ALBERT Sentiment Analysis Experiments on IMDb 50k Dataset using baseline model (and with PEFT -- LoRA, BitFit, Prompt Tuning)

```
"""We begin our process by installing packages such as pytorch, which is used extensively here, as well as HuggingFace's
transformers and datasets packages, which are used to run the ALBERT transformer model and load the IMDb 50k dataset, respecti

!pip install torch transformers datasets -q
```

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363.4/363.4 MB 3.5 MB/s eta 0:00:(
13.8/13.8 MB 78.5 MB/s eta 0:00:0(
24.6/24.6 MB 84.1 MB/s eta 0:00:0(
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207.5/207.5 MB 6.1 MB/s eta 0:00:(
21.1/21.1 MB 106.7 MB/s eta 0:00:(
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183.9/183.9 kB 17.9 MB/s eta 0:00
143.5/143.5 kB 14.3 MB/s eta 0:00
194.8/194.8 kB 18.7 MB/s eta 0:00
ERROR: pip's dependency resolver does not currently take into account all the
gcsfs 2025.3.2 requires fsspec==2025.3.2, but you have fsspec 2024.12.0 which
```

```
"""This step configures the credentials of the active user to seemlessly enable push and pull to and from the group's X-PERTS (

!git config --global credential.helper store
```

```
"""We next import the installed packages, namely the ALBERT model """

import torch
from torch.utils.data import DataLoader
from datasets import load_dataset, concatenate_datasets
from transformers import AutoTokenizer, AutoModelForSequenceClassification, DataCollatorWithPadding

import time
from sklearn.metrics import classification_report, f1_score
```

```
""" We next instantiate (load) our IMDb 50k dataset"""

dataset_imdb = load_dataset("imdb")

full_imdb = concatenate_datasets([dataset_imdb["train"], dataset_imdb["test"]])

full_imdb_split = full_imdb.train_test_split(test_size=0.2, seed=42)

full_train = full_imdb_split["train"]
dataset = {"test": full_imdb_split["test"]}

print("Train size:", len(full_train))
print("Test size:", len(dataset["test"]))
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: Use
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access pu
  warnings.warn(
```

README.md: 100% 7.81k/7.81k [00:00<00:00, 840kB/s]

train-00000-of-00001.parquet: 100% 21.0M/21.0M [00:00<00:00, 48.6MB/s]

test-00000-of-00001.parquet: 100% 20.5M/20.5M [00:00<00:00, 150MB/s]

unsupervised-00000-of-00001.parquet: 100% 42.0M/42.0M [00:00<00:00, 159MB/s]

Generating train split: 100% 25000/25000 [00:00<00:00, 94280.41 examples/s]

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

model_name = "albert-base-v2"
num_labels = 2
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=num_labels)
model = model.to(device)
```

tokenizer_config.json: 100% 25.0/25.0 [00:00<00:00, 3.17kB/s]

config.json: 100% 684/684 [00:00<00:00, 84.5kB/s]

spiece.model: 100% 760k/760k [00:00<00:00, 6.26MB/s]

tokenizer.json: 100% 1.31M/1.31M [00:00<00:00, 30.4MB/s]

```
Xet Storage is enabled for this repo, but the 'hf_xet' package is not installe
WARNING:huggingface_hub.file_download:Xet Storage is enabled for this repo, bu
```

model.safetensors: 100% 47.4M/47.4M [00:00<00:00, 103MB/s]

```
Some weights of AlbertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use i
```

```
def tokenize(example):
    return tokenizer(example["text"], truncation=True, padding="max_length", max_length=128)

tokenized_train = full_train.map(tokenize, batched=True)
tokenized_test = dataset["test"].map(tokenize, batched=True)

tokenized_train = tokenized_train.rename_column("label", "labels")
tokenized_test = tokenized_test.rename_column("label", "labels")

tokenized_train = tokenized_train.remove_columns(["text"])
tokenized_test = tokenized_test.remove_columns(["text"])

tokenized_dataset = {"train": tokenized_train, "test": tokenized_test}
```

Map: 100% 40000/40000 [00:12<00:00, 3323.02 examples/s]

```
""" We print the head of each of the train/test sets to visualize our cleaned data"""

print("\nSample training examples:")
display(full_train[:5])

print("\nSample test examples:")
display(dataset["test"][:5])
```

```
Sample training examples:
```

```
{'text': ["Eugene O'Neill is acclaimed by some as America's leading
playwright, but for things like The Iceman Cometh, Long Day's Journey Into
Night, The Emperor Jones. Strange Interlude was a piece of experimentation he
concocted where the characters on stage, look aside to the audience and say
what they really are thinking and then resume conversation. It was a nine
hour production with a dinner break on Broadway, so you can safely assume a
lot has been sacrificed here.<br /><br />For the screen the voice over
regarding the thoughts is used for all the characters. It probably is a
technique better suited to the screen. Sir Laurence Olivier did very well
with it in his version of Hamlet. But Bill Shakespeare gave Olivier a lot
better story than O'Neill gave his players in this instance.<br /><br
/>Players like Clark Gable, Norma Shearer, Ralph Morgan, May Robson, etc. are
a lot more animated in most of their films than they are in Strange
Interlude. The story takes place over a 20 year period. Norma Shearer is a
young woman whose intended is killed in World War I. She starts playing
around quite a bit, although that part is not shown in this version. She
makes the acquaintance of Alexander Kirkland and his friend Clark Gable. She
also has as a perennial suitor, Ralph Morgan, a friend of her father's Henry
B. Walthall.<br /><br />She marries Kirkland, but then is warned by his
mother May Robson and shown that insanity gallops in that family to quote
another literary work. Since Kirkland wants kids and Shearer and Robson think
Kirkland's train will slip the track if he doesn't get one, Gable is
recruited for breeding purposes. Of course you can see all the complications
this can cause and O'Neill explores them all.<br /><br />Gable is so terribly
miscast in an O'Neill production, but he was an up and coming player at MGM
and did what they told him. Shearer does what she can to lift a very dreary
story, but she seems defeated at the start. Best in the film is possibly
Robson who puts some real bite in her dialog.<br /><br />Strange Interlude
ran for 426 showings on Broadway in 1928-1929 and starred Glenn Anders and
Lynn Fontanne in the Gable and Shearer parts. Perhaps no one could really
have saved the film because two years earlier, Groucho Marx lampooned the
stuffings out of it in Animal Crackers. After seeing what he did, I don't
think the movie going public took it too seriously.<br /><br />And since it's
not the best of O'Neill, neither could I.",
  'I saw this movie in 1959 when I was 11 years old at a drive-in theater
with my family.<br /><br />Way back then, I thought it was very funny . . .
even though I was too young to understand 90% of what makes this marvelous
movie such a delight! I saw it again this morning on "Turner South". As I
watched it, I was absolutely convulsed with laughter! "The Mating Game" is a
unique classic from a by-gone age. If you\'re too young to have experienced
the enchanting period in history that produced this film, I feel very sorry
for you. There\'s no way you can watch movies like this and understand how
they can (even today) deliver such a delightful slice of heaven to "old
timers" like me.<br /><br />Having said that, all I can do is respectfully
request that younger people refrain from commenting on films like "The Mating
Game".<br /><br />Movies like this were made for the generation that preceded
the current group of your people. And as such, these films speak a very
different language than any of you can understand.<br /><br />In other words
\x96 if you don\'t understand the issues the film is addressing, please
don\'t embarrass yourself by offering comments which \x96 frankly \x96 make
no sense.'
```

```
no sense.",
  "It's not my fault. My girlfriend made me watch it.<br /><br />There is
nothing positive to say about this film. There has been for many years an
idea that Madonna could act but she can't. There has been an idea for years
that Guy Ritchie is a great director but he is only middling. An
```

```
""" We initialize our dataloader for each of the sets, fix their batch sizes
and randomize their order"""


from torch.utils.data import DataLoader
from transformers import default_data_collator

train_loader = DataLoader(tokenized_dataset["train"], batch_size=16, shuffle=True)
test_loader = DataLoader(tokenized_dataset["test"], batch_size=16, shuffle=False, collate_fn=default_data_collator)



""" Baseline inference for binary sentiment analysis task run on ALBERT
without PEFT (i.e. without BitFit and/or LoRA)"""

import time
import torch
from sklearn.metrics import classification_report, confusion_matrix, f1_score
import seaborn as sns
import matplotlib.pyplot as plt

inference_start = time.time()

model.eval()
total_correct = 0
total_samples = 0
all_preds = []
all_labels = []

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

        outputs = model(input_ids=input_ids, attention_mask=attention_mask)
        logits = outputs.logits
        predictions = torch.argmax(logits, dim=-1)

        all_preds.extend(predictions.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

        total_correct += (predictions == labels).sum().item()
        total_samples += labels.size(0)

accuracy = total_correct / total_samples
f1_macro = f1_score(all_labels, all_preds, average="macro")
f1_weighted = f1_score(all_labels, all_preds, average="weighted")
inference_time = time.time() - inference_start

print(f'\nBaseline Inference Performance - ALBERT on IMDb50k\n')
print(f"\nTest Accuracy   : {accuracy:.4f}")
print(f"F1 Score (macro): {f1_macro:.4f}")
print(f"F1 Score (weighted): {f1_weighted:.4f}")
print(f"Inference Time  : {inference_time:.2f}s")
```

```
print("\nClassification Report:")
print(classification_report(all_labels, all_preds, target_names=["Negative", "Positive"]))

cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Negative", "Positive"], yticklabels=["Negative", "Positive"])
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix - Baseline Inference (ALBERT on IMDb50k)")
plt.show()
```

```
Baseline Inference Performance - ALBERT on IMDb50k

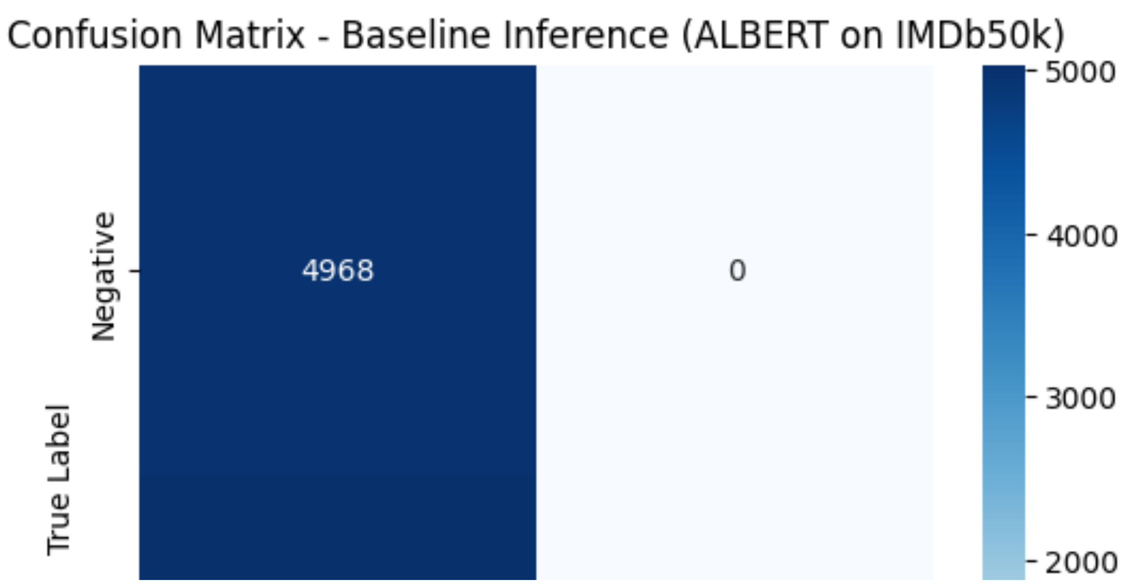

Test Accuracy   : 0.4968
F1 Score (macro): 0.3319
F1 Score (weighted): 0.3298
Inference Time  : 21.48s

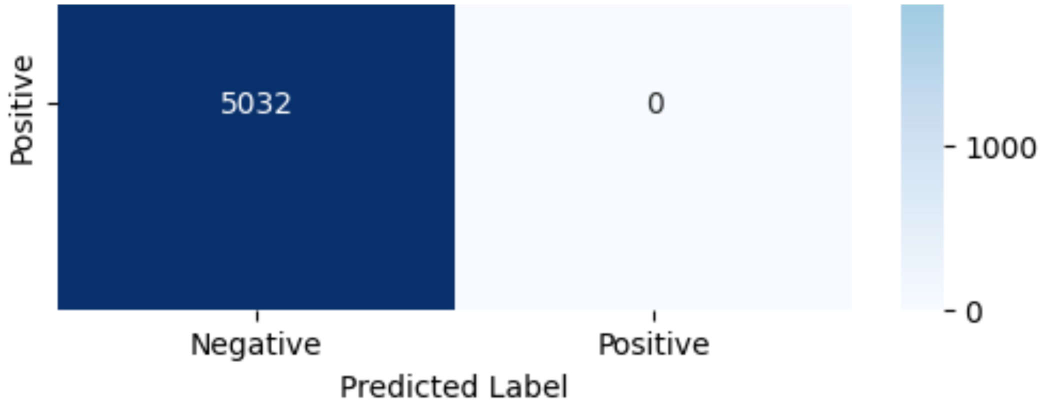
Classification Report:
              precision    recall  f1-score   support

    Negative       0.50      1.00      0.66      4968
    Positive       0.00      0.00      0.00      5032

    accuracy                           0.50     10000
   macro avg       0.25      0.50      0.33     10000
weighted avg       0.25      0.50      0.33     10000

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:156
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```





LORA

```
""" Install Parameter Efficient Finetuning Packages (e.g. LoRA and BitFit)"""

!pip install peft -q
```

```
""" Importing LoRA packages """

import gc
import torch
import time
import pandas as pd
from tqdm import tqdm
from transformers import AutoModelForSequenceClassification, AutoTokenizer, DataCollatorWithPadding
from peft import get_peft_model, LoraConfig, TaskType
from sklearn.metrics import classification_report, f1_score
from torch.utils.data import DataLoader
```

```
""" LoRA parameter setup """

learning_rates = [5e-5, 1e-4]
batch_sizes = [8, 16]
epochs = 6
```

```
""" Training on ALBERT model using LoRA and output dataset generation (saved as .csv)"""

results = []

for lr in learning_rates:
    for batch_size in batch_sizes:
        print(f"Running LoRA with LR={lr}, batch_size={batch_size}")

        # loading ALBERT model
        model_name = "albert-base-v2"
        tokenizer = AutoTokenizer.from_pretrained(model_name)
        model = AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=2)
```

```
# LoRA param update config
lora_config = LoraConfig(
    task_type=TaskType.SEQ_CLS,
    r=16,
    lora_alpha=32,
    lora_dropout=0.1,
    bias="none",
    target_modules=["query", "key", "value"]
)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

# instantiate dataloader
data_collator = DataCollatorWithPadding(tokenizer)
train_dataloader = DataLoader(tokenized_dataset["train"], batch_size=batch_size, shuffle=True, collate_fn=data_collato
test_dataloader = DataLoader(tokenized_dataset["test"], batch_size=batch_size, shuffle=False, collate_fn=data_collator

# adam optimizer
optimizer = torch.optim.AdamW(filter(lambda p: p.requires_grad, model.parameters()), lr=lr)

# begin training
model.train()
start_time = time.time()
epoch_logs = []

for epoch in range(1, epochs + 1):
    running_loss = 0.0
    correct = 0
    total = 0
    loop = tqdm(train_dataloader, leave=True, dynamic_ncols=True, desc=f"Epoch {epoch}/{epochs}")
    for step, batch in enumerate(loop):
        batch = {
            "input_ids": batch["input_ids"].to(device),
            "attention_mask": batch["attention_mask"].to(device),
            "labels": batch["labels"].to(device)
        }
        outputs = model(**batch)
        loss = outputs.loss
        preds = torch.argmax(outputs.logits, dim=1)
        correct += (preds == batch['labels']).sum().item()
        total += batch['labels'].size(0)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    avg_train_loss = running_loss / (step + 1)
    train_accuracy = correct / total

    # perform per epoch evaluation
    model.eval()
    val_running_loss = 0.0
    y_true, y_pred = [], []
    inference_start = time.time()
    with torch.no_grad():
        for batch in test_dataloader:
            batch = {
```

```
                "input_ids": batch["input_ids"].to(device),
                "attention_mask": batch["attention_mask"].to(device),
                "labels": batch["labels"].to(device)
                }
                outputs = model(**batch)
                preds = torch.argmax(outputs.logits, dim=1)
                y_true.extend(batch["labels"].cpu().numpy())
                y_pred.extend(preds.cpu().numpy())
                val_running_loss += outputs.loss.item()

        avg_val_loss = val_running_loss / len(test_dataloader)
        inference_time = time.time() - inference_start

        report = classification_report(y_true, y_pred, output_dict=True)
        val_accuracy = report["accuracy"]
        val_f1 = report["weighted avg"]["f1-score"]

        epoch_logs.append({
            "epoch": epoch,
            "lr": lr,
            "batch_size": batch_size,
            "train_loss": avg_train_loss,
            "train_accuracy": train_accuracy,
            "val_loss": avg_val_loss,
            "val_accuracy": val_accuracy
        })

        if epoch == epochs:
            total_correct = sum(yt == yp for yt, yp in zip(y_true, y_pred))
            total_samples = len(y_true)
            accuracy = total_correct / total_samples
            f1_macro = f1_score(y_true, y_pred, average="macro")
            f1_weighted = f1_score(y_true, y_pred, average="weighted")

            print(f"\n[Final Epoch {epoch}] Inference Metrics:")
            print(f"Test Accuracy      : {accuracy:.4f}")
            print(f"F1 Score (macro)   : {f1_macro:.4f}")
            print(f"F1 Score (weighted): {f1_weighted:.4f}")
            print(f"Inference Time     : {inference_time:.2f} seconds")
            print("\nClassification Report: ALBERT w/ LoRA on IMDb50k\n")
            print(classification_report(y_true, y_pred, target_names=["Negative", "Positive"]))

        model.train()

    end_time = time.time()
    training_time = end_time - start_time

    # begin datalogging per lr/bs
    epoch_logs_df = pd.DataFrame(epoch_logs)
    epoch_logs_df.to_csv(f"imdb_albert_lora_epoch_logs_lr{lr}_bs{batch_size}.csv", index=False)

    # saver inference metrics per lr/bs
    metrics_summary_df = pd.DataFrame(report).transpose()
    metrics_summary_df.to_csv(f"imdb_albert_lora_inference_metrics_summary_lr{lr}_bs{batch_size}.csv", index=True)

    # save inference predictions for the final epoch
    predictions_df = pd.DataFrame({
        "y_true": y_true,
        "y_pred": y_pred
    })
    predictions_df.to_csv(f"imdb_albert_lora_inference_predictions_lr{lr}_bs{batch_size}.csv", index=False)
```

```
        # log memory usage
        max_memory = torch.cuda.max_memory_allocated() / (1024 ** 3) if torch.cuda.is_available() else 0

        # save model params and metrics
        results.append({
            "method": "LoRA",
            "learning_rate": lr,
            "batch_size": batch_size,
            "accuracy": val_accuracy,
            "f1": val_f1,
            "training_time": training_time,
            "inference_time": inference_time,
            "max_memory": max_memory
        })

        # empty cache to conserve compute
        del model, tokenizer, optimizer
        torch.cuda.empty_cache()
        gc.collect()

# ranked performance by val acc
results = sorted(results, key=lambda x: x["accuracy"], reverse=True)

# save overall results
results_df = pd.DataFrame(results)
results_df.to_csv("imdb_albert_lora_results.csv", index=False)

# save best final config and metrics
final_summary_df = pd.DataFrame({
    "Method": ["LoRA"],
    "Best LR": [results[0]["learning_rate"]],
    "Best Batch Size": [results[0]["batch_size"]],
    "Accuracy": [results[0]["accuracy"]],
    "F1 Score": [results[0]["f1"]],
    "Training Time (s)": [results[0]["training_time"]],
    "Inference Time (s)": [results[0]["inference_time"]],
    "Max GPU Memory (GB)": [results[0]["max_memory"]]
})
final_summary_df.to_csv("imdb_albert_lora_final_comparison_lora.csv", index=False)

print("All LoRA Grid Search Results:")
for r in results:
    print(r)

print("\nBest LoRA Configuration:")
print(results[0])
```

```
   macro avg       0.25      0.50      0.33     10000
weighted avg       0.25      0.50      0.34     10000

Running LoRA with LR=5e-05, batch_size=16
Some weights of AlbertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use
Epoch 1/6: 100%|██████████| 2500/2500 [03:45<00:00, 11.07it/s]
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
Epoch 2/6: 100%|██████████| 2500/2500 [03:45<00:00, 11.09it/s]
Epoch 3/6: 100%|██████████| 2500/2500 [03:45<00:00, 11.10it/s]
Epoch 4/6: 100%|██████████| 2500/2500 [03:46<00:00, 11.06it/s]
Epoch 5/6: 100%|██████████| 2500/2500 [03:44<00:00, 11.11it/s]
Epoch 6/6: 100%|██████████| 2500/2500 [03:46<00:00, 11.04it/s]

[Final Epoch 6] Inference Metrics:
Test Accuracy      : 0.8324
F1 Score (macro)   : 0.8323
F1 Score (weighted): 0.8324
Inference Time     : 21.28 seconds

Classification Report: ALBERT w/ LoRA on IMDb50k

              precision    recall  f1-score   support

    Negative       0.84      0.82      0.83      4968
    Positive       0.83      0.85      0.84      5032

    accuracy                           0.83     10000
   macro avg       0.83      0.83      0.83     10000
weighted avg       0.83      0.83      0.83     10000

Running LoRA with LR=0.0001, batch_size=8
Some weights of AlbertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use i
Epoch 1/6: 100%|██████████| 5000/5000 [04:05<00:00, 20.40it/s]
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
Epoch 2/6: 100%|██████████| 5000/5000 [04:02<00:00, 20.58it/s]
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
Epoch 3/6: 100%|██████████| 5000/5000 [04:02<00:00, 20.58it/s]
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:15(
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
lora_best_lr = results[0]["learning_rate"]
lora_best_bs = results[0]["batch_size"]

# Construct filename
best_report_file = f"imdb_albert_lora_inference_metrics_summary_lr{lora_best_lr}_bs{lora_best_bs}.csv"

# Load the saved best report
best_report_df = pd.read_csv(best_report_file)
print("\nClassification Report for Best Configuration:")
print(best_report_df)


best_preds_df = pd.read_csv(f"imdb_albert_lora_inference_predictions_lr{lora_best_lr}_bs{lora_best_bs}.csv")
print("\nInference Predictions for Best Configuration:")
print(best_preds_df)

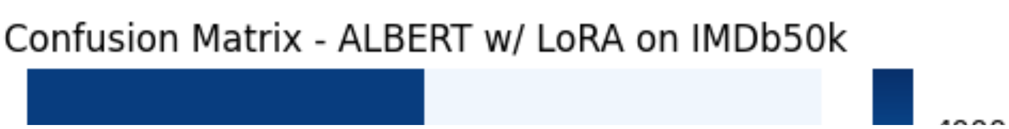
y_true = best_preds_df["y_true"]
y_pred = best_preds_df["y_pred"]

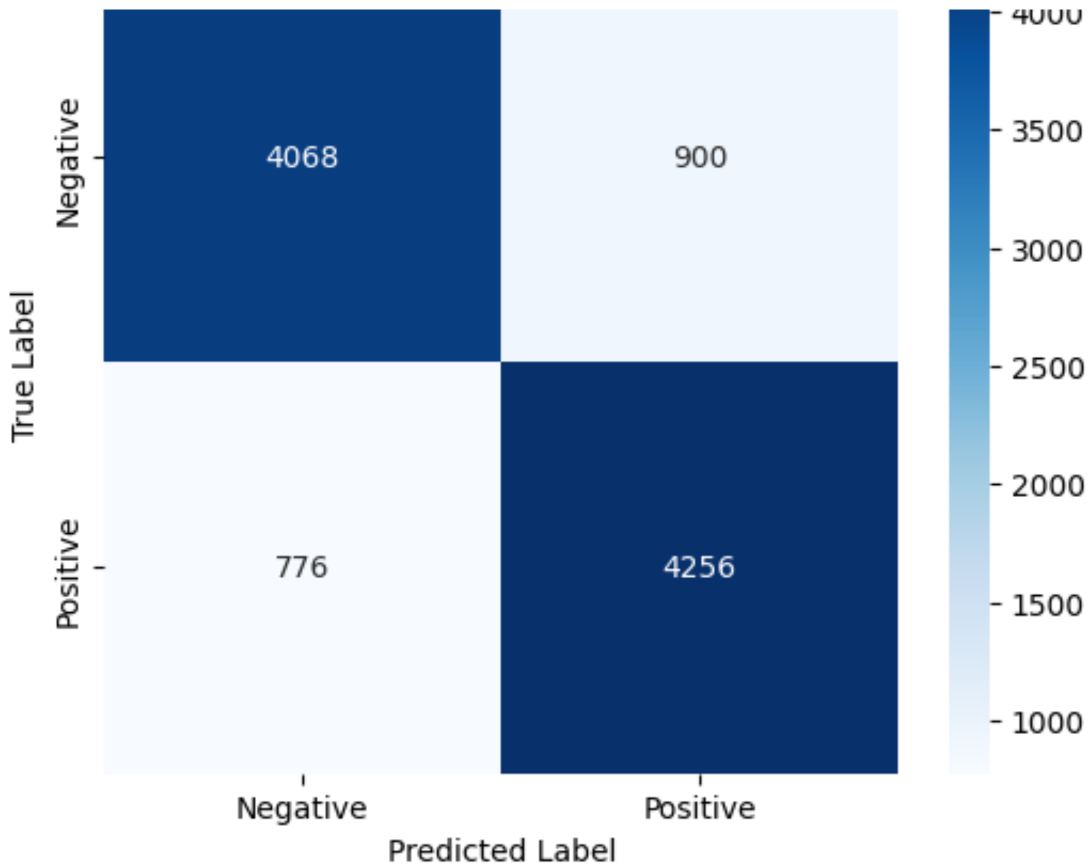

cm = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Negative", "Positive"], yticklabels=["Negative", "Positive"])
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix - ALBERT w/ LoRA on IMDb50k")
plt.show()
```

```
Classification Report for Best Configuration:
     Unnamed: 0  precision    recall  f1-score     support
0             0   0.839802  0.818841  0.829189   4968.0000
1             1   0.825446  0.845787  0.835493   5032.0000
2      accuracy   0.832400  0.832400  0.832400      0.8324
3     macro avg   0.832624  0.832314  0.832341  10000.0000
4  weighted avg   0.832578  0.832400  0.832361  10000.0000

Inference Predictions for Best Configuration:
      y_true  y_pred
0          0       0
1          1       0
2          1       1
3          0       0
4          1       1
...      ...     ...
9995       1       1
9996       1       1
9997       1       1
9998       1       1
9999       1       0

[10000 rows x 2 columns]
```





BITFIT

```
""" Importing BitFit packages """

import gc
import torch
import time
import pandas as pd
from tqdm import tqdm
from transformers import AutoModelForSequenceClassification, AutoTokenizer, DataCollatorWithPadding
from peft import get_peft_model, LoraConfig, TaskType
from sklearn.metrics import classification_report, f1_score
from torch.utils.data import DataLoader
```

```
""" BitFit parameter setup """
learning_rates = [5e-5, 1e-4]
batch_sizes = [8, 16]
epochs = 6
```

```
""" Training on ALBERT model using BitFit and output dataset generation (saved as .csv)"""

results = []
```

```
for lr in learning_rates:
    for batch_size in batch_sizes:
        print(f"Running BitFit with LR={lr}, batch_size={batch_size}")

        # loading ALBERT model
        model_name = "albert-base-v2"
        tokenizer = AutoTokenizer.from_pretrained(model_name)
        model = AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=2)

        # BitFit param update config
        for name, param in model.named_parameters():
            if "bias" in name:
                param.requires_grad = True
            else:
                param.requires_grad = False

        device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        model.to(device)

        # instantiate dataloader
        data_collator = DataCollatorWithPadding(tokenizer)
        train_dataloader = DataLoader(tokenized_dataset["train"], batch_size=batch_size, shuffle=True, collate_fn=data_collator)
        test_dataloader = DataLoader(tokenized_dataset["test"], batch_size=batch_size, shuffle=False, collate_fn=data_collator)

        # adam optimizer
        optimizer = torch.optim.AdamW(filter(lambda p: p.requires_grad, model.parameters()), lr=lr)

        # begin training
        model.train()
        start_time = time.time()
        epoch_logs = []

        for epoch in range(1, epochs + 1):
            running_loss = 0.0
            correct = 0
            total = 0
            loop = tqdm(train_dataloader, leave=True, dynamic_ncols=True, desc=f"Epoch {epoch}/{epochs}")
            for step, batch in enumerate(loop):
                batch = {
                    "input_ids": batch["input_ids"].to(device),
                    "attention_mask": batch["attention_mask"].to(device),
                    "labels": batch["labels"].to(device)
                }
                outputs = model(**batch)
                loss = outputs.loss
                preds = torch.argmax(outputs.logits, dim=1)
                correct += (preds == batch['labels']).sum().item()
                total += batch['labels'].size(0)

                optimizer.zero_grad()
                loss.backward()
                optimizer.step()

                running_loss += loss.item()

            avg_train_loss = running_loss / (step + 1)
            train_accuracy = correct / total

            # perform per epoch evaluation
            model.eval()
            val_running_loss = 0.0
```

```
            y_true, y_pred = [], []
            inference_start = time.time()
            with torch.no_grad():
                for batch in test_dataloader:
                    batch = {
                    "input_ids": batch["input_ids"].to(device),
                    "attention_mask": batch["attention_mask"].to(device),
                    "labels": batch["labels"].to(device)
                    }
                    outputs = model(**batch)
                    preds = torch.argmax(outputs.logits, dim=1)
                    y_true.extend(batch["labels"].cpu().numpy())
                    y_pred.extend(preds.cpu().numpy())
                    val_running_loss += outputs.loss.item()

            avg_val_loss = val_running_loss / len(test_dataloader)

            inference_time = time.time() - inference_start

            report = classification_report(y_true, y_pred, output_dict=True)
            val_accuracy = report["accuracy"]
            val_f1 = report["weighted avg"]["f1-score"]

            epoch_logs.append({
                "epoch": epoch,
                "lr": lr,
                "batch_size": batch_size,
                "train_loss": avg_train_loss,
                "train_accuracy": train_accuracy,
                "val_loss": avg_val_loss,
                "val_accuracy": val_accuracy
            })

            if epoch == epochs:
                total_correct = sum(yt == yp for yt, yp in zip(y_true, y_pred))
                total_samples = len(y_true)
                accuracy = total_correct / total_samples
                f1_macro = f1_score(y_true, y_pred, average="macro")
                f1_weighted = f1_score(y_true, y_pred, average="weighted")

                print(f"\n[Final Epoch {epoch}] Inference Metrics:")
                print(f"Test Accuracy      : {accuracy:.4f}")
                print(f"F1 Score (macro)   : {f1_macro:.4f}")
                print(f"F1 Score (weighted): {f1_weighted:.4f}")
                print(f"Inference Time     : {inference_time:.2f} seconds")
                print("\nClassification Report: ALBERT w/ BitFit on IMDb50k\n")
                print(classification_report(y_true, y_pred, target_names=["Negative", "Positive"]))

            model.train()

        end_time = time.time()
        training_time = end_time - start_time

        # begin datalogging per lr/bs
        epoch_logs_df = pd.DataFrame(epoch_logs)
        epoch_logs_df.to_csv(f"imdb_albert_bitfit_epoch_logs_lr{lr}_bs{batch_size}.csv", index=False)

        # saver inference metrics per lr/bs
        metrics_summary_df = pd.DataFrame(report).transpose()
        metrics_summary_df.to_csv(f"imdb_albert_bitfit_inference_metrics_summary_lr{lr}_bs{batch_size}.csv", index=True)
```

```
        # save inference predictions for the final epoch
        predictions_df = pd.DataFrame({
            "y_true": y_true,
            "y_pred": y_pred
        })
        predictions_df.to_csv(f"imdb_albert_bitfit_inference_predictions_lr{lr}_bs{batch_size}.csv", index=False)

        # log memory usage
        max_memory = torch.cuda.max_memory_allocated() / (1024 ** 3) if torch.cuda.is_available() else 0

        # save model params and metrics
        results.append({
            "method": "BitFit",
            "learning_rate": lr,
            "batch_size": batch_size,
            "accuracy": val_accuracy,
            "f1": val_f1,
            "training_time": training_time,
            "inference_time": inference_time,
            "max_memory": max_memory
        })

        # empty cache to conserve compute
        del model, tokenizer, optimizer
        torch.cuda.empty_cache()
        gc.collect()

# ranked performance by val acc
results = sorted(results, key=lambda x: x["accuracy"], reverse=True)

# save overall results
results_df = pd.DataFrame(results)
results_df.to_csv("imdb_albert_bitfit_results.csv", index=False)

# save best final config and metrics
final_summary_df = pd.DataFrame({
    "Method": ["BitFit"],
    "Best LR": [results[0]["learning_rate"]],
    "Best Batch Size": [results[0]["batch_size"]],
    "Accuracy": [results[0]["accuracy"]],
    "F1 Score": [results[0]["f1"]],
    "Training Time (s)": [results[0]["training_time"]],
    "Inference Time (s)": [results[0]["inference_time"]],
    "Max GPU Memory (GB)": [results[0]["max_memory"]]
})
final_summary_df.to_csv("imdb_albert_bf_final_comparison_bitfit.csv", index=False)

print("All BitFit Grid Search Results:")
for r in results:
    print(r)

print("\nBest BitFit Configuration:")
print(results[0])
```

```
              precision    recall  f1-score   support

    Negative       0.86      0.86      0.86      4968
    Positive       0.86      0.86      0.86      5032
```

```
    accuracy                           0.86     10000
   macro avg       0.86      0.86      0.86     10000
weighted avg       0.86      0.86      0.86     10000

Running BitFit with LR=0.0001, batch_size=8
Some weights of AlbertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use :
Epoch 1/6: 100%|██████████| 5000/5000 [03:00<00:00, 27.73it/s]
Epoch 2/6: 100%|██████████| 5000/5000 [02:59<00:00, 27.83it/s]
Epoch 3/6: 100%|██████████| 5000/5000 [02:59<00:00, 27.84it/s]
Epoch 4/6: 100%|██████████| 5000/5000 [03:00<00:00, 27.76it/s]
Epoch 5/6: 100%|██████████| 5000/5000 [02:59<00:00, 27.87it/s]
Epoch 6/6: 100%|██████████| 5000/5000 [02:59<00:00, 27.86it/s]

[Final Epoch 6] Inference Metrics:
Test Accuracy      : 0.8648
F1 Score (macro)   : 0.8647
F1 Score (weighted): 0.8647
Inference Time     : 21.86 seconds

Classification Report: ALBERT w/ BitFit on IMDb50k

              precision    recall  f1-score   support

    Negative       0.84      0.89      0.87      4968
    Positive       0.89      0.84      0.86      5032

    accuracy                           0.86     10000
   macro avg       0.87      0.86      0.86     10000
weighted avg       0.87      0.86      0.86     10000

Running BitFit with LR=0.0001, batch_size=16
Some weights of AlbertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use :
Epoch 1/6: 100%|██████████| 2500/2500 [02:48<00:00, 14.85it/s]
Epoch 2/6: 100%|██████████| 2500/2500 [02:48<00:00, 14.82it/s]
Epoch 3/6: 100%|██████████| 2500/2500 [02:48<00:00, 14.83it/s]
Epoch 4/6: 100%|██████████| 2500/2500 [02:48<00:00, 14.85it/s]
Epoch 5/6: 100%|██████████| 2500/2500 [02:48<00:00, 14.86it/s]
Epoch 6/6: 100%|██████████| 2500/2500 [02:48<00:00, 14.84it/s]

[Final Epoch 6] Inference Metrics:
Test Accuracy      : 0.8618
F1 Score (macro)   : 0.8617
F1 Score (weighted): 0.8617
Inference Time     : 21.24 seconds

Classification Report: ALBERT w/ BitFit on IMDb50k
```

```
              precision    recall  f1-score   support

    Negative       0.84      0.89      0.86      4968
    Positive       0.88      0.83      0.86      5032
```

```
bf_best_lr = results[0]["learning_rate"]
bf_best_bs = results[0]["batch_size"]

# Construct filename
best_report_file = f"imdb_albert_bitfit_inference_metrics_summary_lr{bf_best_lr}_bs{bf_best_bs}.csv"

# Load the saved best report
best_report_df = pd.read_csv(best_report_file)
print("\nClassification Report for Best Configuration:")
print(best_report_df)


best_preds_df = pd.read_csv(f"imdb_albert_bitfit_inference_predictions_lr{bf_best_lr}_bs{bf_best_bs}.csv")
print("\nInference Predictions for Best Configuration:")
print(best_preds_df)

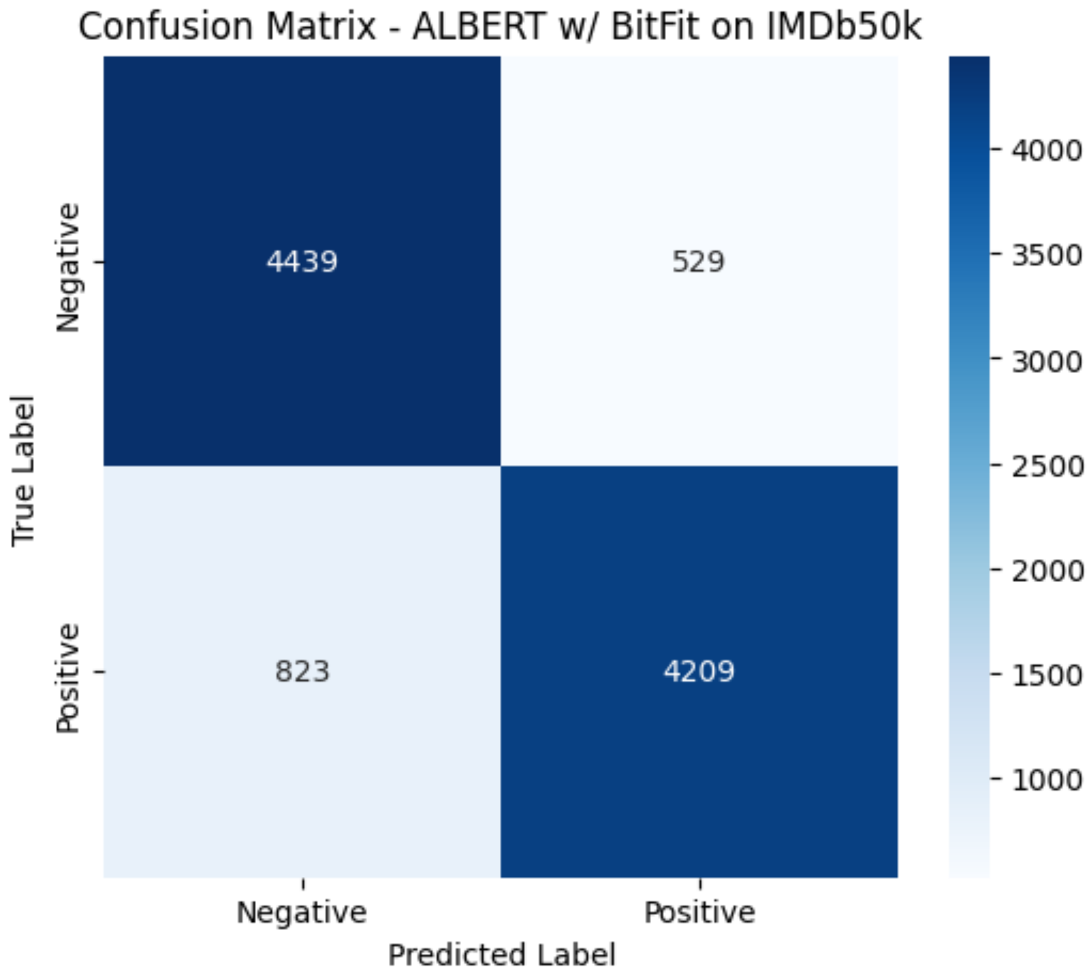
y_true = best_preds_df["y_true"]
y_pred = best_preds_df["y_pred"]


cm = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Negative", "Positive"], yticklabels=["Negative", "Positive"])
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix - ALBERT w/ BitFit on IMDb50k")
plt.show()
```

```
Classification Report for Best Configuration:
     Unnamed: 0  precision    recall  f1-score     support
0             0   0.843596  0.893519  0.867840   4968.0000
1             1   0.888350  0.836447  0.861617   5032.0000
2      accuracy   0.864800  0.864800  0.864800      0.8648
3     macro avg   0.865973  0.864983  0.864728  10000.0000
4  weighted avg   0.866116  0.864800  0.864709  10000.0000

Inference Predictions for Best Configuration:
      y_true  y_pred
0          0       0
1          1       1
2          1       1
3          0       0
4          1       1
...      ...     ...
9995       1       1
9996       1       1
9997       1       1
9998       1       1
9999       1       0
```

[10000 rows x 2 columns]



Prompt Tuning

```
""" Importing prompt tuning packages from PEFT """

import gc
from peft import PromptTuningConfig, PromptTuningInit, get_peft_model, TaskType
```

```
""" Prompt tuning parameter setup """

lrs = [5e-5, 1e-4]
bs = [8, 16]
num_tokens = 20
epochs = 6
```

```
""" Training and evaluation loop with hyperparamter grid search """

from torch import autocast
```

```
results = []

for lr in lrs:
    for batch_size in bs:
        print(f"Running Prompt Tuning with LR={lr}, batch_size={batch_size}")

        # loading ALBERT model
        model_name = "albert-base-v2"
        tokenizer = AutoTokenizer.from_pretrained(model_name)
        model = AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=2)

        # prompt tuning config
        peft_config = PromptTuningConfig(
            task_type=TaskType.SEQ_CLS,
            num_virtual_tokens=num_tokens,
            tokenizer_name_or_path=tokenizer.name_or_path,
            prompt_tuning_init=PromptTuningInit.RANDOM,
        )
        prompt_model = get_peft_model(model, peft_config)
        device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        prompt_model.to(device)

        # instantiate dataloader
        data_collator = DataCollatorWithPadding(tokenizer)
        train_dataloader = DataLoader(tokenized_dataset["train"], batch_size=batch_size, shuffle=True, collate_fn=data_collator)
        test_dataloader = DataLoader(tokenized_dataset["test"], batch_size=batch_size, shuffle=False, collate_fn=data_collator)

        # adam optimization
        optimizer = torch.optim.AdamW(prompt_model.parameters(), lr=lr)

        # begin training
        prompt_model.train()
        start_time = time.time()
        epoch_logs = []

        for epoch in range(1, epochs + 1):
            running_loss = 0.0
            correct = 0
            total = 0
            loop = tqdm(train_dataloader, leave=True, dynamic_ncols=True, desc=f"Epoch {epoch}/{epochs}")
            for step, batch in enumerate(loop):
                batch = {
                    "input_ids": batch["input_ids"].to(device),
                    "attention_mask": batch["attention_mask"].to(device),
                    "labels": batch["labels"].to(device)
                }

                with autocast(device_type='cuda'):
                    outputs = model(**batch)
                    loss = outputs.loss
                    preds = torch.argmax(outputs.logits, dim=1)
                    correct += (preds == batch['labels']).sum().item()
                    total += batch['labels'].size(0)

                    optimizer.zero_grad()
                    loss.backward()
                    optimizer.step()

                    running_loss += loss.item()
```

```
        avg_train_loss = running_loss / (step + 1)
        train_accuracy = correct / total

        # perform per epoch evaluation
        prompt_model.eval()
        val_running_loss = 0.0
        y_true, y_pred = [], []
        with torch.no_grad():
            with autocast(device_type='cuda'):
                for batch in test_dataloader:
                    batch = {
                        "input_ids": batch["input_ids"].to(device),
                        "attention_mask": batch["attention_mask"].to(device),
                        "labels": batch["labels"].to(device)
                    }
                    outputs = model(**batch)
                    preds = torch.argmax(outputs.logits, dim=1)
                    y_true.extend(batch["labels"].cpu().numpy())
                    y_pred.extend(preds.cpu().numpy())
                    val_running_loss += outputs.loss.item()

        avg_val_loss = val_running_loss / len(test_dataloader)

        inference_time = time.time() - start_time

        report = classification_report(y_true, y_pred, output_dict=True)
        val_accuracy = report["accuracy"]
        val_f1 = report["weighted avg"]["f1-score"]

        epoch_logs.append({
            "epoch": epoch,
            "lr": lr,
            "batch_size": batch_size,
            "train_loss": avg_train_loss,
            "train_accuracy": train_accuracy,
            "val_loss": avg_val_loss,
            "val_accuracy": val_accuracy
        })

        if epoch == epochs:
            total_correct = sum(yt == yp for yt, yp in zip(y_true, y_pred))
            total_samples = len(y_true)
            accuracy = total_correct / total_samples
            f1_macro = f1_score(y_true, y_pred, average="macro")
            f1_weighted = f1_score(y_true, y_pred, average="weighted")

            print(f"\n[Final Epoch {epoch}] Inference Metrics:")
            print(f"Test Accuracy      : {accuracy:.4f}")
            print(f"F1 Score (macro)   : {f1_macro:.4f}")
            print(f"F1 Score (weighted): {f1_weighted:.4f}")
            print(f"Inference Time     : {inference_time:.2f} seconds")
            print("\nClassification Report: ALBERT w/ Prompt Tuning on IMDb50k\n")
            print(classification_report(y_true, y_pred, target_names=["Negative", "Positive"]))

        prompt_model.train()

    end_time = time.time()
    training_time = end_time - start_time

    # begin datalogging per lr/bs
```

```
        epoch_logs_df = pd.DataFrame(epoch_logs)
        epoch_logs_df.to_csv(f"imdb_albert_prompt_epoch_logs_lr{lr}_bs{batch_size}.csv", index=False)

        # save inference metrics per lr/bs
        metrics_summary_df = pd.DataFrame(report).transpose()
        metrics_summary_df.to_csv(f"imdb_albert_prompt_inference_metrics_summary_lr{lr}_bs{batch_size}.csv", index=True)

        # Save inference predictions for the final epoch
        predictions_df = pd.DataFrame({
            "y_true": y_true,
            "y_pred": y_pred
        })
        predictions_df.to_csv(f"imdb_albert_prompt_inference_predictions_lr{lr}_bs{batch_size}.csv", index=False)

        # log memory usage
        max_memory = torch.cuda.max_memory_allocated() / (1024 ** 3) if torch.cuda.is_available() else 0

        # save model params and metrics
        results.append({
            "method": "Prompt Tuning",
            "learning_rate": lr,
            "batch_size": batch_size,
            "accuracy": val_accuracy,
            "f1": val_f1,
            "training_time": training_time,
            "inference_time": inference_time,
            "max_memory": max_memory
        })

        # empty cache to conserve compute
        del prompt_model, model, tokenizer, optimizer
        torch.cuda.empty_cache()
        gc.collect()

# ranked performance by val acc
results = sorted(results, key=lambda x: x["accuracy"], reverse=True)

# save overall results
results_df = pd.DataFrame(results)
results_df.to_csv("imdb_albert_prompt_results.csv", index=False)

# save best final config and metrics
final_summary_df = pd.DataFrame({
    "Method": ["Prompt Tuning"],
    "Best LR": [results[0]["learning_rate"]],
    "Best Batch Size": [results[0]["batch_size"]],
    "Accuracy": [results[0]["accuracy"]],
    "F1 Score": [results[0]["f1"]],
    "Training Time (s)": [results[0]["training_time"]],
    "Max GPU Memory (GB)": [results[0]["max_memory"]]
})
final_summary_df.to_csv("imdb_albert_prompt_final_comparison_prompt_tuning.csv", index=False)

print("All Prompt Tuning Grid Search Results:")
for r in results:
    print(r)

print("\nBest Configuration:")
print(results[0])
```

```
              precision    recall  f1-score   support

    Negative       0.71      0.73      0.72      4968
    Positive       0.73      0.70      0.71      5032

    accuracy                           0.72     10000
   macro avg       0.72      0.72      0.72     10000
weighted avg       0.72      0.72      0.72     10000

Running Prompt Tuning with LR=0.0001, batch_size=8
Some weights of AlbertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use
Epoch 1/6: 100%|██████████| 5000/5000 [01:29<00:00, 55.61it/s]
Epoch 2/6: 100%|██████████| 5000/5000 [01:30<00:00, 55.38it/s]
Epoch 3/6: 100%|██████████| 5000/5000 [01:30<00:00, 55.31it/s]
Epoch 4/6: 100%|██████████| 5000/5000 [01:30<00:00, 55.05it/s]
Epoch 5/6: 100%|██████████| 5000/5000 [01:30<00:00, 55.07it/s]
Epoch 6/6: 100%|██████████| 5000/5000 [01:30<00:00, 55.11it/s]

[Final Epoch 6] Inference Metrics:
Test Accuracy      : 0.7358
F1 Score (macro)   : 0.7358
F1 Score (weighted): 0.7358
Inference Time     : 668.64 seconds

Classification Report: ALBERT w/ Prompt Tuning on IMDb50k

              precision    recall  f1-score   support

    Negative       0.73      0.75      0.74      4968
    Positive       0.74      0.73      0.73      5032

    accuracy                           0.74     10000
   macro avg       0.74      0.74      0.74     10000
weighted avg       0.74      0.74      0.74     10000

Running Prompt Tuning with LR=0.0001, batch_size=16
Some weights of AlbertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use
Epoch 1/6: 100%|██████████| 2500/2500 [00:51<00:00, 48.95it/s]
Epoch 2/6: 100%|██████████| 2500/2500 [00:51<00:00, 48.58it/s]
Epoch 3/6: 100%|██████████| 2500/2500 [00:51<00:00, 48.30it/s]
Epoch 4/6: 100%|██████████| 2500/2500 [00:51<00:00, 48.42it/s]
Epoch 5/6: 100%|██████████| 2500/2500 [00:51<00:00, 48.52it/s]
Epoch 6/6: 100%|██████████| 2500/2500 [00:51<00:00, 48.18it/s]

[Final Epoch 6] Inference Metrics:
Test Accuracy      : 0.7229
F1 Score (macro)   : 0.7213
F1 Score (weighted): 0.7212
```

```
Inference Time     : 380.87 seconds

Classification Report: ALBERT w/ Prompt Tuning on IMDb50k

              precision    recall  f1-score   support

    Negative       0.69      0.80      0.74      4968
    Positive       0.77      0.64      0.70      5032
```

```
prompt_best_lr = results[0]["learning_rate"]
prompt_best_bs = results[0]["batch_size"]

# Construct filename
best_report_file = f"imdb_albert_prompt_inference_metrics_summary_lr{prompt_best_lr}_bs{prompt_best_bs}.csv"

# Load the saved best report
best_report_df = pd.read_csv(best_report_file)
print("\nClassification Report for Best Configuration:")
print(best_report_df)


best_preds_df = pd.read_csv(f"imdb_albert_prompt_inference_predictions_lr{prompt_best_lr}_bs{prompt_best_bs}.csv")
print("\nInference Predictions for Best Configuration:")
print(best_preds_df)

y_true = best_preds_df["y_true"]
y_pred = best_preds_df["y_pred"]

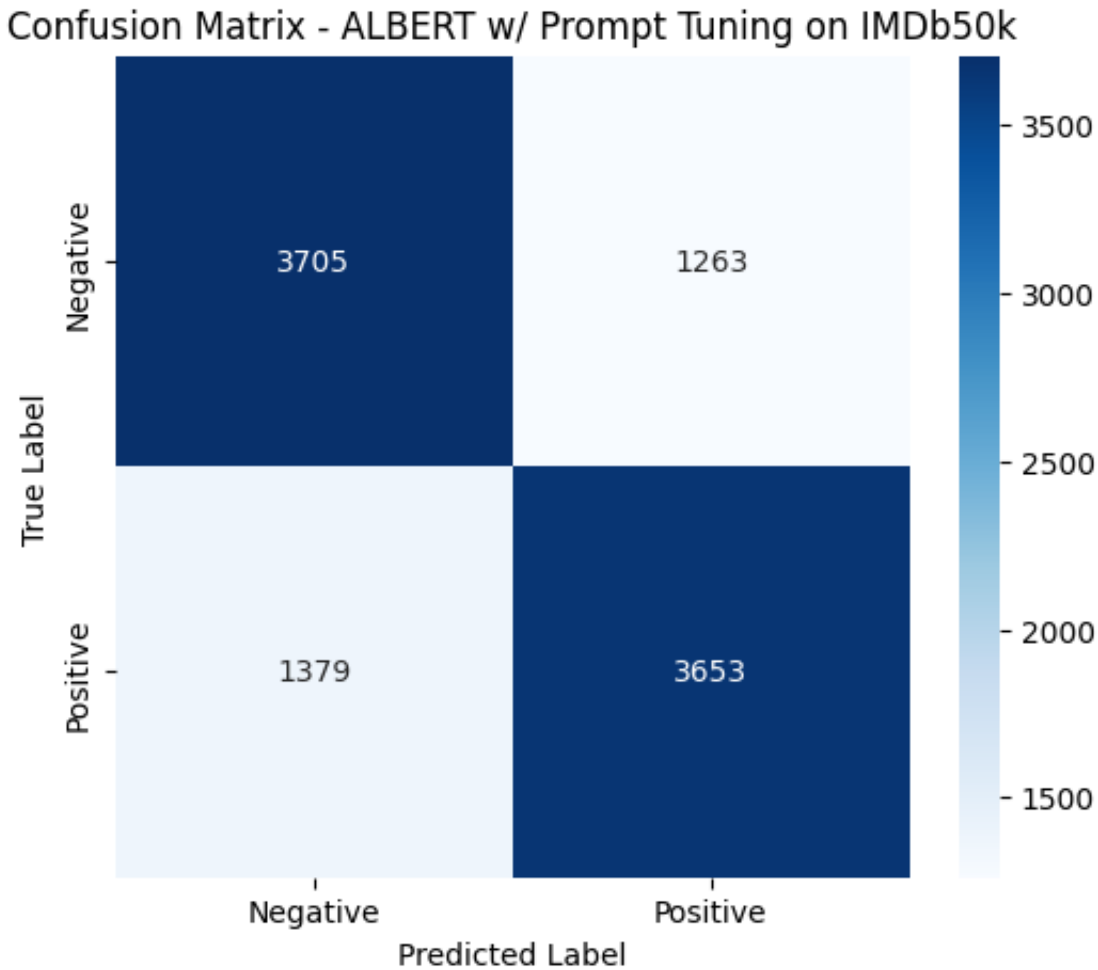

cm = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Negative", "Positive"], yticklabels=["Negative", "Positive"])
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix - ALBERT w/ Prompt Tuning on IMDb50k")
plt.show()
```

```
Classification Report for Best Configuration:
     Unnamed: 0  precision    recall  f1-score     support
0             0   0.728757  0.745773  0.737167   4968.0000
1             1   0.743084  0.725954  0.734419   5032.0000
2      accuracy   0.735800  0.735800  0.735800      0.7358
3     macro avg   0.735920  0.735863  0.735793  10000.0000
4  weighted avg   0.735966  0.735800  0.735784  10000.0000

Inference Predictions for Best Configuration:
      y_true  y_pred
0          0       0
1          1       0
2          1       1
3          0       0
4          1       1
...      ...     ...
9995       1       1
```

```
9996        1         1
9997        1         1
9998        1         1
9999        1         0

[10000 rows x 2 columns]
```



Begin Visualization of IMDb 50k Results

Load all dataframes from above training of 3 PEFT methods

```
""" Output from our ALBERT_Sentiment140_IMDb50k.ipynb file, we read in the .csv files here.
Note that these .csv file paths suggest they should be uploaded to session storage"""

# ALBERT PEFT-wise results across bf/lora/prompt tuning
albert_bf_results = pd.read_csv('/content/imdb_albert_bitfit_results.csv')
albert_lora_results = pd.read_csv('/content/imdb_albert_lora_results.csv')
albert_prompt_results = pd.read_csv('/content/imdb_albert_prompt_results.csv')

# ALBERT per-epoch performance logs (for LC generation) across bf/lora/prompt tuning
albert_lora_epochs_lr5_bs8 = pd.read_csv('/content/imdb_albert_lora_epoch_logs_lr5e-05_bs8.csv')
albert_lora_epochs_lr5_bs16 = pd.read_csv('/content/imdb_albert_lora_epoch_logs_lr5e-05_bs16.csv')
albert_lora_epochs_lr1_bs8 = pd.read_csv('/content/imdb_albert_lora_epoch_logs_lr0.0001_bs8.csv')
albert_lora_epochs_lr1_bs16 = pd.read_csv('/content/imdb_albert_lora_epoch_logs_lr0.0001_bs16.csv')
albert_bf_epochs_lr5_bs8 = pd.read_csv('/content/imdb_albert_bitfit_epoch_logs_lr5e-05_bs8.csv')
albert_bf_epochs_lr5_bs16 = pd.read_csv('/content/imdb_albert_bitfit_epoch_logs_lr5e-05_bs16.csv')
albert_bf_epochs_lr1_bs8 = pd.read_csv('/content/imdb_albert_bitfit_epoch_logs_lr0.0001_bs8.csv')
albert_bf_epochs_lr1_bs16 = pd.read_csv('/content/imdb_albert_bitfit_epoch_logs_lr0.0001_bs16.csv')
albert_prompt_epochs_lr5_bs8 = pd.read_csv('/content/imdb_albert_prompt_epoch_logs_lr5e-05_bs8.csv')
albert_prompt_epochs_lr5_bs16 = pd.read_csv('/content/imdb_albert_prompt_epoch_logs_lr5e-05_bs16.csv')
albert_prompt_epochs_lr1_bs8 = pd.read_csv('/content/imdb_albert_prompt_epoch_logs_lr0.0001_bs8.csv')
albert_prompt_epochs_lr1_bs16 = pd.read_csv('/content/imdb_albert_prompt_epoch_logs_lr0.0001_bs16.csv')

# ALBERT inference performance metric summary across bf/lora/prompt tuning
albert_bf_inf_lr5_bs8 = pd.read_csv('/content/imdb_albert_bitfit_inference_metrics_summary_lr5e-05_bs8.csv')
albert_bf_inf_lr5_bs16 = pd.read_csv('/content/imdb_albert_bitfit_inference_metrics_summary_lr5e-05_bs16.csv')
albert_bf_inf_lr1_bs8 = pd.read_csv('/content/imdb_albert_bitfit_inference_metrics_summary_lr0.0001_bs8.csv')
albert_bf_inf_lr1_bs16 = pd.read_csv('/content/imdb_albert_bitfit_inference_metrics_summary_lr0.0001_bs16.csv')
albert_lora_inf_lr5_bs8 = pd.read_csv('/content/imdb_albert_lora_inference_metrics_summary_lr5e-05_bs8.csv')
albert_lora_inf_lr5_bs16 = pd.read_csv('/content/imdb_albert_lora_inference_metrics_summary_lr5e-05_bs16.csv')
albert_lora_inf_lr1_bs8 = pd.read_csv('/content/imdb_albert_lora_inference_metrics_summary_lr0.0001_bs8.csv')
albert_lora_inf_lr1_bs16 = pd.read_csv('/content/imdb_albert_lora_inference_metrics_summary_lr0.0001_bs16.csv')
albert_prompt_inf_lr5_bs8 = pd.read_csv('/content/imdb_albert_prompt_inference_metrics_summary_lr5e-05_bs8.csv')
albert_prompt_inf_lr5_bs16 = pd.read_csv('/content/imdb_albert_prompt_inference_metrics_summary_lr5e-05_bs16.csv')
albert_prompt_inf_lr1_bs8 = pd.read_csv('/content/imdb_albert_prompt_inference_metrics_summary_lr0.0001_bs8.csv')
albert_prompt_inf_lr1_bs16 = pd.read_csv('/content/imdb_albert_prompt_inference_metrics_summary_lr0.0001_bs16.csv')

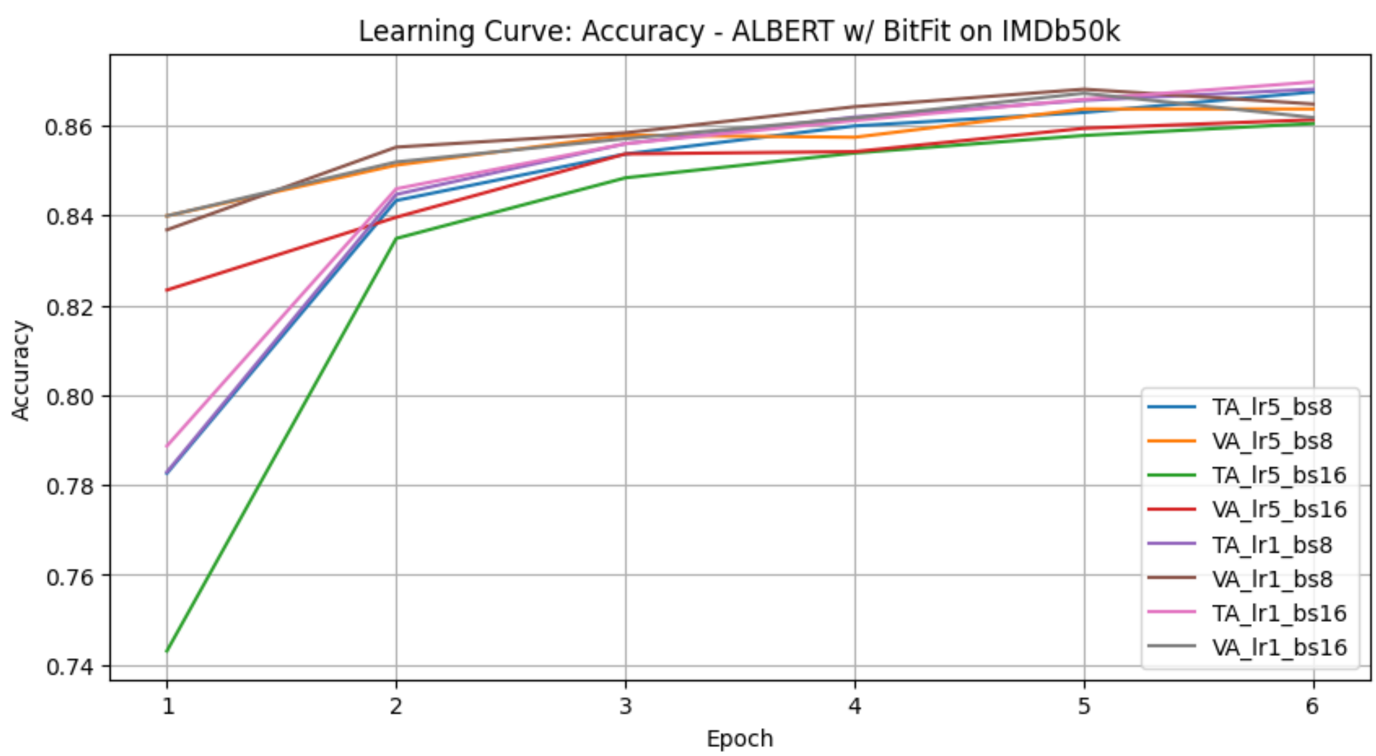
# ALBERT inference predictions across bf/lora/prompt tuning
albert_bf_preds_lr5_bs8 = pd.read_csv('/content/imdb_albert_bitfit_inference_predictions_lr5e-05_bs8.csv')
albert_bf_preds_lr5_bs16 = pd.read_csv('/content/imdb_albert_bitfit_inference_predictions_lr5e-05_bs16.csv')
albert_bf_preds_lr1_bs8 = pd.read_csv('/content/imdb_albert_bitfit_inference_predictions_lr0.0001_bs8.csv')
albert_bf_preds_lr1_bs16 = pd.read_csv('/content/imdb_albert_bitfit_inference_predictions_lr0.0001_bs16.csv')
albert_lora_preds_lr5_bs8 = pd.read_csv('/content/imdb_albert_lora_inference_predictions_lr5e-05_bs8.csv')
albert_lora_preds_lr5_bs16 = pd.read_csv('/content/imdb_albert_lora_inference_predictions_lr5e-05_bs16.csv')
albert_lora_preds_lr1_bs8 = pd.read_csv('/content/imdb_albert_lora_inference_predictions_lr0.0001_bs8.csv')
albert_lora_preds_lr1_bs16 = pd.read_csv('/content/imdb_albert_lora_inference_predictions_lr0.0001_bs16.csv')
albert_prompt_preds_lr5_bs8 = pd.read_csv('/content/imdb_albert_prompt_inference_predictions_lr5e-05_bs8.csv')
albert_prompt_preds_lr5_bs16 = pd.read_csv('/content/imdb_albert_prompt_inference_predictions_lr5e-05_bs16.csv')
albert_prompt_preds_lr1_bs8 = pd.read_csv('/content/imdb_albert_prompt_inference_predictions_lr0.0001_bs8.csv')
albert_prompt_preds_lr1_bs16 = pd.read_csv('/content/imdb_albert_prompt_inference_predictions_lr0.0001_bs16.csv')

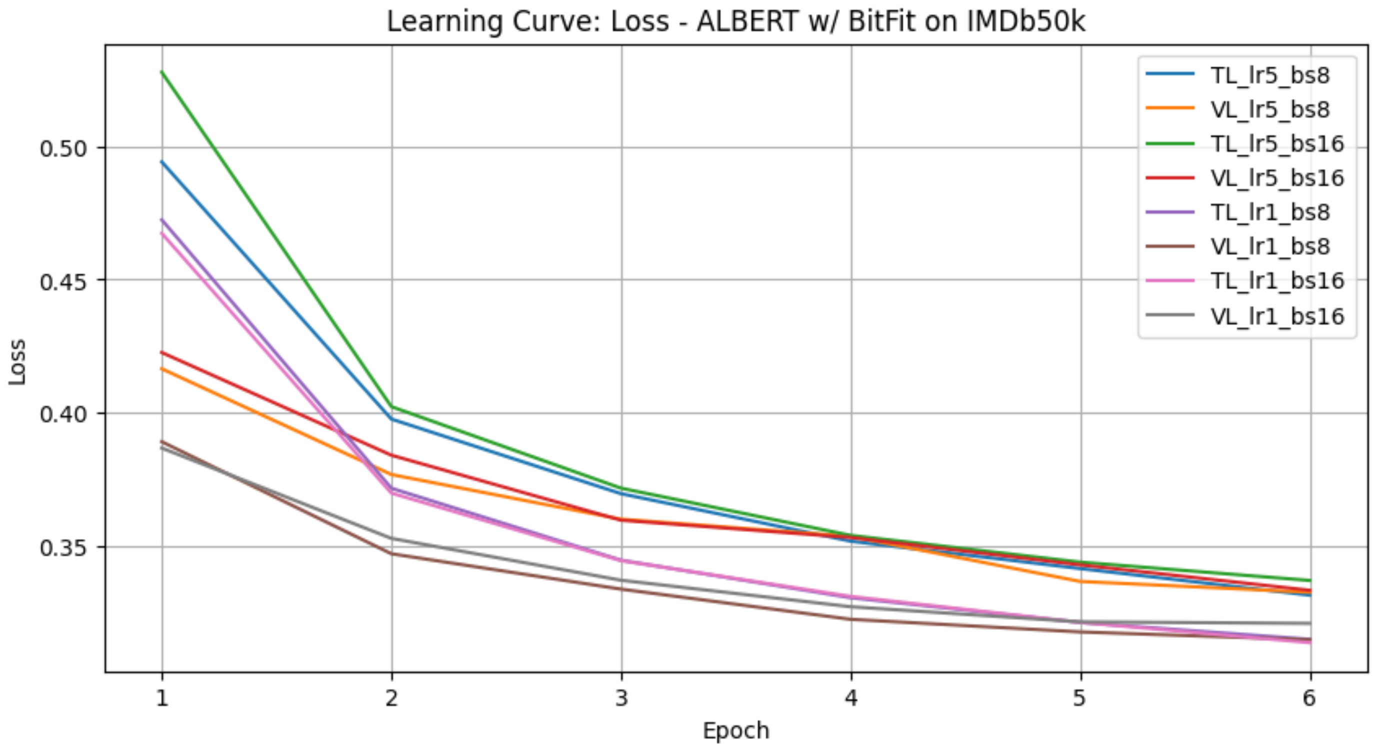
# ALBERT PEFT method intra-comparison based on hyperparameter settings, per bf/lora/prompt tuning
albert_bf_final_comparison = pd.read_csv('/content/imdb_albert_bf_final_comparison_bitfit.csv')
albert_lora_final_comparison = pd.read_csv('/content/imdb_albert_lora_final_comparison_lora.csv')
albert_prompt_final_comparison = pd.read_csv('/content/imdb_albert_prompt_final_comparison_prompt_tuning.csv')
```

BitFit Learning Curves

```
# All BitFit Train/Val Acc Learning Curve
plt.figure(figsize=(10,5))
sns.lineplot(data=albert_bf_epochs_lr5_bs8, x="epoch", y="train_accuracy", label="TA_lr5_bs8")
sns.lineplot(data=albert_bf_epochs_lr5_bs8, x="epoch", y="val_accuracy", label="VA_lr5_bs8")
sns.lineplot(data=albert_bf_epochs_lr5_bs16, x="epoch", y="train_accuracy", label="TA_lr5_bs16")
sns.lineplot(data=albert_bf_epochs_lr5_bs16, x="epoch", y="val_accuracy", label="VA_lr5_bs16")
sns.lineplot(data=albert_bf_epochs_lr1_bs8, x="epoch", y="train_accuracy", label="TA_lr1_bs8")
sns.lineplot(data=albert_bf_epochs_lr1_bs8, x="epoch", y="val_accuracy", label="VA_lr1_bs8")
sns.lineplot(data=albert_bf_epochs_lr1_bs16, x="epoch", y="train_accuracy", label="TA_lr1_bs16")
sns.lineplot(data=albert_bf_epochs_lr1_bs16, x="epoch", y="val_accuracy", label="VA_lr1_bs16")
plt.title("Learning Curve: Accuracy - ALBERT w/ BitFit on IMDb50k")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()

# All BitFit Training and Validation Loss
plt.figure(figsize=(10,5))
sns.lineplot(data=albert_bf_epochs_lr5_bs8, x="epoch", y="train_loss", label="TL_lr5_bs8")
sns.lineplot(data=albert_bf_epochs_lr5_bs8, x="epoch", y="val_loss", label="VL_lr5_bs8")
sns.lineplot(data=albert_bf_epochs_lr5_bs16, x="epoch", y="train_loss", label="TL_lr5_bs16")
sns.lineplot(data=albert_bf_epochs_lr5_bs16, x="epoch", y="val_loss", label="VL_lr5_bs16")
sns.lineplot(data=albert_bf_epochs_lr1_bs8, x="epoch", y="train_loss", label="TL_lr1_bs8")
sns.lineplot(data=albert_bf_epochs_lr1_bs8, x="epoch", y="val_loss", label="VL_lr1_bs8")
sns.lineplot(data=albert_bf_epochs_lr1_bs16, x="epoch", y="train_loss", label="TL_lr1_bs16")
sns.lineplot(data=albert_bf_epochs_lr1_bs16, x="epoch", y="val_loss", label="VL_lr1_bs16")
plt.title("Learning Curve: Loss - ALBERT w/ BitFit on IMDb50k")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()
```






```
# Best BitFit Train/Val Acc Learning Curve

albert_bf_epochs_map = {
    (5, 8): albert_bf_epochs_lr5_bs8,
    (5, 16): albert_bf_epochs_lr5_bs16,
    (1, 8): albert_bf_epochs_lr1_bs8,
    (1, 16): albert_bf_epochs_lr1_bs16
}

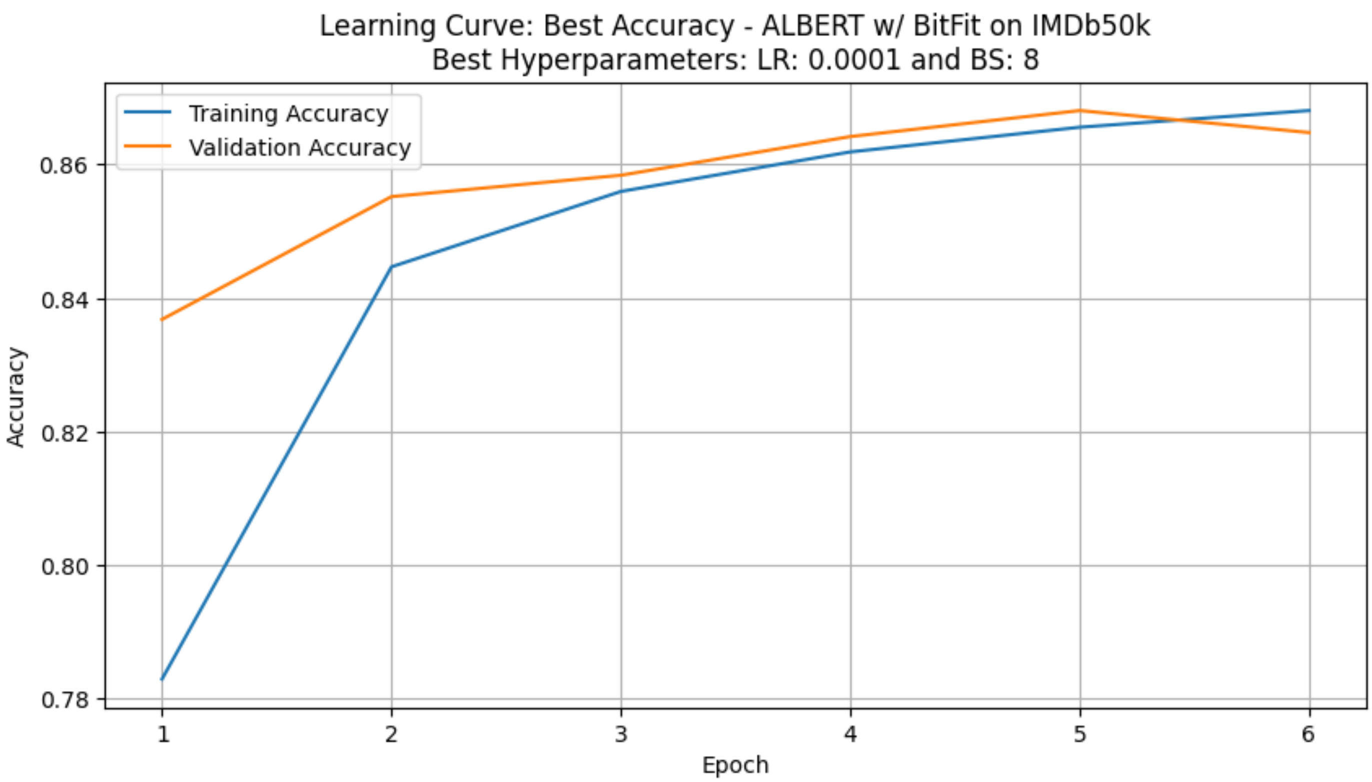
bf_lr_mapping = {
    5e-5: 5,
    1e-4: 1
}

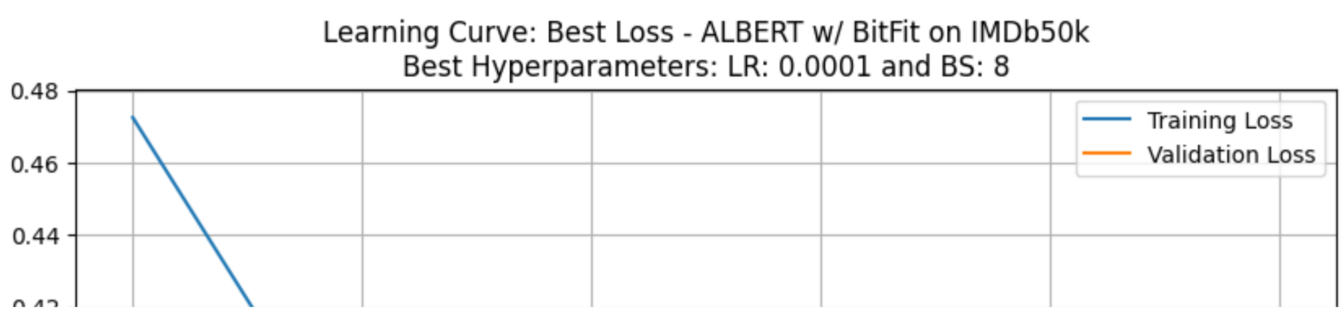
bf_best_lr_tag = bf_lr_mapping[bf_best_lr]
bf_best_bs_tag = bf_best_bs
```

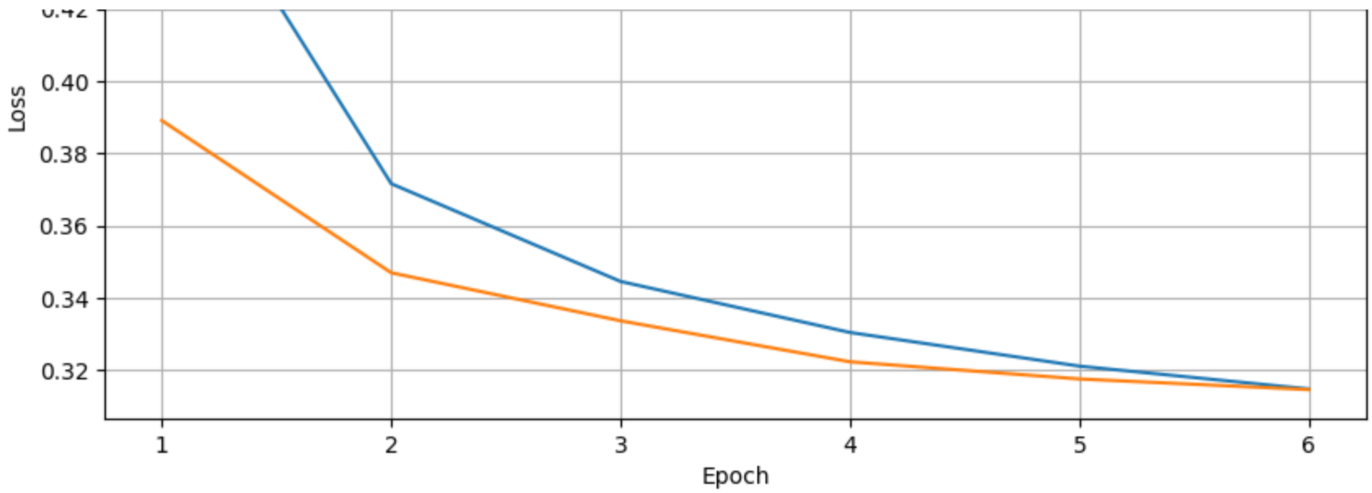
```
bf_epochs = albert_bf_epochs_map[(bf_best_lr_tag, bf_best_bs_tag)]

# Best BitFit Training and Validation Accuracy
plt.figure(figsize=(10,5))
sns.lineplot(data=bf_epochs, x="epoch", y="train_accuracy", label="Training Accuracy")
sns.lineplot(data=bf_epochs, x="epoch", y="val_accuracy", label="Validation Accuracy")
plt.title(f"Learning Curve: Best Accuracy - ALBERT w/ BitFit on IMDb50k\nBest Hyperparameters: LR: {bf_best_lr} and BS: {bf_be
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()

# Best BitFit Training and Validation Loss
plt.figure(figsize=(10,5))
sns.lineplot(data=bf_epochs, x="epoch", y="train_loss", label="Training Loss")
sns.lineplot(data=bf_epochs, x="epoch", y="val_loss", label="Validation Loss")
plt.title(f"Learning Curve: Best Loss - ALBERT w/ BitFit on IMDb50k\nBest Hyperparameters: LR: {bf_best_lr} and BS: {bf_best_b
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()
```





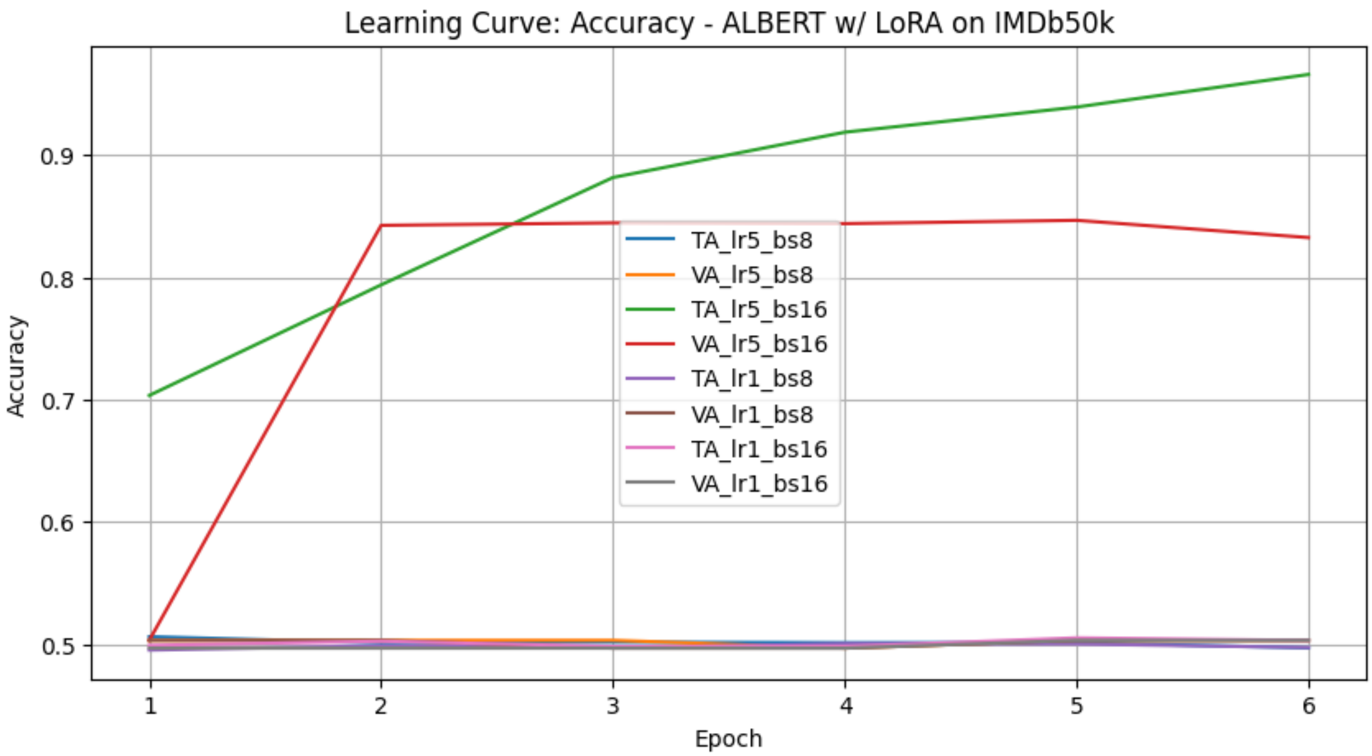


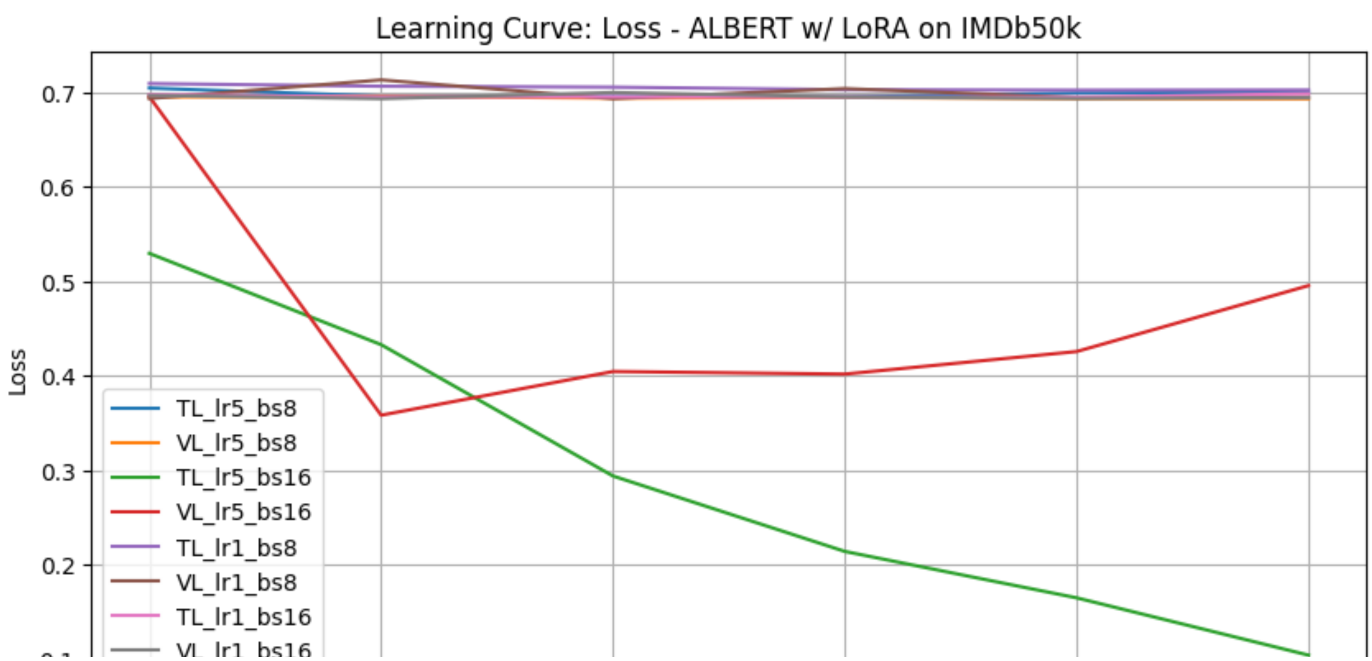
LoRA Learning Curves

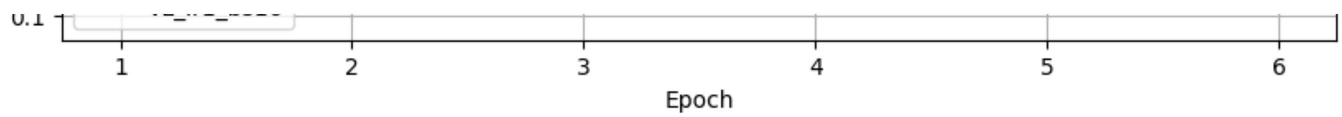
```
# All LoRA Train/Val Acc Learning Curve (ALBERT)
plt.figure(figsize=(10,5))
sns.lineplot(data=albert_lora_epochs_lr5_bs8, x="epoch", y="train_accuracy", label="TA_lr5_bs8")
sns.lineplot(data=albert_lora_epochs_lr5_bs8, x="epoch", y="val_accuracy", label="VA_lr5_bs8")
sns.lineplot(data=albert_lora_epochs_lr5_bs16, x="epoch", y="train_accuracy", label="TA_lr5_bs16")
sns.lineplot(data=albert_lora_epochs_lr5_bs16, x="epoch", y="val_accuracy", label="VA_lr5_bs16")
sns.lineplot(data=albert_lora_epochs_lr1_bs8, x="epoch", y="train_accuracy", label="TA_lr1_bs8")
sns.lineplot(data=albert_lora_epochs_lr1_bs8, x="epoch", y="val_accuracy", label="VA_lr1_bs8")
sns.lineplot(data=albert_lora_epochs_lr1_bs16, x="epoch", y="train_accuracy", label="TA_lr1_bs16")
sns.lineplot(data=albert_lora_epochs_lr1_bs16, x="epoch", y="val_accuracy", label="VA_lr1_bs16")
plt.title("Learning Curve: Accuracy - ALBERT w/ LoRA on IMDb50k")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()

# All LoRA Training and Validation Loss (ALBERT)
plt.figure(figsize=(10,5))
sns.lineplot(data=albert_lora_epochs_lr5_bs8, x="epoch", y="train_loss", label="TL_lr5_bs8")
sns.lineplot(data=albert_lora_epochs_lr5_bs8, x="epoch", y="val_loss", label="VL_lr5_bs8")
sns.lineplot(data=albert_lora_epochs_lr5_bs16, x="epoch", y="train_loss", label="TL_lr5_bs16")
```

```
sns.lineplot(data=albert_lora_epochs_lr5_bs16, x="epoch", y="val_loss", label="VL_lr5_bs16")
sns.lineplot(data=albert_lora_epochs_lr1_bs8, x="epoch", y="train_loss", label="TL_lr1_bs8")
sns.lineplot(data=albert_lora_epochs_lr1_bs8, x="epoch", y="val_loss", label="VL_lr1_bs8")
sns.lineplot(data=albert_lora_epochs_lr1_bs16, x="epoch", y="train_loss", label="TL_lr1_bs16")
sns.lineplot(data=albert_lora_epochs_lr1_bs16, x="epoch", y="val_loss", label="VL_lr1_bs16")
plt.title("Learning Curve: Loss - ALBERT w/ LoRA on IMDb50k")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()
```








```
# Best LoRA Train/Val Acc Learning Curve

albert_lora_epochs_map = {
    (5, 8): albert_lora_epochs_lr5_bs8,
    (5, 16): albert_lora_epochs_lr5_bs16,
    (1, 8): albert_lora_epochs_lr1_bs8,
    (1, 16): albert_lora_epochs_lr1_bs16
}

lora_lr_mapping = {
    5e-5: 5,
    1e-4: 1
}

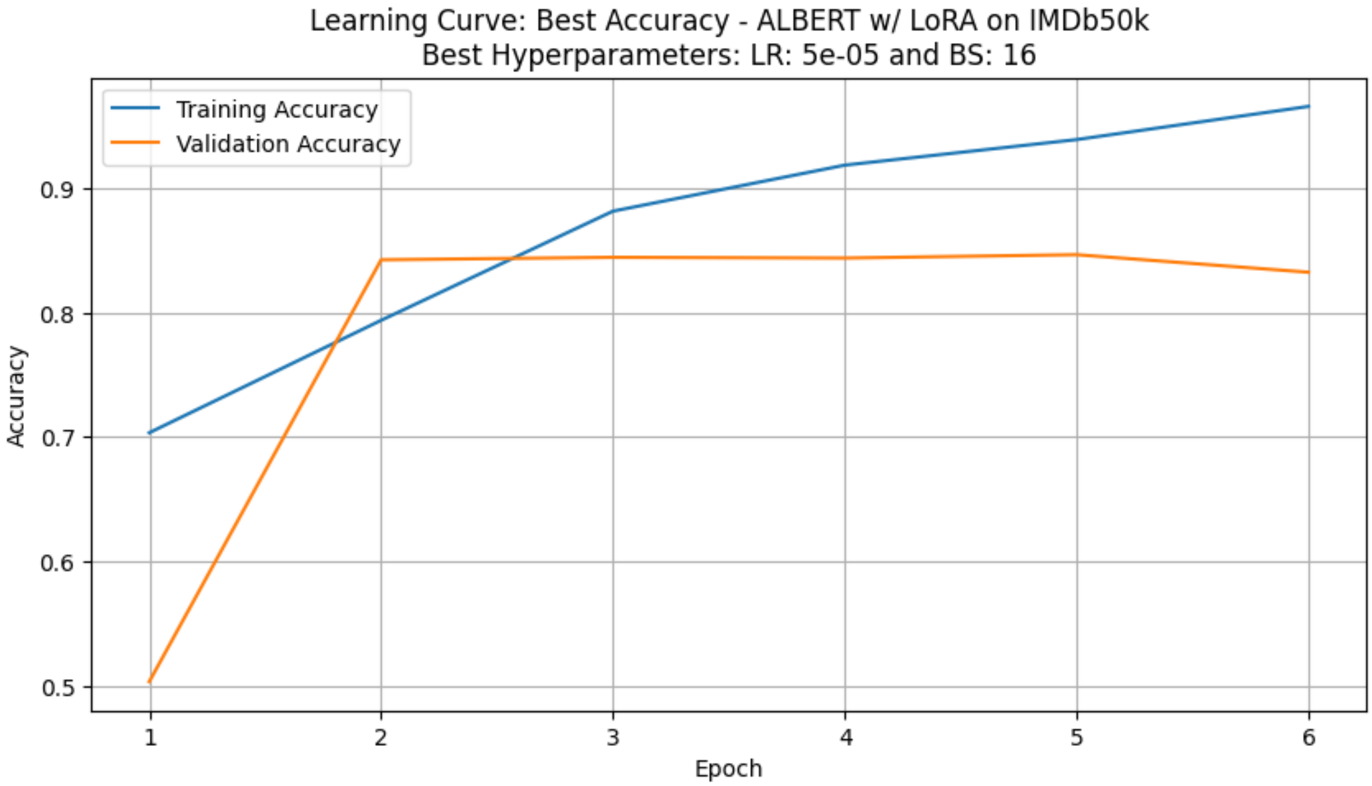
lora_best_lr_tag = lora_lr_mapping[lora_best_lr]
lora_best_bs_tag = lora_best_bs

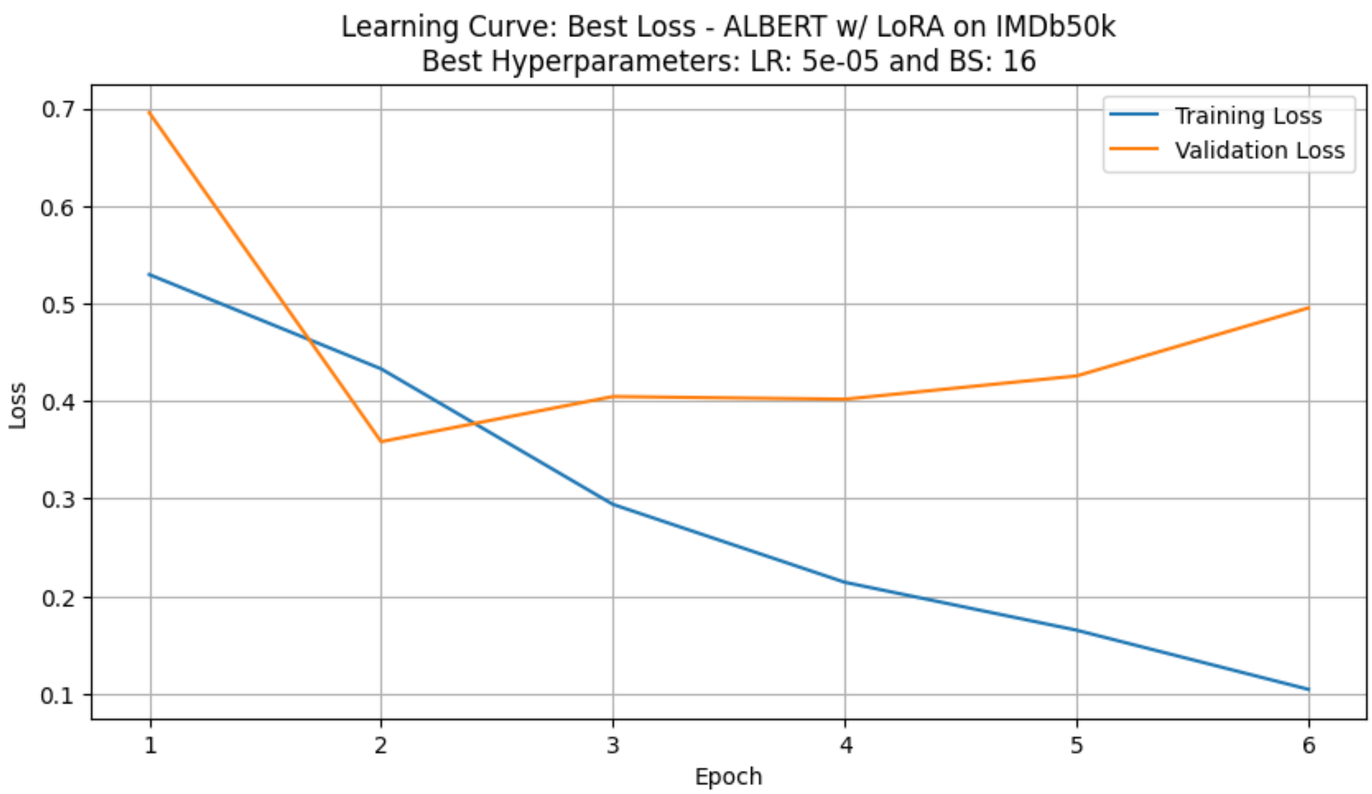
lora_epochs = albert_lora_epochs_map[(lora_best_lr_tag, lora_best_bs_tag)]

# Best LoRA Training and Validation Accuracy
plt.figure(figsize=(10,5))
sns.lineplot(data=lora_epochs, x="epoch", y="train_accuracy", label="Training Accuracy")
sns.lineplot(data=lora_epochs, x="epoch", y="val_accuracy", label="Validation Accuracy")
plt.title(f"Learning Curve: Best Accuracy - ALBERT w/ LoRA on IMDb50k\nBest Hyperparameters: LR: {lora_best_lr} and BS: {lora_
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()

# Best LoRA Training and Validation Loss
plt.figure(figsize=(10,5))
sns.lineplot(data=lora_epochs, x="epoch", y="train_loss", label="Training Loss")
sns.lineplot(data=lora_epochs, x="epoch", y="val_loss", label="Validation Loss")
plt.title(f"Learning Curve: Best Loss - ALBERT w/ LoRA on IMDb50k\nBest Hyperparameters: LR: {lora_best_lr} and BS: {lora_best_
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
```

```
plt.show()
```

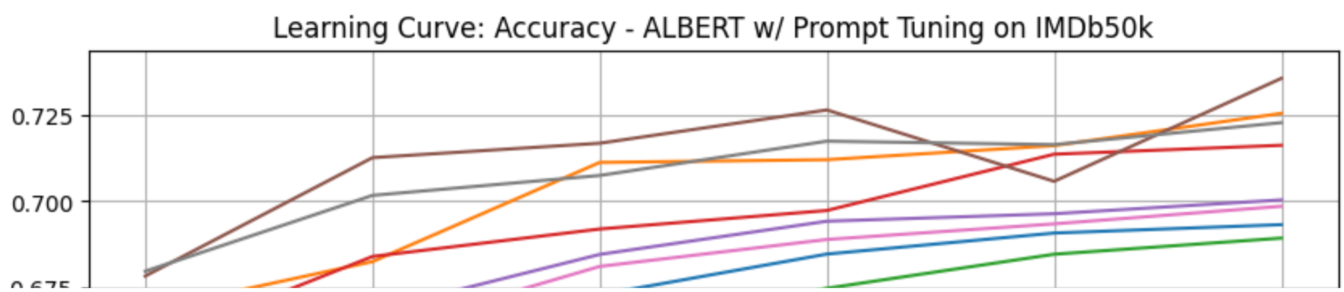

Learning Curve: Best Accuracy - ALBERT w/ LoRA on IMDb50k
Best Hyperparameters: LR: 5e-05 and BS: 16
Training Accuracy
Validation Accuracy
Accuracy
Epoch
0.5
0.6
0.7
0.8
0.9
1
2
3
4
5
6

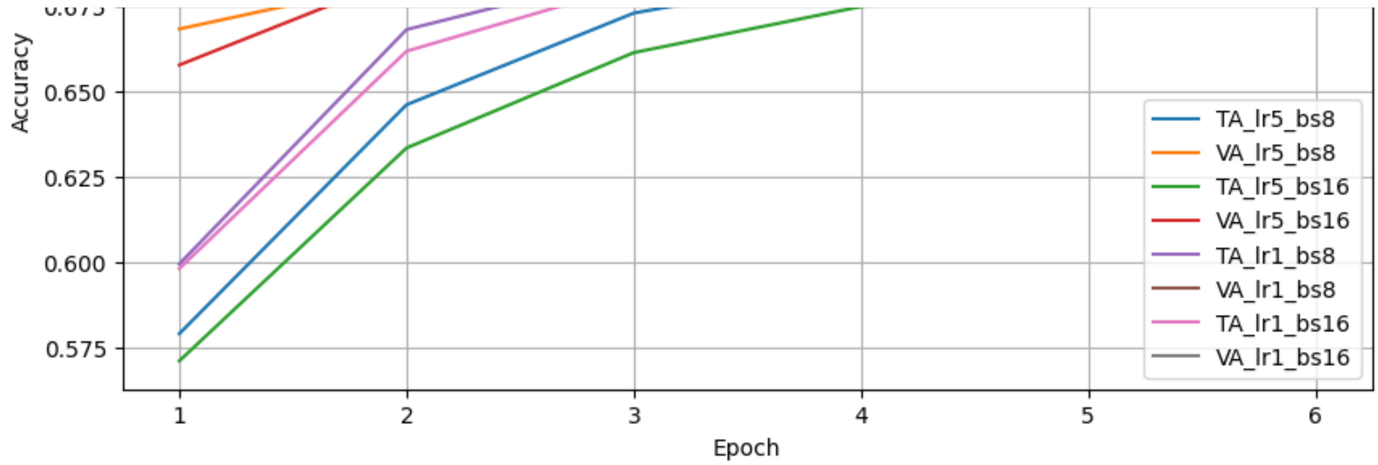

Learning Curve: Best Loss - ALBERT w/ LoRA on IMDb50k
Best Hyperparameters: LR: 5e-05 and BS: 16
Training Loss
Validation Loss
Loss
Epoch
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1
2
3
4
5
6

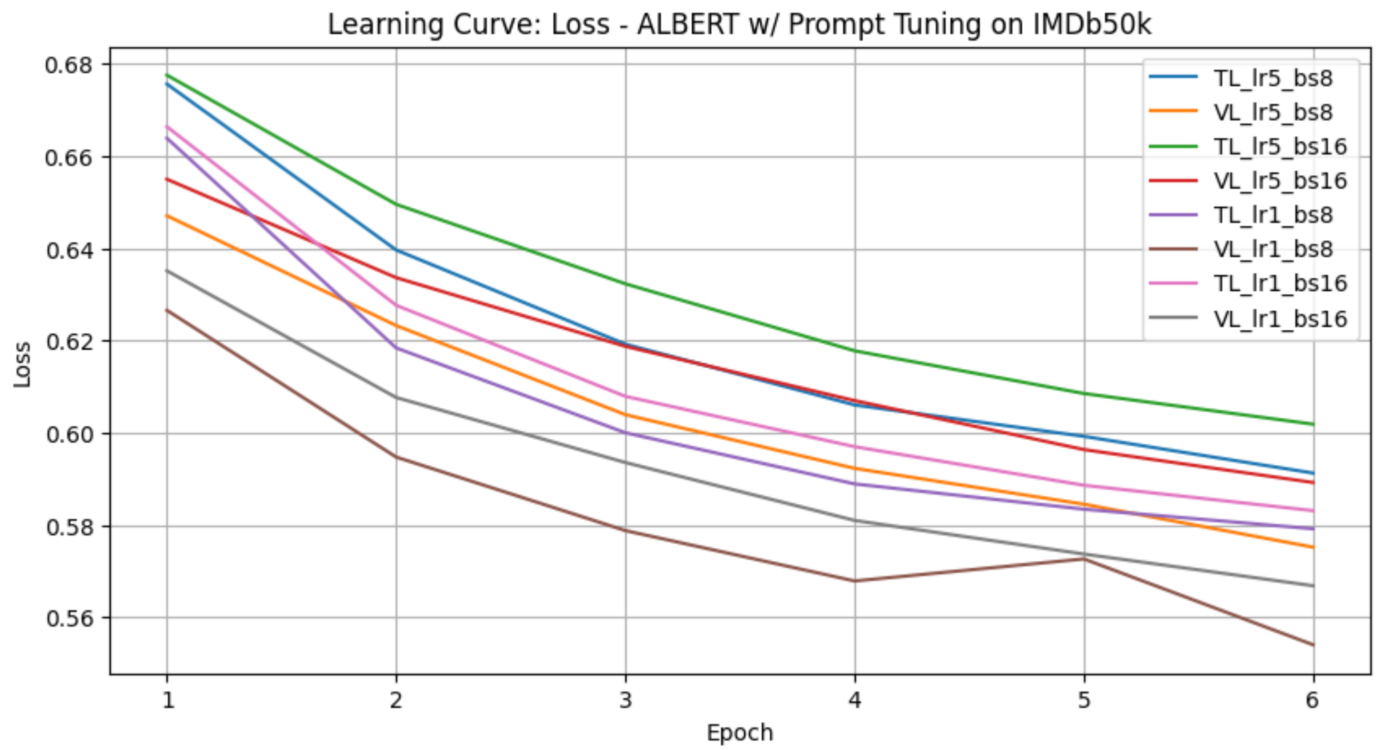
Prompt Tuning Learning Curves

```
# All Prompt Tuning Train/Val Acc Learning Curve
plt.figure(figsize=(10,5))
sns.lineplot(data=albert_prompt_epochs_lr5_bs8, x="epoch", y="train_accuracy", label="TA_lr5_bs8")
sns.lineplot(data=albert_prompt_epochs_lr5_bs8, x="epoch", y="val_accuracy", label="VA_lr5_bs8")
sns.lineplot(data=albert_prompt_epochs_lr5_bs16, x="epoch", y="train_accuracy", label="TA_lr5_bs16")
sns.lineplot(data=albert_prompt_epochs_lr5_bs16, x="epoch", y="val_accuracy", label="VA_lr5_bs16")
sns.lineplot(data=albert_prompt_epochs_lr1_bs8, x="epoch", y="train_accuracy", label="TA_lr1_bs8")
sns.lineplot(data=albert_prompt_epochs_lr1_bs8, x="epoch", y="val_accuracy", label="VA_lr1_bs8")
sns.lineplot(data=albert_prompt_epochs_lr1_bs16, x="epoch", y="train_accuracy", label="TA_lr1_bs16")
sns.lineplot(data=albert_prompt_epochs_lr1_bs16, x="epoch", y="val_accuracy", label="VA_lr1_bs16")
plt.title("Learning Curve: Accuracy - ALBERT w/ Prompt Tuning on IMDb50k")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()

# All Prompt Tuning Training and Validation Loss
plt.figure(figsize=(10,5))
sns.lineplot(data=albert_prompt_epochs_lr5_bs8, x="epoch", y="train_loss", label="TL_lr5_bs8")
sns.lineplot(data=albert_prompt_epochs_lr5_bs8, x="epoch", y="val_loss", label="VL_lr5_bs8")
sns.lineplot(data=albert_prompt_epochs_lr5_bs16, x="epoch", y="train_loss", label="TL_lr5_bs16")
sns.lineplot(data=albert_prompt_epochs_lr5_bs16, x="epoch", y="val_loss", label="VL_lr5_bs16")
sns.lineplot(data=albert_prompt_epochs_lr1_bs8, x="epoch", y="train_loss", label="TL_lr1_bs8")
sns.lineplot(data=albert_prompt_epochs_lr1_bs8, x="epoch", y="val_loss", label="VL_lr1_bs8")
sns.lineplot(data=albert_prompt_epochs_lr1_bs16, x="epoch", y="train_loss", label="TL_lr1_bs16")
sns.lineplot(data=albert_prompt_epochs_lr1_bs16, x="epoch", y="val_loss", label="VL_lr1_bs16")
plt.title("Learning Curve: Loss - ALBERT w/ Prompt Tuning on IMDb50k")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()
```








```
# Best Prompt Tuning Train/Val Acc Learning Curve
```

```
albert_prompt_epochs_map = {
    (5, 8): albert_prompt_epochs_lr5_bs8,
    (5, 16): albert_prompt_epochs_lr5_bs16,
    (1, 8): albert_prompt_epochs_lr1_bs8,
    (1, 16): albert_prompt_epochs_lr1_bs16
}

prompt_lr_mapping = {
    5e-5: "5e-5",
    1e-4: "41e-"
}

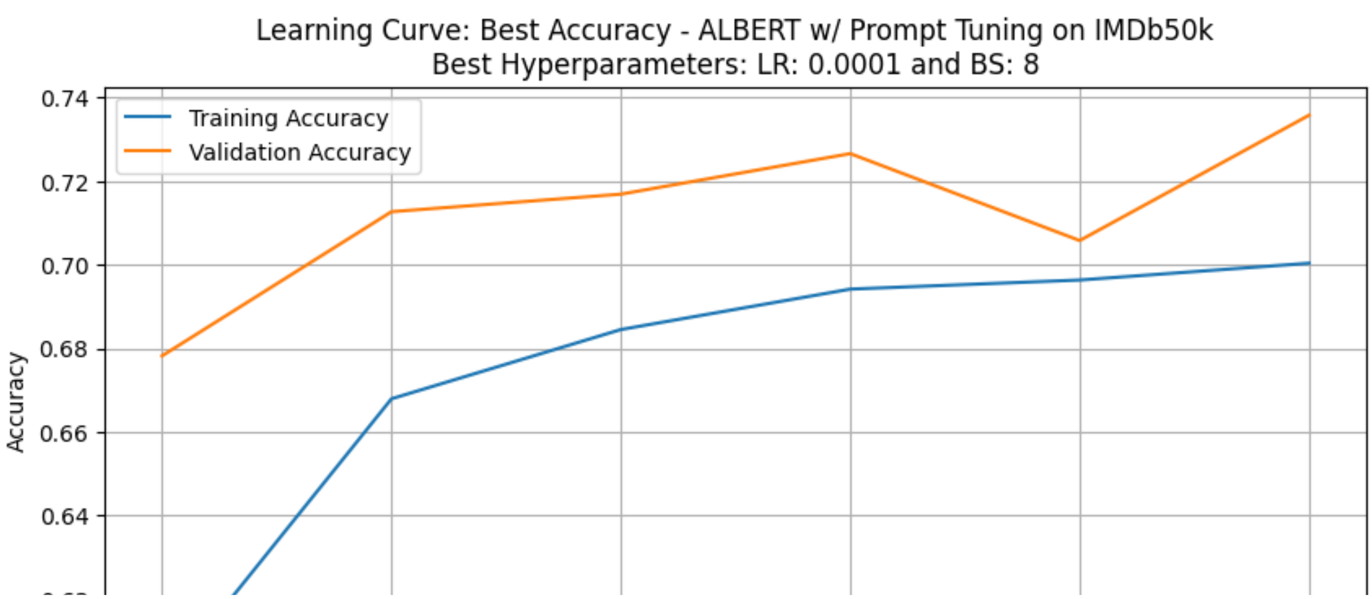
prompt_best_lr_tag_for_map = {5e-5: 5, 1e-4: 1}[prompt_best_lr]

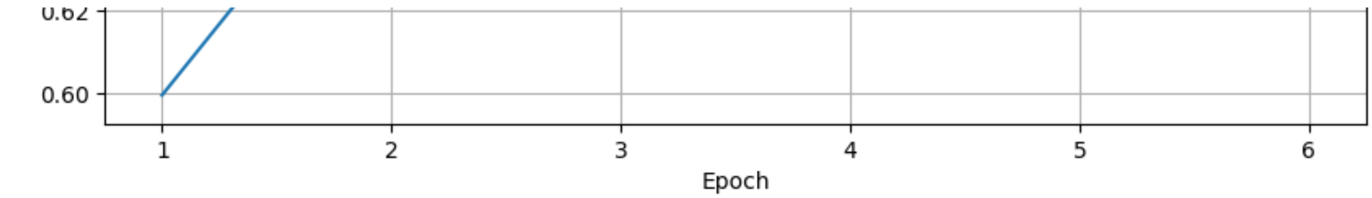
prompt_best_bs_tag = prompt_best_bs

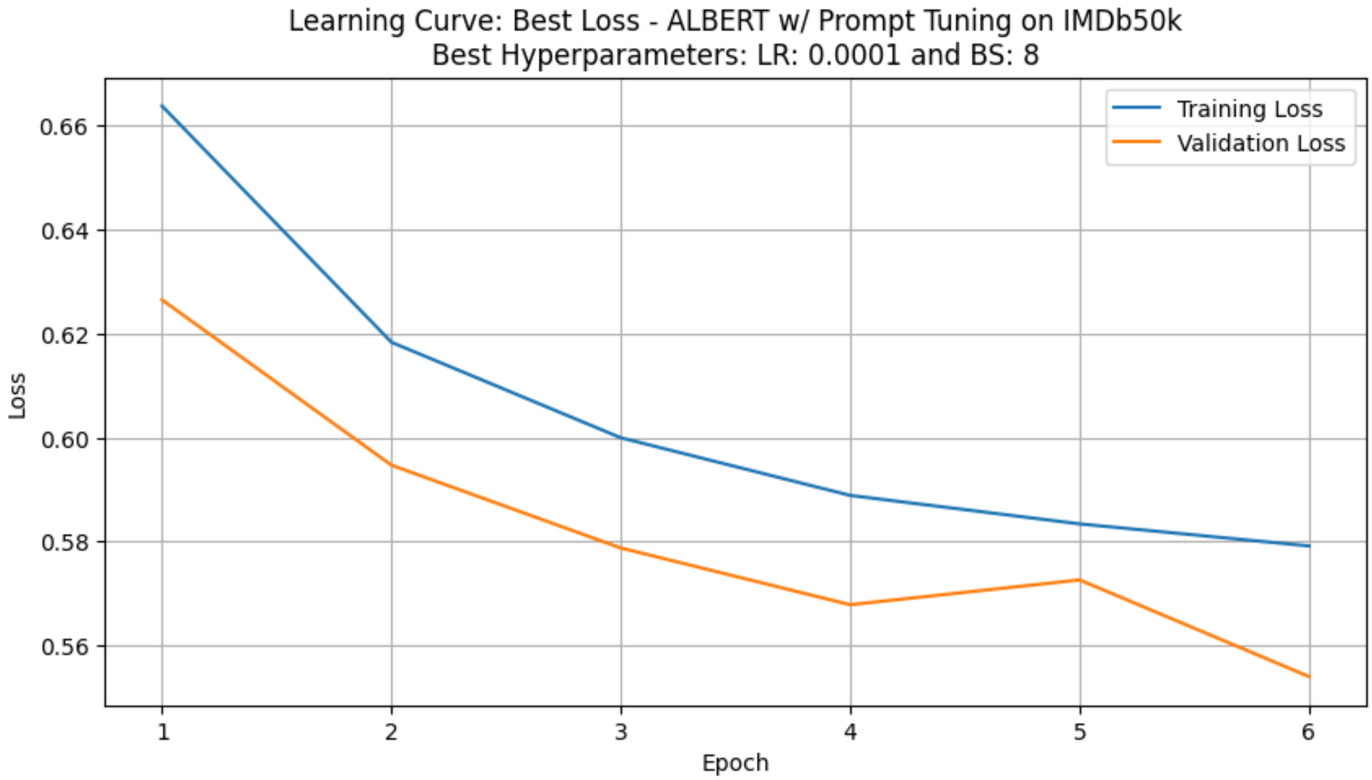
prompt_epochs = albert_prompt_epochs_map[(prompt_best_lr_tag_for_map, prompt_best_bs_tag)]

# Best Prompt Tuning Training and Validation Accuracy
plt.figure(figsize=(10,5))
sns.lineplot(data=prompt_epochs, x="epoch", y="train_accuracy", label="Training Accuracy")
sns.lineplot(data=prompt_epochs, x="epoch", y="val_accuracy", label="Validation Accuracy")
plt.title(f"Learning Curve: Best Accuracy - ALBERT w/ Prompt Tuning on IMDb50k\nBest Hyperparameters: LR: {prompt_best_lr} and
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()

# Best Prompt Tuning Training and Validation Loss
plt.figure(figsize=(10,5))
sns.lineplot(data=prompt_epochs, x="epoch", y="train_loss", label="Training Loss")
sns.lineplot(data=prompt_epochs, x="epoch", y="val_loss", label="Validation Loss")
plt.title(f"Learning Curve: Best Loss - ALBERT w/ Prompt Tuning on IMDb50k\nBest Hyperparameters: LR: {prompt_best_lr} and BS:
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()
```







PEFT Method Comparison:

```
# Final results per BitFit/LoRA/Prompt Tuning Implementation

albert_bf_results = pd.read_csv('/content/imdb_albert_bitfit_results.csv')
albert_lora_results = pd.read_csv('/content/imdb_albert_lora_results.csv')
albert_prompt_results = pd.read_csv('/content/imdb_albert_prompt_results.csv')

# Table of comparisons
comparison = pd.DataFrame({
    "Method": ["BitFit", "LoRA", "Prompt Tuning"],
    "Best Validation F1": [
        albert_bf_results["f1"].max(),
        albert_lora_results["f1"].max(),
        albert_prompt_results["f1"].max()
    ],
    "Best Validation Accuracy": [
        albert_bf_results["accuracy"].max(),
        albert_lora_results["accuracy"].max(),
        albert_prompt_results["accuracy"].max()
    ],
    "Runtime (sec)": [
        albert_bf_results["training_time"].sum(),
        albert_lora_results["training_time"].sum(),
        albert_prompt_results["training_time"].sum()
    ],
    "Inference Time (sec)": [
        albert_bf_results["inference_time"].sum(),
        albert_lora_results["inference_time"].sum(),
        albert_prompt_results["inference_time"].sum()
    ],
    "Max GPU Memory (GB)": [
        albert_bf_results["max_memory"].max(),
        albert_lora_results["max_memory"].max(),
        albert_prompt_results["max_memory"].max()
    ]
})

print("\nFinal Validation Performance PEFT Comparison - ALBERT on IMDb50k:")
display(comparison)
```

Final Validation Performance PEFT Comparison - ALBERT on IMDb50k:

	Method	Best Validation F1	Best Validation Accuracy	Runtime (sec)	Inference Time (sec)	Max GPU Memory (GB)
0	BitFit	0.864709	0.8648	4736.257788	86.522556	2.270576
1	LoRA	0.832361	0.8324	6141.177546	86.203370	2.270576

Next steps: Generate code with comparison | View recommended plots | New interactive sheet

```
# Load overall results where inference_time is stored
albert_prompt_results = pd.read_csv('/content/imdb_albert_prompt_results.csv')
albert_bf_results = pd.read_csv('/content/imdb_albert_bitfit_results.csv')
```

```
albert_lora_results = pd.read_csv('/content/imdb_albert_lora_results.csv')

# Manually map best learning rates to filename tags (from before)
lr_tag_mapping = {
    5e-5: "5e-05",
    1e-4: "0.0001"
}
bf_best_lr_tag = lr_tag_mapping[bf_best_lr]
lora_best_lr_tag = lr_tag_mapping[lora_best_lr]
prompt_best_lr_tag = lr_tag_mapping[prompt_best_lr]

# Load best inference metric summaries
bf_inf = pd.read_csv(f'/content/imdb_albert_bitfit_inference_metrics_summary_lr{bf_best_lr_tag}_bs{bf_best_bs}.csv', index_col=0)
lora_inf = pd.read_csv(f'/content/imdb_albert_lora_inference_metrics_summary_lr{lora_best_lr_tag}_bs{lora_best_bs}.csv', index_co
prompt_inf = pd.read_csv(f'/content/imdb_albert_prompt_inference_metrics_summary_lr{prompt_best_lr_tag}_bs{prompt_best_bs}.csv',

# Extract inference times
bf_inference_time = albert_bf_results[
    (albert_bf_results["learning_rate"] == bf_best_lr) &
    (albert_bf_results["batch_size"] == bf_best_bs)
]["inference_time"].values[0]

lora_inference_time = albert_lora_results[
    (albert_bf_results["learning_rate"] == lora_best_lr) &
    (albert_lora_results["batch_size"] == lora_best_bs)
]["inference_time"].values[0]

prompt_inference_time = albert_prompt_results[
    (albert_prompt_results["learning_rate"] == prompt_best_lr) &
    (albert_prompt_results["batch_size"] == prompt_best_bs)
]["inference_time"].values[0]

# Table of best per-implementation metrics (based on best lr and bs per PEFT method)
final_test_results = pd.DataFrame({
    "Method": ["BitFit", "LoRA", "Prompt Tuning"],
    "Test Accuracy": [
        bf_inf.loc["accuracy", "precision"],
        lora_inf.loc["accuracy", "precision"],
        prompt_inf.loc["accuracy", "precision"]
    ],
    "F1 Macro": [
        bf_inf.loc["macro avg", "f1-score"],
        lora_inf.loc["macro avg", "f1-score"],
        prompt_inf.loc["macro avg", "f1-score"]
    ],
    "F1 Weighted": [
        bf_inf.loc["weighted avg", "f1-score"],
        lora_inf.loc["weighted avg", "f1-score"],
        prompt_inf.loc["weighted avg", "f1-score"]
    ],
    "Inference Time (sec)": [
        bf_inference_time,
        lora_inference_time,
        prompt_inference_time
    ]
})

print("\nFinal Test Set Inference Performance PEFT Comparison - ALBERT on IMDb50k:")
display(final_test_results)
```

Final Test Set Inference Performance PEFT Comparison - ALBERT on IMDb50k:

	Method	Test Accuracy	F1 Macro	F1 Weighted	Inference Time (sec)
0	BitFit	0.8648	0.864728	0.864709	21.858219
1	LoRA	0.8324	0.832341	0.832361	21.190696
2	Prompt	0.7358	0.735793	0.735784	668.641231

Next steps: Generate code with final_test_results View recommended plots New interactive s

```
# Zip the entire /content folder
!zip -r /content/ALBERT_IMDb_solo.zip /content

# Download the zipped file
from google.colab import files
files.download('/content/ALBERT_IMDb_solo.zip')
```