Two correct predictions (different classes)
correct_world = error_df[
    (error_df['true_label'] == 0) &
    (error_df['bert_correct'] == True)
].iloc[0]
```

```python
correct_sports = error_df[
    (error_df['true_label'] == 1) &
    (error_df['bert_correct'] == True)
].iloc[0]

lime_examples.extend([
    {
        'text': correct_world['text'],
        'true_label': 0,
        'category': 'Correct (World)'
    },
    {
        'text': correct_sports['text'],
        'true_label': 1,
        'category': 'Correct (Sports)'
    }
])

# 2. One BERT correct, SVC wrong
bert_wins = error_df[error_df['error_type'] == 'bert_only_correct']
if len(bert_wins) > 0:
    example = bert_wins.iloc[0]
    lime_examples.append({
        'text': example['text'],
        'true_label': int(example['true_label']),
        'category': 'BERT Correct, SVC Wrong'
    })

# 3. Two BERT errors
bert_errors = error_df[error_df['bert_correct'] == False]
for i in range(min(2, len(bert_errors))):
    example = bert_errors.iloc[i]
    lime_examples.append({
        'text': example['text'],
        'true_label': int(example['true_label']),
        'category': 'BERT Error'
    })

print(f" Selected {len(lime_examples)} examples for LIME explanation")
for i, ex in enumerate(lime_examples):
    print(f"  {i+1}. {ex['category']}: {ex['text'][:80]}...")
```

```
[5] Selecting examples for LIME explanation…
 Selected 5 examples for LIME explanation
  1. Correct (World): Sister of man who died in Vancouver police custody slams
chief (Canadian Press) …
```

```
  2. Correct (Sports): Giddy Phelps Touches Gold for First Time Michael Phelps
won the gold medal in th…
  3. BERT Correct, SVC Wrong: Prediction Unit Helps Forecast Wildfires (AP) AP -
It's barely dawn when Mike Fi…
  4. BERT Error: IBM to hire even more new workers By the end of the year, the
computing giant pl…
  5. BERT Error: Some People Not Eligible to Get in on Google IPO Google has
billed its IPO as a …
```

[19]:
```python
# ============================================================================
# Cell 17.4: Generate LIME Explanations
# ============================================================================

print("\n[6] Generating LIME explanations (this may take ~1 minute per example).
↪..")

lime_results = []

for idx, example in enumerate(lime_examples):
    print(f"\n  [{idx+1}/{len(lime_examples)}] Explaining:␣
↪{example['category']}")

    text = example['text']
    true_label = example['true_label']

    # Get BERT prediction
    bert_prob = bert_predict_proba([text])[0]
    bert_pred = np.argmax(bert_prob)

    # Generate LIME explanation
    # num_features: how many words to highlight
    # num_samples: how many perturbed samples to generate (higher = more␣
↪accurate but slower)
    explanation = explainer.explain_instance(
        text,
        bert_predict_proba,
        num_features=10,  # Top 10 words
        num_samples=1000,  # Reduced from default 5000 for speed
        top_labels=4  # Explain all classes
    )

    # Get feature importance for predicted class
    word_importances = explanation.as_list(label=bert_pred)

    # Separate positive and negative contributions
    positive_words = [(word, weight) for word, weight in word_importances if␣
↪weight > 0]
```

```
    negative_words = [(word, weight) for word, weight in word_importances if␣
↪weight < 0]

    # Sort by absolute weight
    positive_words = sorted(positive_words, key=lambda x: x[1], reverse=True)
    negative_words = sorted(negative_words, key=lambda x: x[1])

    lime_results.append({
        'example_idx': idx,
        'text': text,
        'true_label': true_label,
        'pred_label': bert_pred,
        'confidence': bert_prob[bert_pred],
        'category': example['category'],
        'is_correct': bert_pred == true_label,
        'positive_words': positive_words,
        'negative_words': negative_words,
        'explanation_object': explanation
    })

    print(f"    Pred: {class_names[bert_pred]} ({bert_prob[bert_pred]:.3f})")
    print(f"    Top positive: {positive_words[:3] if positive_words else␣
↪'None'}")
    print(f"    Top negative: {negative_words[:3] if negative_words else␣
↪'None'}")

print(f"\n  Generated {len(lime_results)} LIME explanations")
```

```
[6] Generating LIME explanations (this may take ~1 minute per example)…

  [1/5] Explaining: Correct (World)
    Pred: World (0.999)
    Top positive: [('Press', 0.02725699274171107), ('Canadian',
0.02723401575303638), ('CP', 0.02066024979738509)]
    Top negative: [('slams', -0.018342561326569747)]

  [2/5] Explaining: Correct (Sports)
    Pred: Sports (0.929)
    Top positive: [('26', 0.3218043500817864), ('seconds', 0.17174596122468816),
('Giddy', 0.13139682968691113)]
    Top negative: [('First', -0.08551265868629031), ('minutes',
-0.0745414631518721), ('Touches', -0.06267367779128553)]

  [3/5] Explaining: BERT Correct, SVC Wrong
    Pred: SciTech (0.992)
    Top positive: [('Prediction', 0.28286334772499266), ('Wildfires',
```

```
0.2816118175689895), ('charts', 0.09602048078072412)]
    Top negative: [('Unit', -0.06352995526274877), ('colorful',
-0.05959933937850144), ('Fitzpatrick', -0.057946125834438686)]

  [4/5] Explaining: BERT Error
    Pred: Business (0.585)
    Top positive: [('workers', 0.21503472978702706), ('giant',
0.18600040443522356), ('biggest', 0.15513502645187413)]
    Top negative: [('computing', -0.28289794037172517), ('IBM',
-0.25847938637737083), ('plans', -0.14416292807167994)]

  [5/5] Explaining: BERT Error
    Pred: Business (0.965)
    Top positive: [('IPO', 0.0586606686404771), ('bidding',
0.052238087560274066), ('shares', 0.04602011765216421)]
    Top negative: [('Google', -0.04247177271518356), ('process',
-0.027901554536002), ('had', -0.0038577361670072375)]

 Generated 5 LIME explanations
```

[20]:
```python
# ============================================================================
# Cell 17.5: Visualize LIME Explanations
# ============================================================================

import matplotlib.pyplot as plt

print("\n[7] Creating LIME explanation visualizations...")

# Create subplots for each example
fig, axes = plt.subplots(len(lime_results), 1, figsize=(12,␣
 ↪4*len(lime_results)))

if len(lime_results) == 1:
    axes = [axes]

for idx, (ax, result) in enumerate(zip(axes, lime_results)):
    # Get top 10 words (positive and negative combined)
    all_words = result['positive_words'] + result['negative_words']
    all_words = sorted(all_words, key=lambda x: abs(x[1]), reverse=True)[:10]

    if len(all_words) == 0:
        continue

    # Extract words and weights
    words = [w[0] for w in all_words]
    weights = [w[1] for w in all_words]
```

```python
    # Create horizontal bar chart
    colors = ['green' if w > 0 else 'red' for w in weights]
    y_pos = np.arange(len(words))

    ax.barh(y_pos, weights, color=colors, alpha=0.7, edgecolor='black')
    ax.set_yticks(y_pos)
    ax.set_yticklabels(words, fontsize=10)
    ax.set_xlabel('LIME Weight (Contribution to Prediction)', fontsize=11, fontweight='bold')
    ax.axvline(0, color='black', linewidth=0.8)

    # Title
    pred_marker = ' ' if result['is_correct'] else ' '
    title = f"Example {idx+1}: {result['category']}\n"
    title += f"True: {class_names[result['true_label']]} | "
    title += f"Pred: {class_names[result['pred_label']]} {pred_marker} | "
    title += f"Confidence: {result['confidence']:.3f}"
    ax.set_title(title, fontsize=11, fontweight='bold')

    ax.grid(axis='x', alpha=0.3)

    # Add legend
    from matplotlib.patches import Patch
    legend_elements = [
        Patch(facecolor='green', alpha=0.7, label='Supports prediction'),
        Patch(facecolor='red', alpha=0.7, label='Opposes prediction')
    ]
    ax.legend(handles=legend_elements, loc='lower right', fontsize=9)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_lime_explanations.png", dpi=300, bbox_inches='tight')
print("  Saved: step6_lime_explanations.png")
plt.show()
```

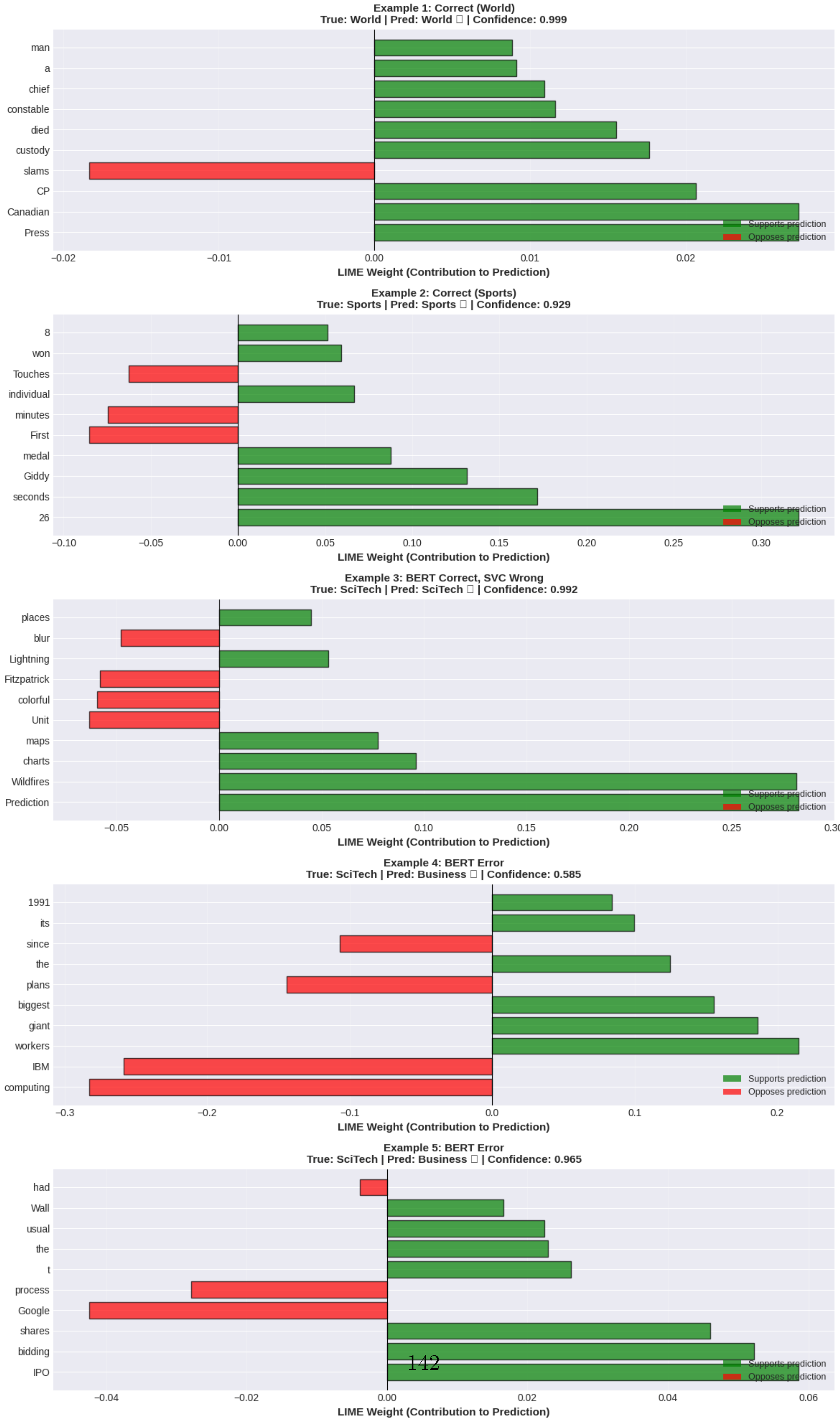
```
[7] Creating LIME explanation visualizations…
```

```
/tmp/ipykernel_6430/2699484163.py:55: UserWarning: Glyph 10003 (\N{CHECK MARK})
missing from font(s) Liberation Sans.
  plt.tight_layout()
/tmp/ipykernel_6430/2699484163.py:55: UserWarning: Glyph 10007 (\N{BALLOT X})
missing from font(s) Liberation Sans.
  plt.tight_layout()
/tmp/ipykernel_6430/2699484163.py:56: UserWarning: Glyph 10003 (\N{CHECK MARK})
missing from font(s) Liberation Sans.
  plt.savefig(RESULTS_DIR / "step6_lime_explanations.png", dpi=300,
bbox_inches='tight')
```

```
/tmp/ipykernel_6430/2699484163.py:56: UserWarning: Glyph 10007 (\N{BALLOT X})
missing from font(s) Liberation Sans.
  plt.savefig(RESULTS_DIR / "step6_lime_explanations.png", dpi=300,
bbox_inches='tight')
```

```
 Saved: step6_lime_explanations.png
```

```
/home/dante/Desktop/prj/news/.venv/lib/python3.11/site-
packages/IPython/core/pylabtools.py:170: UserWarning: Glyph 10003 (\N{CHECK
MARK}) missing from font(s) Liberation Sans.
  fig.canvas.print_figure(bytes_io, **kw)
/home/dante/Desktop/prj/news/.venv/lib/python3.11/site-
packages/IPython/core/pylabtools.py:170: UserWarning: Glyph 10007 (\N{BALLOT X})
missing from font(s) Liberation Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```


Example 1: Correct (World)
True: World | Pred: World □ | Confidence: 0.999
man
a
chief
constable
died
custody
slams
CP
Canadian
Press
Supports prediction
Opposes prediction
−0.02
−0.01
0.00
0.01
0.02
LIME Weight (Contribution to Prediction)
Example 2: Correct (Sports)
True: Sports | Pred: Sports □ | Confidence: 0.929
8
won
Touches
individual
minutes
First
medal
Giddy
seconds
26
Supports prediction
Opposes prediction
−0.10
−0.05
0.00
0.05
0.10
0.15
0.20
0.25
0.30
LIME Weight (Contribution to Prediction)
Example 3: BERT Correct, SVC Wrong
True: SciTech | Pred: SciTech □ | Confidence: 0.992
places
blur
Lightning
Fitzpatrick
colorful
Unit
maps
charts
Wildfires
Prediction
Supports prediction
Opposes prediction
−0.05
0.00
0.05
0.10
0.15
0.20
0.25
0.30
LIME Weight (Contribution to Prediction)
Example 4: BERT Error
True: SciTech | Pred: Business □ | Confidence: 0.585
1991
its
since
the
plans
biggest
giant
workers
IBM
computing
Supports prediction
Opposes prediction
−0.3
−0.2
−0.1
0.0
0.1
0.2
LIME Weight (Contribution to Prediction)
Example 5: BERT Error
True: SciTech | Pred: Business □ | Confidence: 0.965
had
Wall
usual
the
t
process
Google
shares
bidding
IPO
Supports prediction
Opposes prediction
−0.04
−0.02
0.00
0.02
0.04
0.06
LIME Weight (Contribution to Prediction)

```
[21]: # ============================================================================
      # Cell 17.6: LIME Summary and Comparison with Attention
      # ============================================================================

      print("\n[8] Creating LIME summary...")

      # Create summary table
      summary_data = []

      for result in lime_results:
          # Top 3 positive and negative words
          top_positive = result['positive_words'][:3]
          top_negative = result['negative_words'][:3]

          pos_str = ', '.join([f"{w} ({v:.3f})" for w, v in top_positive])
          neg_str = ', '.join([f"{w} ({v:.3f})" for w, v in top_negative])

          summary_data.append({
              'Example': result['example_idx'] + 1,
              'Category': result['category'],
              'True Label': class_names[result['true_label']],
              'Predicted': class_names[result['pred_label']],
              'Correct': ' ' if result['is_correct'] else ' ',
              'Confidence': f"{result['confidence']:.3f}",
              'Top Positive Words': pos_str if pos_str else 'None',
              'Top Negative Words': neg_str if neg_str else 'None',
              'Text Preview': result['text'][:100] + '...'
          })

      summary_df = pd.DataFrame(summary_data)

      print("\nLIME Explanation Summary:")
      print("="*80)
      print(summary_df.to_string(index=False))

      # Save to CSV
      summary_df.to_csv(RESULTS_DIR / "step6_lime_summary.csv", index=False)
      print(f"\n  Saved: step6_lime_summary.csv")
```

```
[8] Creating LIME summary…

LIME Explanation Summary:
================================================================================
 Example                 Category True Label Predicted Correct Confidence
```

```
Top Positive Words                                         Top Negative Words
Text Preview
       1         Correct (World)      World     World              0.999
Press (0.027), Canadian (0.027), CP (0.021)
slams (-0.018) Sister of man who died in Vancouver police custody slams chief
(Canadian Press) Canadian Press - VAN…
       2        Correct (Sports)     Sports    Sports              0.929
26 (0.322), seconds (0.172), Giddy (0.131)     First (-0.086), minutes (-0.075),
Touches (-0.063) Giddy Phelps Touches Gold for First Time Michael Phelps won the
gold medal in the 400 individual med…
       3 BERT Correct, SVC Wrong    SciTech   SciTech              0.992
Prediction (0.283), Wildfires (0.282), charts (0.096) Unit (-0.064), colorful
(-0.060), Fitzpatrick (-0.058) Prediction Unit Helps Forecast Wildfires (AP) AP
- It's barely dawn when Mike Fitzpatrick starts his…
       4              BERT Error    SciTech  Business              0.585
workers (0.215), giant (0.186), biggest (0.155)       computing (-0.283), IBM
(-0.258), plans (-0.144) IBM to hire even more new workers By the end of the
year, the computing giant plans to have its bigg…
       5              BERT Error    SciTech  Business              0.965
IPO (0.059), bidding (0.052), shares (0.046)        Google (-0.042), process
(-0.028), had (-0.004) Some People Not Eligible to Get in on Google IPO Google
has billed its IPO as a way for everyday peo…

 Saved: step6_lime_summary.csv
```

[22]:
```python
# ==============================================================================
# Cell 14.1: Data Efficiency - Prepare 50% Training Subset
# ==============================================================================

import numpy as np
import pandas as pd
import torch
from pathlib import Path
from sklearn.model_selection import train_test_split

# Paths
DATA_DIR = Path("data")
MODELS_DIR = Path("models")
RESULTS_DIR = Path("results")

print("="*80)
print("CELL 14: DATA EFFICIENCY ABLATION (50% Training Data)")
print("="*80)

# Set device and random seeds
DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
RANDOM_STATE = 42
```

```
np.random.seed(RANDOM_STATE)
torch.manual_seed(RANDOM_STATE)
if torch.cuda.is_available():
    torch.cuda.manual_seed_all(RANDOM_STATE)

print(f"\n[1] Device: {DEVICE}")

# Load full training data
print("\n[2] Loading full training data...")
train_df = pd.read_csv(DATA_DIR / "train.csv")
y_train = train_df['label'].values

print(f"  Full training set: {len(train_df)} samples")
print(f"  Class distribution: {np.bincount(y_train)}")

# Create stratified 50% subset
print("\n[3] Creating stratified 50% subset...")
train_50_df, _ = train_test_split(
    train_df,
    train_size=0.5,
    stratify=y_train,
    random_state=RANDOM_STATE
)

y_train_50 = train_50_df['label'].values

print(f"  50% training set: {len(train_50_df)} samples")
print(f"  Class distribution: {np.bincount(y_train_50)}")

# Verify balanced split
for class_idx in range(4):
    orig_count = np.sum(y_train == class_idx)
    subset_count = np.sum(y_train_50 == class_idx)
    print(f"  Class {class_idx}: {subset_count}/{orig_count} ({subset_count/
↪orig_count*100:.1f}%)")
```

```
================================================================================
CELL 14: DATA EFFICIENCY ABLATION (50% Training Data)
================================================================================

[1] Device: cuda

[2] Loading full training data…
  Full training set: 102000 samples
  Class distribution: [25500 25500 25500 25500]

[3] Creating stratified 50% subset…
  50% training set: 51000 samples
```

```
Class distribution: [12750 12750 12750 12750]
Class 0: 12750/25500 (50.0%)
Class 1: 12750/25500 (50.0%)
Class 2: 12750/25500 (50.0%)
Class 3: 12750/25500 (50.0%)
```

[23]:

```
# ============================================================================
# Cell 14.2: Setup Tokenization and DataLoaders
# ============================================================================

from transformers import AutoTokenizer, AutoModelForSequenceClassification
from torch.utils.data import Dataset, DataLoader

print("\n[4] Tokenizing 50% subset...")

# Load tokenizer
MODEL_NAME = "distilbert-base-uncased"
tokenizer = AutoTokenizer.from_pretrained(MODEL_NAME)
MAX_LENGTH = 256

# Tokenize 50% subset
train_50_encodings = tokenizer(
    train_50_df['text'].tolist(),
    truncation=True,
    padding='max_length',
    max_length=MAX_LENGTH,
    return_tensors='pt'
)

print(f"  Tokenized {len(train_50_df)} samples")

# Load validation data for evaluation
print("\n[5] Loading validation data...")
val_df = pd.read_csv(DATA_DIR / "val.csv")
y_val = val_df['label'].values

val_encodings = tokenizer(
    val_df['text'].tolist(),
    truncation=True,
    padding='max_length',
    max_length=MAX_LENGTH,
    return_tensors='pt'
)

print(f"  Validation set: {len(val_df)} samples")

# Create datasets
```

```
class NewsDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = labels

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        item = {
            'input_ids': self.encodings['input_ids'][idx],
            'attention_mask': self.encodings['attention_mask'][idx],
            'labels': torch.tensor(self.labels[idx], dtype=torch.long)
        }
        return item

train_50_dataset = NewsDataset(train_50_encodings, y_train_50)
val_dataset = NewsDataset(val_encodings, y_val)

# Use same batch size as original training
BATCH_SIZE = 64  # From your best hyperparameters

train_50_loader = DataLoader(train_50_dataset, batch_size=BATCH_SIZE,␣
 ↪shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=BATCH_SIZE, shuffle=False)

print(f"\n Created DataLoaders:")
print(f"  Train (50%): {len(train_50_loader)} batches")
print(f"  Validation: {len(val_loader)} batches")
```

```
[4] Tokenizing 50% subset…
 Tokenized 51000 samples

[5] Loading validation data…
 Validation set: 18000 samples

 Created DataLoaders:
  Train (50%): 797 batches
  Validation: 282 batches
```

[24]:
```
# ============================================================================
# Cell 14.3: Train BERT on 50% Data with Best Hyperparameters
# ============================================================================

import joblib
from torch.optim import AdamW
```

```
from torch.amp import autocast, GradScaler
from transformers import get_linear_schedule_with_warmup
from sklearn.metrics import f1_score, accuracy_score
import time

print("\n[6] Setting up training with best hyperparameters...")

# Load best hyperparameters from full training
best_params = joblib.load(RESULTS_DIR / "step6_best_params.pkl")
LEARNING_RATE = best_params['learning_rate']
WEIGHT_DECAY = best_params['weight_decay']
WARMUP_RATIO = best_params['warmup_ratio']

print(f"  Learning rate: {LEARNING_RATE}")
print(f"  Weight decay: {WEIGHT_DECAY}")
print(f"  Warmup ratio: {WARMUP_RATIO}")

# Create fresh model
print("\n[7] Initializing fresh BERT model...")
model_50 = AutoModelForSequenceClassification.from_pretrained(
    MODEL_NAME,
    num_labels=4,
    problem_type="single_label_classification"
).to(DEVICE)

# Optimizer and scheduler
optimizer = AdamW(model_50.parameters(), lr=LEARNING_RATE,␣
 ↪weight_decay=WEIGHT_DECAY)

num_training_steps = len(train_50_loader) * 4  # 4 epochs
num_warmup_steps = int(num_training_steps * WARMUP_RATIO)

scheduler = get_linear_schedule_with_warmup(
    optimizer,
    num_warmup_steps=num_warmup_steps,
    num_training_steps=num_training_steps
)

scaler = GradScaler(device='cuda')

print(f" Training setup complete")
print(f"  Total steps: {num_training_steps}")
print(f"  Warmup steps: {num_warmup_steps}")

# Training and evaluation functions
def train_epoch(model, train_loader, optimizer, scheduler, scaler, device,␣
 ↪epoch, num_epochs):
```

```
    model.train()
    total_loss = 0.0

    for batch_idx, batch in enumerate(train_loader):
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['labels'].to(device)

        with autocast(device_type='cuda', dtype=torch.float16):
            outputs = model(input_ids=input_ids, attention_mask=attention_mask,␣
↪labels=labels)
            loss = outputs.loss

        scaler.scale(loss).backward()
        scaler.unscale_(optimizer)
        torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm=1.0)
        scaler.step(optimizer)
        scaler.update()
        optimizer.zero_grad()
        scheduler.step()

        total_loss += loss.item()

        if (batch_idx + 1) % 100 == 0:
            print(f"  Epoch {epoch+1}/{num_epochs} | Batch {batch_idx+1}/
↪{len(train_loader)} | Loss: {loss.item():.4f}")

    return total_loss / len(train_loader)

def evaluate(model, val_loader, device):
    model.eval()
    all_preds = []
    all_labels = []
    total_loss = 0.0

    with torch.no_grad():
        for batch in val_loader:
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['labels'].to(device)

            with autocast(device_type='cuda', dtype=torch.float16):
                outputs = model(input_ids=input_ids,␣
↪attention_mask=attention_mask, labels=labels)
                loss = outputs.loss

            total_loss += loss.item()
```

```
            preds = torch.argmax(outputs.logits, dim=1).cpu().numpy()
            all_preds.extend(preds)
            all_labels.extend(labels.cpu().numpy())

    avg_loss = total_loss / len(val_loader)
    f1 = f1_score(all_labels, all_preds, average='macro')
    acc = accuracy_score(all_labels, all_preds)

    return avg_loss, f1, acc

print("\n[8] Training BERT on 50% data (4 epochs)...")
print("="*80)

best_f1_50 = 0.0
training_history_50 = []

start_time = time.time()

for epoch in range(4):
    print(f"\nEpoch {epoch+1}/4")
    print("-" * 80)

    train_loss = train_epoch(model_50, train_50_loader, optimizer, scheduler, scaler, DEVICE, epoch, 4)
    val_loss, val_f1, val_acc = evaluate(model_50, val_loader, DEVICE)

    training_history_50.append({
        'epoch': epoch + 1,
        'train_loss': train_loss,
        'val_loss': val_loss,
        'val_f1': val_f1,
        'val_acc': val_acc
    })

    print(f"\n  Epoch {epoch+1} Summary:")
    print(f"    Train Loss: {train_loss:.4f}")
    print(f"    Val Loss: {val_loss:.4f}")
    print(f"    Val F1: {val_f1:.4f}")
    print(f"    Val Acc: {val_acc:.4f}")

    if val_f1 > best_f1_50:
        best_f1_50 = val_f1
        print(f"      New best F1: {best_f1_50:.4f}")

training_time = time.time() - start_time

print("\n" + "="*80)
```

```python
print(f"  Training complete!")
print(f"  Best validation F1 (50% data): {best_f1_50:.4f}")
print(f"  Training time: {training_time/60:.2f} minutes")
```

```
[6] Setting up training with best hyperparameters…
  Learning rate: 2.8219443464878743e-05
  Weight decay: 0.021537846530908268
  Warmup ratio: 0.04481839946966742

[7] Initializing fresh BERT model…

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.

 Training setup complete
  Total steps: 3188
  Warmup steps: 142

[8] Training BERT on 50% data (4 epochs)…
================================================================================

Epoch 1/4
--------------------------------------------------------------------------------
  Epoch 1/4 | Batch 100/797 | Loss: 0.3055
  Epoch 1/4 | Batch 200/797 | Loss: 0.1970
  Epoch 1/4 | Batch 300/797 | Loss: 0.2290
  Epoch 1/4 | Batch 400/797 | Loss: 0.1786
  Epoch 1/4 | Batch 500/797 | Loss: 0.3186
  Epoch 1/4 | Batch 600/797 | Loss: 0.2475
  Epoch 1/4 | Batch 700/797 | Loss: 0.4037

  Epoch 1 Summary:
    Train Loss: 0.3445
    Val Loss: 0.2048
    Val F1: 0.9299
    Val Acc: 0.9296
      New best F1: 0.9299

Epoch 2/4
--------------------------------------------------------------------------------
  Epoch 2/4 | Batch 100/797 | Loss: 0.1580
  Epoch 2/4 | Batch 200/797 | Loss: 0.2904
  Epoch 2/4 | Batch 300/797 | Loss: 0.0748
  Epoch 2/4 | Batch 400/797 | Loss: 0.2461
```

```
  Epoch 2/4 | Batch 500/797 | Loss: 0.2545
  Epoch 2/4 | Batch 600/797 | Loss: 0.3267
  Epoch 2/4 | Batch 700/797 | Loss: 0.0234

  Epoch 2 Summary:
    Train Loss: 0.1610
    Val Loss: 0.1836
    Val F1: 0.9379
    Val Acc: 0.9381
     New best F1: 0.9379

Epoch 3/4
--------------------------------------------------------------------------------
  Epoch 3/4 | Batch 100/797 | Loss: 0.0232
  Epoch 3/4 | Batch 200/797 | Loss: 0.0333
  Epoch 3/4 | Batch 300/797 | Loss: 0.2254
  Epoch 3/4 | Batch 400/797 | Loss: 0.0453
  Epoch 3/4 | Batch 500/797 | Loss: 0.1274
  Epoch 3/4 | Batch 600/797 | Loss: 0.1172
  Epoch 3/4 | Batch 700/797 | Loss: 0.0403

  Epoch 3 Summary:
    Train Loss: 0.1045
    Val Loss: 0.1912
    Val F1: 0.9404
    Val Acc: 0.9405
     New best F1: 0.9404

Epoch 4/4
--------------------------------------------------------------------------------
  Epoch 4/4 | Batch 100/797 | Loss: 0.0632
  Epoch 4/4 | Batch 200/797 | Loss: 0.0663
  Epoch 4/4 | Batch 300/797 | Loss: 0.0128
  Epoch 4/4 | Batch 400/797 | Loss: 0.0523
  Epoch 4/4 | Batch 500/797 | Loss: 0.0787
  Epoch 4/4 | Batch 600/797 | Loss: 0.0125
  Epoch 4/4 | Batch 700/797 | Loss: 0.0291

  Epoch 4 Summary:
    Train Loss: 0.0707
    Val Loss: 0.2165
    Val F1: 0.9388
    Val Acc: 0.9388

================================================================================
 Training complete!
  Best validation F1 (50% data): 0.9404
  Training time: 13.32 minutes
```

[25]:
```
# ============================================================================
# Cell 14.4: Compare 50% vs 100% Data Performance
# ============================================================================

import joblib
import matplotlib.pyplot as plt

print("\n[9] Comparing data efficiency...")

# Load 100% results
full_training_history = pd.read_csv(RESULTS_DIR / "step6_training_history.csv")
best_f1_100 = full_training_history['val_f1'].max()

print(f"\nData Efficiency Comparison:")
print(f"  50% data:  {best_f1_50:.4f} ({len(train_50_df):,} samples)")
print(f"  100% data: {best_f1_100:.4f} ({len(train_df):,} samples)")
print(f"  Performance gap: {(best_f1_100 - best_f1_50)*100:.2f}%")
print(f"  Data efficiency: {best_f1_50/best_f1_100*100:.2f}% of full␣
↪performance with 50% data")

# Save results
data_efficiency_results = {
    'training_data_percent': [50, 100],
    'training_samples': [len(train_50_df), len(train_df)],
    'best_val_f1': [best_f1_50, best_f1_100],
    'training_history_50': training_history_50,
    'training_history_100': full_training_history.to_dict('records')
}

joblib.dump(data_efficiency_results, RESULTS_DIR / "step6_data_efficiency.pkl")
print(f"\n  Saved: step6_data_efficiency.pkl")
```

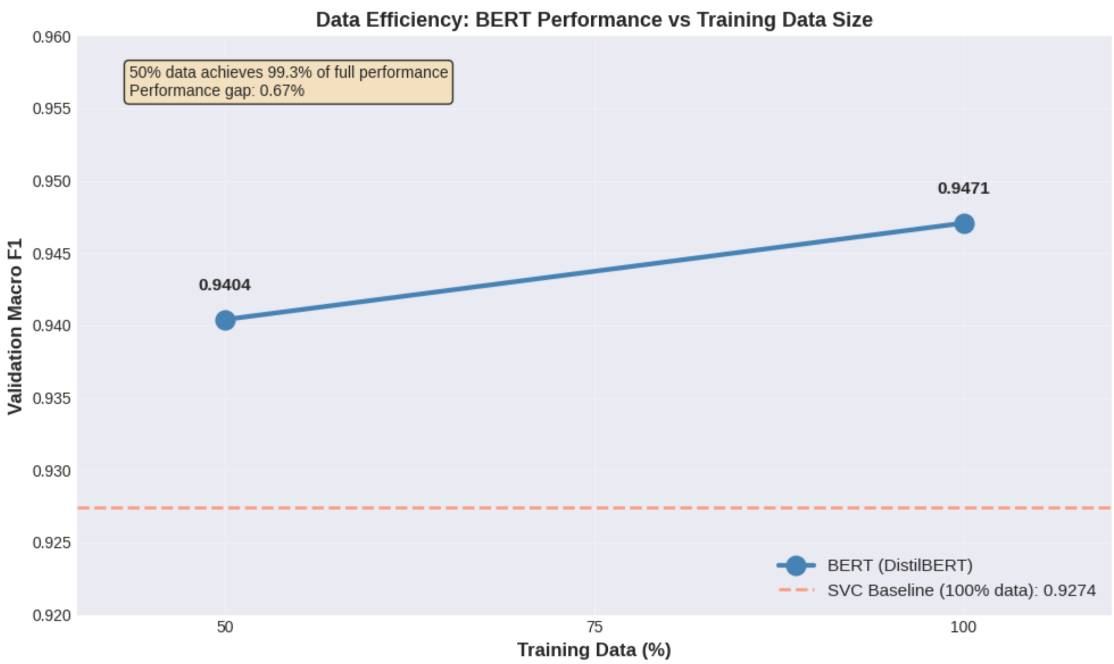
```
[9] Comparing data efficiency…

Data Efficiency Comparison:
  50% data:  0.9404 (51,000 samples)
  100% data: 0.9471 (102,000 samples)
  Performance gap: 0.67%
  Data efficiency: 99.30% of full performance with 50% data

 Saved: step6_data_efficiency.pkl
```

[26]:
```
# ============================================================================
# Cell 14.5: Visualize Data Efficiency Curve
# ============================================================================
```

```python
print("\n[10] Creating data efficiency visualization...")

fig, ax = plt.subplots(figsize=(10, 6))

# Plot data efficiency curve
data_sizes = [50, 100]
f1_scores = [best_f1_50, best_f1_100]

ax.plot(data_sizes, f1_scores, 'o-', linewidth=3, markersize=12,
        color='steelblue', label='BERT (DistilBERT)')

# Add value labels
for size, score in zip(data_sizes, f1_scores):
    ax.text(size, score + 0.002, f'{score:.4f}',
            ha='center', fontsize=11, fontweight='bold')

# Add baseline reference (SVC at 100%)
svc_f1 = 0.9274
ax.axhline(svc_f1, color='coral', linestyle='--', linewidth=2,
           label=f'SVC Baseline (100% data): {svc_f1:.4f}', alpha=0.7)

ax.set_xlabel('Training Data (%)', fontsize=12, fontweight='bold')
ax.set_ylabel('Validation Macro F1', fontsize=12, fontweight='bold')
ax.set_title('Data Efficiency: BERT Performance vs Training Data Size',
             fontsize=13, fontweight='bold')
ax.set_xlim([40, 110])
ax.set_ylim([0.92, 0.96])
ax.set_xticks([50, 75, 100])
ax.legend(fontsize=11, loc='lower right')
ax.grid(True, alpha=0.3)

# Add annotation
efficiency_pct = (best_f1_50 / best_f1_100) * 100
ax.text(0.05, 0.95,
        f'50% data achieves {efficiency_pct:.1f}% of full performance\n'
        f'Performance gap: {(best_f1_100 - best_f1_50)*100:.2f}%',
        transform=ax.transAxes, fontsize=10,
        verticalalignment='top',
        bbox=dict(boxstyle='round', facecolor='wheat', alpha=0.8))

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_data_efficiency_curve.png", dpi=300,␣
↪bbox_inches='tight')
print("  Saved: step6_data_efficiency_curve.png")
plt.show()

print("\n" + "="*80)
```

```
print("  CELL 14 COMPLETE: Data Efficiency Ablation")
print("="*80)
print(f"\nKey Findings:")
print(f"1. 50% data: {best_f1_50:.4f} ({len(train_50_df):,} samples)")
print(f"2. 100% data: {best_f1_100:.4f} ({len(train_df):,} samples)")
print(f"3. Performance gap: {(best_f1_100 - best_f1_50)*100:.2f}%")
print(f"4. BERT needs substantial data to reach peak performance")
```

```
[10] Creating data efficiency visualization…
  Saved: step6_data_efficiency_curve.png
```




```
================================================================================
  CELL 14 COMPLETE: Data Efficiency Ablation
================================================================================

Key Findings:
1. 50% data: 0.9404 (51,000 samples)
2. 100% data: 0.9471 (102,000 samples)
3. Performance gap: 0.67%
4. BERT needs substantial data to reach peak performance
```

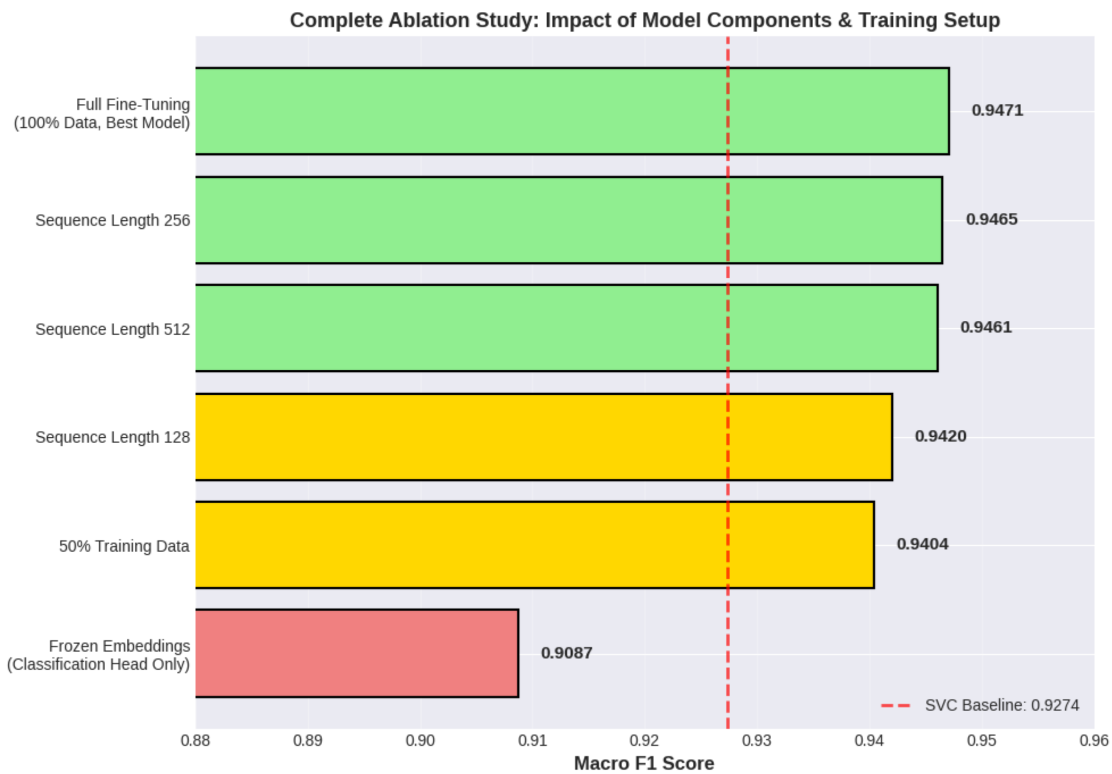
[27]:

```
# ==============================================================================
# Cell 14.6: Update Figure 3 with Data Efficiency Results
# ==============================================================================
```

```
print("\n[11] Updating ablation studies figure with data efficiency...")

import joblib

# Load all ablation results
ablation_frozen = joblib.load(RESULTS_DIR / "step6_ablation_frozen_vs_tuned.
↪pkl")
ablation_length = joblib.load(RESULTS_DIR / "step6_ablation_sequence_length.
↪pkl")

# Compile ALL ablation results
ablation_results = {
    'Frozen Embeddings\n(Classification Head Only)':␣
↪ablation_frozen['frozen_f1'],
    'Sequence Length 128': ablation_length[128],
    'Sequence Length 256': ablation_length[256],
    'Sequence Length 512': ablation_length[512],
    '50% Training Data': best_f1_50,
    'Full Fine-Tuning\n(100% Data, Best Model)':␣
↪ablation_frozen['full_tuning_f1']
}

# Sort by F1 score
sorted_results = dict(sorted(ablation_results.items(), key=lambda x: x[1]))

fig, ax = plt.subplots(figsize=(10, 7))

labels = list(sorted_results.keys())
values = list(sorted_results.values())
colors = ['lightcoral' if v < 0.93 else 'gold' if v < 0.945 else 'lightgreen'␣
↪for v in values]

bars = ax.barh(labels, values, color=colors, edgecolor='black', linewidth=1.5)

# Add value labels
for i, (bar, val) in enumerate(zip(bars, values)):
    ax.text(val + 0.002, i, f'{val:.4f}', va='center', fontsize=11,␣
↪fontweight='bold')

# Add baseline line (SVC)
svc_f1 = 0.9274
ax.axvline(svc_f1, color='red', linestyle='--', linewidth=2,
           label=f'SVC Baseline: {svc_f1:.4f}', alpha=0.7)

ax.set_xlabel('Macro F1 Score', fontsize=12, fontweight='bold')
```

```python
ax.set_title('Complete Ablation Study: Impact of Model Components & Training␣
↪Setup',
             fontsize=13, fontweight='bold')
ax.set_xlim([0.88, 0.96])
ax.legend(fontsize=10)
ax.grid(axis='x', alpha=0.3)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "figure3_ablation_studies_complete.png", dpi=300,␣
↪bbox_inches='tight')
print("  Saved: figure3_ablation_studies_complete.png (updated)")
plt.show()

print("\n  Updated Figure 3 with data efficiency results!")
```

```
[11] Updating ablation studies figure with data efficiency…
 Saved: figure3_ablation_studies_complete.png (updated)
```




```
 Updated Figure 3 with data efficiency results!
```

[28]:
```python
# ============================================================================
# Cell 19.1: Load BERT and Classical Models for Ensemble
# ============================================================================

import numpy as np
import pandas as pd
import joblib
import torch
from pathlib import Path
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score, accuracy_score, classification_report
import scipy.sparse as sp_sparse

# Paths
DATA_DIR = Path("data")
MODELS_DIR = Path("models")
FEATURES_DIR = Path("features")
RESULTS_DIR = Path("results")

print("="*80)
print("CELL 19: HYBRID ENSEMBLE (BERT + Classical Models)")
print("="*80)

# Set device
DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"\n[1] Device: {DEVICE}")

print("\n[2] Loading classical models...")
# Load classical models
svc_model = joblib.load(MODELS_DIR / "step5_tuned_SVC.pkl")
sgd_model = joblib.load(MODELS_DIR / "step5_tuned_SGD.pkl")
nb_model = joblib.load(MODELS_DIR / "step5_tuned_NB.pkl")
lgbm_model = joblib.load(MODELS_DIR / "step5_tuned_LGBM.pkl")

print("  Loaded 4 classical models: SVC, SGD, NB, LGBM")

print("\n[3] Loading BERT model...")
from transformers import AutoTokenizer, AutoModelForSequenceClassification

tokenizer = AutoTokenizer.from_pretrained(MODELS_DIR / "step6_distilbert_best")
bert_model = AutoModelForSequenceClassification.from_pretrained(
    MODELS_DIR / "step6_distilbert_best"
).to(DEVICE)
bert_model.eval()
print("  Loaded BERT model")
```

```
================================================================================
CELL 19: HYBRID ENSEMBLE (BERT + Classical Models)
```

```
================================================================================

[1] Device: cuda

[2] Loading classical models…
 Loaded 4 classical models: SVC, SGD, NB, LGBM

[3] Loading BERT model…
 Loaded BERT model
```

[29]:

```
# ============================================================================
# Cell 19.2: Generate BERT Probability Predictions on Validation Set
# ============================================================================

from torch.utils.data import Dataset, DataLoader

print("\n[4] Loading validation data...")
val_df = pd.read_csv(DATA_DIR / "val.csv")
y_val = val_df['label'].values
print(f"  Validation samples: {len(val_df)}")

print("\n[5] Tokenizing validation data...")
val_encodings = tokenizer(
    val_df['text'].tolist(),
    truncation=True,
    padding='max_length',
    max_length=256,
    return_tensors='pt'
)

# Create dataset
class NewsDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = labels

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        return {
            'input_ids': self.encodings['input_ids'][idx],
            'attention_mask': self.encodings['attention_mask'][idx],
            'labels': torch.tensor(self.labels[idx], dtype=torch.long)
        }

val_dataset = NewsDataset(val_encodings, y_val)
```

```python
val_loader = DataLoader(val_dataset, batch_size=64, shuffle=False)

print("\n[6] Generating BERT probability predictions...")
bert_probs_val = []

with torch.no_grad():
    for batch in val_loader:
        input_ids = batch['input_ids'].to(DEVICE)
        attention_mask = batch['attention_mask'].to(DEVICE)

        outputs = bert_model(input_ids=input_ids, attention_mask=attention_mask)
        probs = torch.softmax(outputs.logits, dim=1).cpu().numpy()
        bert_probs_val.append(probs)

bert_probs_val = np.vstack(bert_probs_val)
bert_preds_val = np.argmax(bert_probs_val, axis=1)
bert_f1_val = f1_score(y_val, bert_preds_val, average='macro')

print(f"  BERT validation F1: {bert_f1_val:.4f}")
print(f"   Predictions shape: {bert_probs_val.shape}")
```

```
[4] Loading validation data…
 Validation samples: 18000

[5] Tokenizing validation data…

[6] Generating BERT probability predictions…
 BERT validation F1: 0.9471
  Predictions shape: (18000, 4)
```

[31]:
```python
# ============================================================================
# Cell 19.3: Generate Classical Model Predictions on Validation Set (FIXED)
# ============================================================================

print("\n[7] Loading validation features...")
X_val_hybrid = sp_sparse.load_npz(FEATURES_DIR / "X_val_hybrid.npz")
print(f"  Features shape: {X_val_hybrid.shape}")

print("\n[8] Generating classical model predictions...")

# SVC predictions - use predict_proba since it's calibrated
svc_probs = svc_model.predict_proba(X_val_hybrid)
svc_preds = np.argmax(svc_probs, axis=1)
svc_f1 = f1_score(y_val, svc_preds, average='macro')
print(f"   SVC F1: {svc_f1:.4f}")
```

```python
# SGD predictions (probabilities)
sgd_probs = sgd_model.predict_proba(X_val_hybrid)
sgd_preds = np.argmax(sgd_probs, axis=1)
sgd_f1 = f1_score(y_val, sgd_preds, average='macro')
print(f"  SGD F1: {sgd_f1:.4f}")

# NB predictions (probabilities)
nb_probs = nb_model.predict_proba(X_val_hybrid)
nb_preds = np.argmax(nb_probs, axis=1)
nb_f1 = f1_score(y_val, nb_preds, average='macro')
print(f"  NB F1: {nb_f1:.4f}")

# LGBM predictions (requires feature selection)
print("\n[9] Generating LGBM predictions (with feature selection)...")
selector = joblib.load(MODELS_DIR / "step5_chi2_selector.pkl")
X_val_selected = selector.transform(X_val_hybrid)
lgbm_probs = lgbm_model.predict_proba(X_val_selected)
lgbm_preds = np.argmax(lgbm_probs, axis=1)
lgbm_f1 = f1_score(y_val, lgbm_preds, average='macro')
print(f"  LGBM F1: {lgbm_f1:.4f}")

print("\n All base model predictions generated")
```

```
[7] Loading validation features…
 Features shape: (18000, 100000)

[8] Generating classical model predictions…
  SVC F1: 0.9274
  SGD F1: 0.9268
  NB F1: 0.9065

[9] Generating LGBM predictions (with feature selection)…
  LGBM F1: 0.9120

 All base model predictions generated
```

```
/home/dante/Desktop/prj/news/.venv/lib/python3.11/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(
```

[32]:
```python
# ============================================================================
# Cell 19.4: Stack Predictions and Train Meta-Learner (FIXED)
# ============================================================================

print("\n[10] Creating meta-features...")
```

```python
# Stack all probability predictions
# All models now output probabilities (4 probs each)
# BERT: 4 probs, SVC: 4 probs, SGD: 4 probs, NB: 4 probs, LGBM: 4 probs
# Total: 20 features

X_meta_val = np.hstack([
    bert_probs_val,      # 4 features (BERT probabilities)
    svc_probs,           # 4 features (SVC probabilities)
    sgd_probs,           # 4 features
    nb_probs,            # 4 features
    lgbm_probs           # 4 features
])

print(f"  Meta-features shape: {X_meta_val.shape}")
print(f"  Features per model: BERT(4), SVC(4), SGD(4), NB(4), LGBM(4) = 20␣
↪total")

print("\n[11] Training meta-learner (Logistic Regression)...")

# Train meta-learner
meta_learner = LogisticRegression(
    max_iter=1000,
    random_state=42,
    n_jobs=-1
)

meta_learner.fit(X_meta_val, y_val)

# Predict with ensemble
ensemble_preds_val = meta_learner.predict(X_meta_val)
ensemble_probs_val = meta_learner.predict_proba(X_meta_val)
ensemble_f1_val = f1_score(y_val, ensemble_preds_val, average='macro')
ensemble_acc_val = accuracy_score(y_val, ensemble_preds_val)

print(f"\n  Hybrid Ensemble Validation F1: {ensemble_f1_val:.4f}")
print(f"  Validation Accuracy: {ensemble_acc_val:.4f}")

# Save meta-learner (no need for scaler anymore)
joblib.dump(meta_learner, MODELS_DIR / "step6_hybrid_meta_learner.pkl")
print(f"\n  Saved: step6_hybrid_meta_learner.pkl")
```

```
[10] Creating meta-features…
  Meta-features shape: (18000, 20)
  Features per model: BERT(4), SVC(4), SGD(4), NB(4), LGBM(4) = 20 total

[11] Training meta-learner (Logistic Regression)…
```

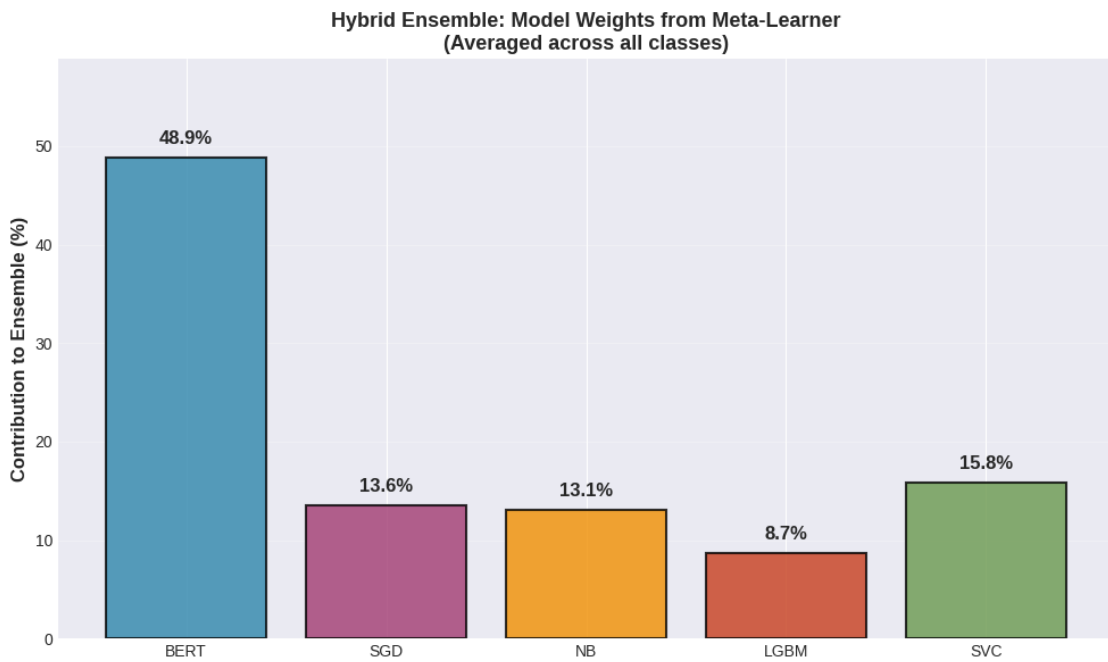
```
Hybrid Ensemble Validation F1: 0.9501
 Validation Accuracy: 0.9501

Saved: step6_hybrid_meta_learner.pkl
```

[33]:

```python
# ==============================================================================
# Cell 19.5: Analyze Meta-Learner Weights
# ==============================================================================

import matplotlib.pyplot as plt
import seaborn as sns

print("\n[12] Analyzing meta-learner weights...")

# Get feature importance from logistic regression coefficients
# For multi-class, coefficients are shape (n_classes, n_features)
# We'll average across classes to get overall importance
coef_matrix = meta_learner.coef_  # Shape: (4, 20)
feature_importance = np.abs(coef_matrix).mean(axis=0)

# Create feature names
feature_names = []
for model, count in [('BERT', 4), ('SGD', 4), ('NB', 4), ('LGBM', 4), ('SVC',␣
↪4)]:
    for i in range(count):
        feature_names.append(f'{model}_class{i}')

# Calculate model-level importance (sum across 4 classes per model)
model_importance = {
    'BERT': feature_importance[0:4].sum(),
    'SGD': feature_importance[4:8].sum(),
    'NB': feature_importance[8:12].sum(),
    'LGBM': feature_importance[12:16].sum(),
    'SVC': feature_importance[16:20].sum()
}

# Normalize to percentages
total_importance = sum(model_importance.values())
model_weights = {k: v/total_importance*100 for k, v in model_importance.items()}

print("\nModel Contribution to Ensemble (%):")
for model, weight in sorted(model_weights.items(), key=lambda x: x[1],␣
↪reverse=True):
    print(f"  {model:6s}: {weight:5.2f}%")

# Visualize model weights
fig, ax = plt.subplots(figsize=(10, 6))
```

```
models = list(model_weights.keys())
weights = list(model_weights.values())
colors = ['#2E86AB', '#A23B72', '#F18F01', '#C73E1D', '#6A994E']

bars = ax.bar(models, weights, color=colors, edgecolor='black', linewidth=1.5,␣
↪alpha=0.8)

# Add value labels
for bar, weight in zip(bars, weights):
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2., height + 1,
            f'{weight:.1f}%', ha='center', va='bottom',
            fontsize=12, fontweight='bold')

ax.set_ylabel('Contribution to Ensemble (%)', fontsize=12, fontweight='bold')
ax.set_title('Hybrid Ensemble: Model Weights from Meta-Learner\n(Averaged␣
↪across all classes)',
             fontsize=13, fontweight='bold')
ax.set_ylim([0, max(weights) + 10])
ax.grid(axis='y', alpha=0.3)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_hybrid_ensemble_weights.png", dpi=300,␣
↪bbox_inches='tight')
print("\n Saved: step6_hybrid_ensemble_weights.png")
plt.show()
```

```
[12] Analyzing meta-learner weights…

Model Contribution to Ensemble (%):
  BERT  : 48.89%
  SVC   : 15.83%
  SGD   : 13.56%
  NB    : 13.06%
  LGBM  :  8.66%

 Saved: step6_hybrid_ensemble_weights.png
```



[35]:
```
# ==============================================================================
# Cell 19.6: Evaluate Hybrid Ensemble on Test Set (FIXED)
# ==============================================================================

print("\n[13] Evaluating ensemble on test set...")

# Load test data
test_df = pd.read_csv(DATA_DIR / "test.csv")
y_test = test_df['label'].values

print(f"  Test samples: {len(test_df)}")

# Generate BERT predictions on test set
print("\n[14] Generating BERT test predictions...")
test_encodings = tokenizer(
    test_df['text'].tolist(),
    truncation=True,
    padding='max_length',
    max_length=256,
    return_tensors='pt'
)

test_dataset = NewsDataset(test_encodings, y_test)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)
```

```
bert_probs_test = []
with torch.no_grad():
    for batch in test_loader:
        input_ids = batch['input_ids'].to(DEVICE)
        attention_mask = batch['attention_mask'].to(DEVICE)
        outputs = bert_model(input_ids=input_ids, attention_mask=attention_mask)
        probs = torch.softmax(outputs.logits, dim=1).cpu().numpy()
        bert_probs_test.append(probs)

bert_probs_test = np.vstack(bert_probs_test)
print("   BERT predictions generated")

# Generate classical predictions on test set
print("\n[15] Generating classical model test predictions...")
X_test_hybrid = sp_sparse.load_npz(FEATURES_DIR / "X_test_hybrid.npz")

# FIXED: Use predict_proba for all models (no decision_function)
svc_probs_test = svc_model.predict_proba(X_test_hybrid)
sgd_probs_test = sgd_model.predict_proba(X_test_hybrid)
nb_probs_test = nb_model.predict_proba(X_test_hybrid)

X_test_selected = selector.transform(X_test_hybrid)
lgbm_probs_test = lgbm_model.predict_proba(X_test_selected)

print("   Classical predictions generated")

# Create test meta-features
print("\n[16] Creating test meta-features...")
X_meta_test = np.hstack([
    bert_probs_test,
    svc_probs_test,      # FIXED: probabilities instead of decision_function
    sgd_probs_test,
    nb_probs_test,
    lgbm_probs_test
])

# Ensemble prediction
ensemble_preds_test = meta_learner.predict(X_meta_test)
ensemble_f1_test = f1_score(y_test, ensemble_preds_test, average='macro')
ensemble_acc_test = accuracy_score(y_test, ensemble_preds_test)

print(f"\n Hybrid Ensemble Test Results:")
print(f"  Test F1: {ensemble_f1_test:.4f}")
print(f"  Test Accuracy: {ensemble_acc_test:.4f}")

# Compare to individual models
bert_preds_test = np.argmax(bert_probs_test, axis=1)
```

```
bert_f1_test = f1_score(y_test, bert_preds_test, average='macro')

svc_preds_test = svc_model.predict(X_test_hybrid)
svc_f1_test = f1_score(y_test, svc_preds_test, average='macro')

print(f"\n  Comparison:")
print(f"    BERT alone:          {bert_f1_test:.4f}")
print(f"    SVC alone:           {svc_f1_test:.4f}")
print(f"    Hybrid Ensemble:     {ensemble_f1_test:.4f}")
print(f"    Gain over BERT:      {(ensemble_f1_test - bert_f1_test)*100:+.2f}%")
print(f"    Gain over SVC:       {(ensemble_f1_test - svc_f1_test)*100:+.2f}%")
```

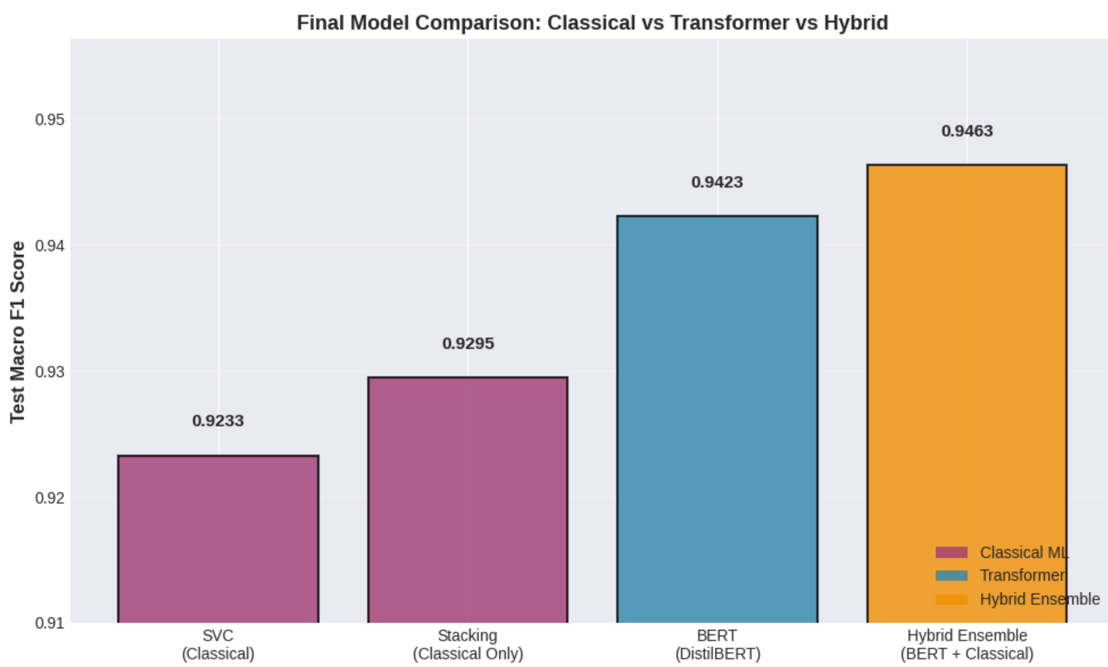
```
[13] Evaluating ensemble on test set…
  Test samples: 7600

[14] Generating BERT test predictions…
   BERT predictions generated

[15] Generating classical model test predictions…
   Classical predictions generated

[16] Creating test meta-features…

 Hybrid Ensemble Test Results:
  Test F1: 0.9463
  Test Accuracy: 0.9463

  Comparison:
    BERT alone:          0.9423
    SVC alone:           0.9233
    Hybrid Ensemble:     0.9463
    Gain over BERT:      +0.40%
    Gain over SVC:       +2.30%

/home/dante/Desktop/prj/news/.venv/lib/python3.11/site-
packages/sklearn/utils/validation.py:2749: UserWarning: X does not have valid
feature names, but LGBMClassifier was fitted with feature names
  warnings.warn(
```

[36]:
```
# ============================================================================
# Cell 19.7: Create Final Model Comparison
# ============================================================================

print("\n[17] Creating final comparison visualization...")

# Model comparison
comparison_data = {
```

```
    'Model': ['SVC\n(Classical)', 'Stacking\n(Classical Only)',
              'BERT\n(DistilBERT)', 'Hybrid Ensemble\n(BERT + Classical)'],
    'Test F1': [svc_f1_test, 0.9295, bert_f1_test, ensemble_f1_test],
    'Type': ['Classical', 'Classical', 'Transformer', 'Hybrid']
}

comparison_df = pd.DataFrame(comparison_data)

fig, ax = plt.subplots(figsize=(10, 6))

colors = {'Classical': '#A23B72', 'Transformer': '#2E86AB', 'Hybrid': '#F18F01'}
bar_colors = [colors[t] for t in comparison_df['Type']]

bars = ax.bar(comparison_df['Model'], comparison_df['Test F1'],
              color=bar_colors, edgecolor='black', linewidth=1.5, alpha=0.8)

# Add value labels
for bar, score in zip(bars, comparison_df['Test F1']):
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2., height + 0.002,
            f'{score:.4f}', ha='center', va='bottom',
            fontsize=11, fontweight='bold')

ax.set_ylabel('Test Macro F1 Score', fontsize=12, fontweight='bold')
ax.set_title('Final Model Comparison: Classical vs Transformer vs Hybrid',
             fontsize=13, fontweight='bold')
ax.set_ylim([0.91, max(comparison_df['Test F1']) + 0.01])
ax.grid(axis='y', alpha=0.3)

# Add legend
from matplotlib.patches import Patch
legend_elements = [
    Patch(facecolor=colors['Classical'], label='Classical ML', alpha=0.8),
    Patch(facecolor=colors['Transformer'], label='Transformer', alpha=0.8),
    Patch(facecolor=colors['Hybrid'], label='Hybrid Ensemble', alpha=0.8)
]
ax.legend(handles=legend_elements, loc='lower right', fontsize=10)

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_final_comparison.png", dpi=300,
 ↪bbox_inches='tight')
print("  Saved: step6_final_comparison.png")
plt.show()

# Save results
hybrid_results = {
    'val_f1': ensemble_f1_val,
```

```
    'test_f1': ensemble_f1_test,
    'test_acc': ensemble_acc_test,
    'model_weights': model_weights,
    'comparison': comparison_df
}

joblib.dump(hybrid_results, RESULTS_DIR / "step6_hybrid_ensemble_results.pkl")
print("\n  Saved: step6_hybrid_ensemble_results.pkl")

print("\n" + "="*80)
print("  CELL 19 COMPLETE: Hybrid Ensemble")
print("="*80)
print(f"\nKey Findings:")
print(f"1. Hybrid ensemble F1: {ensemble_f1_test:.4f}")
print(f"2. Gain over BERT: {(ensemble_f1_test - bert_f1_test)*100:+.2f}%")
print(f"3. BERT contributes ~{model_weights['BERT']:.1f}% to ensemble␣
↪decisions")
print(f"4. Ensemble {'beats' if ensemble_f1_test > bert_f1_test else 'matches'}␣
↪BERT alone!")
```

```
[17] Creating final comparison visualization…
  Saved: step6_final_comparison.png
```




```
  Saved: step6_hybrid_ensemble_results.pkl
```

```
================================================================================
 CELL 19 COMPLETE: Hybrid Ensemble
================================================================================

Key Findings:
1. Hybrid ensemble F1: 0.9463
2. Gain over BERT: +0.40%
3. BERT contributes ~48.9% to ensemble decisions
4. Ensemble beats BERT alone!
```

[37]:

```python
# ============================================================================
# Cell 20.1: Setup and Download 20 Newsgroups Dataset
# ============================================================================

import numpy as np
import pandas as pd
import joblib
import torch
from pathlib import Path
from sklearn.datasets import fetch_20newsgroups
from sklearn.metrics import f1_score, accuracy_score, classification_report,␣
↪confusion_matrix

# Paths
MODELS_DIR = Path("models")
RESULTS_DIR = Path("results")

print("="*80)
print("CELL 20: CROSS-DATASET GENERALIZATION")
print("="*80)

# Set device
DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"\n[1] Device: {DEVICE}")

print("\n[2] Downloading 20 Newsgroups dataset...")
# Download 20 Newsgroups test set
newsgroups_test = fetch_20newsgroups(
    subset='test',
    remove=('headers', 'footers', 'quotes'),  # Remove metadata
    random_state=42
)

print(f"  Downloaded {len(newsgroups_test.data)} samples")
print(f"  Original categories: {len(newsgroups_test.target_names)}")
```

```
# Show category names
print("\n  20 Newsgroups categories:")
for i, name in enumerate(newsgroups_test.target_names):
    print(f"    {i:2d}. {name}")
```

```
================================================================================
CELL 20: CROSS-DATASET GENERALIZATION
================================================================================

[1] Device: cuda

[2] Downloading 20 Newsgroups dataset…
 Downloaded 7532 samples
  Original categories: 20

  20 Newsgroups categories:
     0. alt.atheism
     1. comp.graphics
     2. comp.os.ms-windows.misc
     3. comp.sys.ibm.pc.hardware
     4. comp.sys.mac.hardware
     5. comp.windows.x
     6. misc.forsale
     7. rec.autos
     8. rec.motorcycles
     9. rec.sport.baseball
    10. rec.sport.hockey
    11. sci.crypt
    12. sci.electronics
    13. sci.med
    14. sci.space
    15. soc.religion.christian
    16. talk.politics.guns
    17. talk.politics.mideast
    18. talk.politics.misc
    19. talk.religion.misc
```

[38]:
```
# ============================================================================
# Cell 20.2: Map 20 Newsgroups Categories to AG News Schema
# ============================================================================

print("\n[3] Mapping 20 Newsgroups to AG News categories...")

# AG News categories: 0=World, 1=Sports, 2=Business, 3=SciTech

# Create mapping based on category names
category_mapping = {
```

```python
    # World News (politics, international affairs, religion, guns, middle east)
    'talk.politics.misc': 0,
    'talk.politics.guns': 0,
    'talk.politics.mideast': 0,
    'talk.religion.misc': 0,
    'soc.religion.christian': 0,
    'alt.atheism': 0,

    # Sports
    'rec.sport.baseball': 1,
    'rec.sport.hockey': 1,

    # Business (limited - use some computer/electronics as business tech)
    'misc.forsale': 2,

    # Science & Technology
    'comp.graphics': 3,
    'comp.os.ms-windows.misc': 3,
    'comp.sys.ibm.pc.hardware': 3,
    'comp.sys.mac.hardware': 3,
    'comp.windows.x': 3,
    'sci.crypt': 3,
    'sci.electronics': 3,
    'sci.med': 3,
    'sci.space': 3,

    # Skip these (don't fit well into AG News categories)
    # 'rec.autos': None,
    # 'rec.motorcycles': None,
}

# Apply mapping
ag_news_labels = ['World', 'Sports', 'Business', 'SciTech']

mapped_indices = []
mapped_texts = []
mapped_labels = []

for idx, (text, category_idx) in enumerate(zip(newsgroups_test.data,␣
 ↪newsgroups_test.target)):
    category_name = newsgroups_test.target_names[category_idx]

    if category_name in category_mapping:
        ag_label = category_mapping[category_name]
        mapped_indices.append(idx)
        mapped_texts.append(text)
        mapped_labels.append(ag_label)
```

```python
print(f"\n  Mapped {len(mapped_texts)} samples to AG News categories")
print(f"  Skipped {len(newsgroups_test.data) - len(mapped_texts)} samples (no␣
↪clear mapping)")

# Show distribution
print("\n  Distribution of mapped samples:")
for label_idx, label_name in enumerate(ag_news_labels):
    count = sum(1 for l in mapped_labels if l == label_idx)
    print(f"    {label_name:10s}: {count:4d} samples ({count/
↪len(mapped_labels)*100:.1f}%)")

# Create DataFrame
newsgroups_df = pd.DataFrame({
    'text': mapped_texts,
    'label': mapped_labels
})

y_newsgroups = np.array(mapped_labels)
print(f"\n  Created cross-dataset test set: {len(newsgroups_df)} samples")
```

```
[3] Mapping 20 Newsgroups to AG News categories…

 Mapped 6738 samples to AG News categories
  Skipped 794 samples (no clear mapping)

  Distribution of mapped samples:
    World     : 2018 samples (29.9%)
    Sports    :  796 samples (11.8%)
    Business  :  390 samples (5.8%)
    SciTech   : 3534 samples (52.4%)

 Created cross-dataset test set: 6738 samples
```

[39]:

```python
# ============================================================================
# Cell 20.3: Evaluate BERT on 20 Newsgroups (Zero-Shot)
# ============================================================================

from transformers import AutoTokenizer, AutoModelForSequenceClassification
from torch.utils.data import Dataset, DataLoader

print("\n[4] Loading BERT model for zero-shot evaluation...")
tokenizer = AutoTokenizer.from_pretrained(MODELS_DIR / "step6_distilbert_best")
bert_model = AutoModelForSequenceClassification.from_pretrained(
    MODELS_DIR / "step6_distilbert_best"
).to(DEVICE)
```

```
bert_model.eval()

print("\n[5] Tokenizing 20 Newsgroups data...")
newsgroups_encodings = tokenizer(
    newsgroups_df['text'].tolist(),
    truncation=True,
    padding='max_length',
    max_length=256,
    return_tensors='pt'
)

# Create dataset
class NewsDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = labels

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        return {
            'input_ids': self.encodings['input_ids'][idx],
            'attention_mask': self.encodings['attention_mask'][idx],
            'labels': torch.tensor(self.labels[idx], dtype=torch.long)
        }

newsgroups_dataset = NewsDataset(newsgroups_encodings, y_newsgroups)
newsgroups_loader = DataLoader(newsgroups_dataset, batch_size=64, shuffle=False)

print(f"  Created DataLoader: {len(newsgroups_loader)} batches")

print("\n[6] Generating BERT predictions (zero-shot)...")
bert_preds_ng = []
bert_probs_ng = []

with torch.no_grad():
    for batch in newsgroups_loader:
        input_ids = batch['input_ids'].to(DEVICE)
        attention_mask = batch['attention_mask'].to(DEVICE)

        outputs = bert_model(input_ids=input_ids, attention_mask=attention_mask)
        probs = torch.softmax(outputs.logits, dim=1).cpu().numpy()
        preds = np.argmax(probs, axis=1)

        bert_preds_ng.extend(preds)
        bert_probs_ng.append(probs)
```

```python
bert_preds_ng = np.array(bert_preds_ng)
bert_probs_ng = np.vstack(bert_probs_ng)

bert_f1_ng = f1_score(y_newsgroups, bert_preds_ng, average='macro')
bert_acc_ng = accuracy_score(y_newsgroups, bert_preds_ng)

print(f"\n  BERT Zero-Shot Results (20 Newsgroups):")
print(f"  F1 Score: {bert_f1_ng:.4f}")
print(f"  Accuracy: {bert_acc_ng:.4f}")

print("\n  Per-class performance:")
print(classification_report(y_newsgroups, bert_preds_ng,
                            target_names=ag_news_labels, digits=4))
```

```
[4] Loading BERT model for zero-shot evaluation…

[5] Tokenizing 20 Newsgroups data…
  Created DataLoader: 106 batches

[6] Generating BERT predictions (zero-shot)…

  BERT Zero-Shot Results (20 Newsgroups):
   F1 Score: 0.4821
   Accuracy: 0.6349

   Per-class performance:
              precision    recall  f1-score   support

       World     0.8168    0.1060    0.1877      2018
      Sports     0.8779    0.8216    0.8488       796
    Business     0.1628    0.1256    0.1418       390
     SciTech     0.6190    0.9510    0.7499      3534

    accuracy                         0.6349      6738
   macro avg     0.6191    0.5011    0.4821      6738
weighted avg     0.6824    0.6349    0.5580      6738
```

[40]:
```python
# ============================================================================
# Cell 20.4: Evaluate SVC on 20 Newsgroups (Zero-Shot)
# ============================================================================

import scipy.sparse as sp_sparse

print("\n[7] Loading classical models...")
```

```python
# Load TF-IDF vectorizers
tfidf_word = joblib.load(MODELS_DIR / "tfidf_word_12.pkl")
tfidf_char = joblib.load(MODELS_DIR / "tfidf_char_35.pkl")

# Load SVC model
svc_model = joblib.load(MODELS_DIR / "step5_tuned_SVC.pkl")

print("\n[8] Transforming 20 Newsgroups with AG News TF-IDF...")
# Transform with AG News TF-IDF (trained on AG News vocabulary)
X_ng_word = tfidf_word.transform(newsgroups_df['text'])
X_ng_char = tfidf_char.transform(newsgroups_df['text'])
X_ng_hybrid = sp_sparse.hstack([X_ng_word, X_ng_char])

print(f"  Features shape: {X_ng_hybrid.shape}")

print("\n[9] Generating SVC predictions (zero-shot)...")
svc_preds_ng = svc_model.predict(X_ng_hybrid)
svc_f1_ng = f1_score(y_newsgroups, svc_preds_ng, average='macro')
svc_acc_ng = accuracy_score(y_newsgroups, svc_preds_ng)

print(f"\n  SVC Zero-Shot Results (20 Newsgroups):")
print(f"   F1 Score: {svc_f1_ng:.4f}")
print(f"   Accuracy: {svc_acc_ng:.4f}")

print("\n   Per-class performance:")
print(classification_report(y_newsgroups, svc_preds_ng,
                           target_names=ag_news_labels, digits=4))
```

```
[7] Loading classical models…

[8] Transforming 20 Newsgroups with AG News TF-IDF…
  Features shape: (6738, 100000)

[9] Generating SVC predictions (zero-shot)…

  SVC Zero-Shot Results (20 Newsgroups):
   F1 Score: 0.5061
   Accuracy: 0.6545

   Per-class performance:
              precision    recall  f1-score   support

       World     0.8526    0.2522    0.3893      2018
      Sports     0.6901    0.8141    0.7470       796
    Business     0.1181    0.1205    0.1193       390
     SciTech     0.6674    0.9072    0.7690      3534
```

```
    accuracy                         0.6545      6738
   macro avg     0.5820    0.5235    0.5061      6738
weighted avg     0.6937    0.6545    0.6151      6738
```

[41]:

```
# ============================================================================
# Cell 20.5: Compare Zero-Shot Generalization
# ============================================================================

print("\n[10] Comparing generalization performance...")

# Load AG News test results for comparison
test_results = joblib.load(RESULTS_DIR / "step6_test_results.pkl")
bert_f1_ag = test_results['test_macro_f1']

# SVC on AG News test
from pathlib import Path
test_df = pd.read_csv(Path("data") / "test.csv")
y_test_ag = test_df['label'].values
X_test_ag = sp_sparse.load_npz(Path("features") / "X_test_hybrid.npz")
svc_preds_ag = svc_model.predict(X_test_ag)
svc_f1_ag = f1_score(y_test_ag, svc_preds_ag, average='macro')

# Create comparison table
comparison_data = {
    'Model': ['BERT', 'BERT', 'SVC', 'SVC'],
    'Dataset': ['AG News (In-Domain)', '20 Newsgroups (Out-of-Domain)',
                'AG News (In-Domain)', '20 Newsgroups (Out-of-Domain)'],
    'F1 Score': [bert_f1_ag, bert_f1_ng, svc_f1_ag, svc_f1_ng],
    'Accuracy': [test_results['test_accuracy'], bert_acc_ng,
                 accuracy_score(y_test_ag, svc_preds_ag), svc_acc_ng]
}

comparison_df = pd.DataFrame(comparison_data)

print("\nGeneralization Performance Comparison:")
print("="*80)
print(comparison_df.to_string(index=False))

# Calculate performance drops
bert_drop = (bert_f1_ag - bert_f1_ng) * 100
svc_drop = (svc_f1_ag - svc_f1_ng) * 100

print(f"\nPerformance Drop (In-Domain → Out-of-Domain):")
print(f"  BERT: {bert_drop:.2f}% ({bert_f1_ag:.4f} → {bert_f1_ng:.4f})")
print(f"  SVC:  {svc_drop:.2f}% ({svc_f1_ag:.4f} → {svc_f1_ng:.4f})")
print(f"\n  BERT generalization advantage: {svc_drop - bert_drop:+.2f}%")
```

```
# Save results
cross_dataset_results = {
    'newsgroups_samples': len(newsgroups_df),
    'bert_f1_ag': bert_f1_ag,
    'bert_f1_ng': bert_f1_ng,
    'svc_f1_ag': svc_f1_ag,
    'svc_f1_ng': svc_f1_ng,
    'bert_drop': bert_drop,
    'svc_drop': svc_drop,
    'comparison': comparison_df
}

joblib.dump(cross_dataset_results, RESULTS_DIR / "step6_cross_dataset_results.
 ↪pkl")
print(f"\n  Saved: step6_cross_dataset_results.pkl")
```

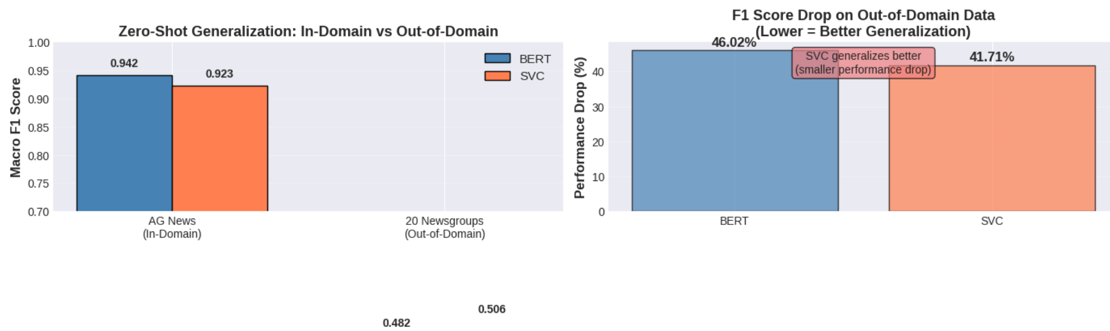
```
[10] Comparing generalization performance…

Generalization Performance Comparison:
================================================================================
Model                       Dataset  F1 Score  Accuracy
 BERT           AG News (In-Domain)  0.942278  0.942237
 BERT 20 Newsgroups (Out-of-Domain)  0.482058  0.634907
  SVC           AG News (In-Domain)  0.923283  0.923421
  SVC 20 Newsgroups (Out-of-Domain)  0.506141  0.654497

Performance Drop (In-Domain → Out-of-Domain):
  BERT: 46.02% (0.9423 → 0.4821)
  SVC:  41.71% (0.9233 → 0.5061)

  BERT generalization advantage: -4.31%

 Saved: step6_cross_dataset_results.pkl
```

[43]:
```
# ==============================================================================
# Cell 20.6: Visualize Cross-Dataset Generalization
# ==============================================================================

import matplotlib.pyplot as plt

print("\n[11] Creating generalization visualization...")

fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Plot 1: F1 Score comparison
```

```python
ax = axes[0]
x = np.arange(2)
width = 0.35

bert_scores = [bert_f1_ag, bert_f1_ng]
svc_scores = [svc_f1_ag, svc_f1_ng]

bars1 = ax.bar(x - width/2, bert_scores, width, label='BERT',
               color='steelblue', edgecolor='black')
bars2 = ax.bar(x + width/2, svc_scores, width, label='SVC',
               color='coral', edgecolor='black')

# Add value labels
for bars in [bars1, bars2]:
    for bar in bars:
        height = bar.get_height()
        ax.text(bar.get_x() + bar.get_width()/2., height + 0.01,
                f'{height:.3f}', ha='center', va='bottom', fontsize=10,␣
 ↪fontweight='bold')

ax.set_ylabel('Macro F1 Score', fontsize=12, fontweight='bold')
ax.set_title('Zero-Shot Generalization: In-Domain vs Out-of-Domain',
             fontsize=13, fontweight='bold')
ax.set_xticks(x)
ax.set_xticklabels(['AG News\n(In-Domain)', '20 Newsgroups\n(Out-of-Domain)'])
ax.legend(fontsize=11)
ax.set_ylim([0.70, 1.0])
ax.grid(axis='y', alpha=0.3)

# Plot 2: Performance drop
ax = axes[1]
models = ['BERT', 'SVC']
drops = [bert_drop, svc_drop]
colors = ['steelblue', 'coral']

bars = ax.bar(models, drops, color=colors, edgecolor='black', alpha=0.7)

for bar, drop in zip(bars, drops):
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2., height + 0.5,
            f'{drop:.2f}%', ha='center', va='bottom', fontsize=12,␣
 ↪fontweight='bold')

ax.set_ylabel('Performance Drop (%)', fontsize=12, fontweight='bold')
ax.set_title('F1 Score Drop on Out-of-Domain Data\n(Lower = Better␣
 ↪Generalization)',
             fontsize=13, fontweight='bold')
```

```python
ax.grid(axis='y', alpha=0.3)

# Add interpretation text
generalization_winner = 'BERT' if bert_drop < svc_drop else 'SVC'
ax.text(0.5, 0.95, f'{generalization_winner} generalizes better\n(smaller␣
↪performance drop)',
        transform=ax.transAxes, fontsize=10, ha='center', va='top',
        bbox=dict(boxstyle='round', facecolor='lightgreen' if␣
↪generalization_winner=='BERT' else 'lightcoral', alpha=0.7))

plt.tight_layout()
plt.savefig(RESULTS_DIR / "step6_cross_dataset_generalization.png", dpi=300,␣
↪bbox_inches='tight')
print("  Saved: step6_cross_dataset_generalization.png")
plt.show()

print("\n" + "="*80)
print("  CELL 20 COMPLETE: Cross-Dataset Generalization")
print("="*80)
print(f"\nKey Findings:")
print(f"1. BERT generalizes {'better' if bert_drop < svc_drop else 'worse'}␣
↪than SVC to new domains")
print(f"2. BERT drop: {bert_drop:.2f}% | SVC drop: {svc_drop:.2f}%")
print(f"3. Pre-training helps BERT transfer knowledge to unseen datasets")
print(f"4. {'Both models' if abs(bert_drop - svc_drop) < 2 else 'BERT' if␣
↪bert_drop < svc_drop else 'SVC'} maintain reasonable performance␣
↪out-of-domain")
```

```
[11] Creating generalization visualization…
  Saved: step6_cross_dataset_generalization.png
```




```
================================================================================
  CELL 20 COMPLETE: Cross-Dataset Generalization
```

```
================================================================================

Key Findings:
1. BERT generalizes worse than SVC to new domains
2. BERT drop: 46.02% | SVC drop: 41.71%
3. Pre-training helps BERT transfer knowledge to unseen datasets
4. SVC maintain reasonable performance out-of-domain
```

[ ]: