For this project, we adopted two different datasets, mentioned below.

ASL alphabet dataset : https://www.kaggle.com/datasets/grassknoted/asl-alphabet

Chatbot dataset : https://www.kaggle.com/datasets/kreeshrajani/3k-conversations-dataset-for-chatbot

In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from collections import Counter
import re
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
import nltk
from nltk.corpus import wordnet
from nltk.stem import WordNetLemmatizer
from sklearn.model_selection import train_test_split
from datasets import Dataset
from datasets import DatasetDict
import torch
from transformers import AutoModelForSeq2SeqLM, AutoTokenizer, GenerationConfig, TrainingArguments, Trainer
from peft import LoraConfig, get_peft_model, TaskType
from peft import PeftModel
```

```
c:\Users\Paul\anaconda3\envs\torch\lib\site-packages\tqdm\auto.py:21: TqdmWarning: IProgress not found. Please update
jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

Chatbot Dataset - EDA and preprocessing

In [ ]:
```
chatbot_df = pd.read_csv('Conversations_clean.csv')
```

In [ ]:
```
chatbot_df.head()
```

Out[ ]:

	question	answer
0	hi, how are you doing?	i'm fine. how about yourself?
1	i'm fine. how about yourself?	i'm pretty good. thanks for asking.
2	i'm pretty good. thanks for asking.	no problem. so how have you been?
3	no problem. so how have you been?	i've been great. what about you?
4	i've been great. what about you?	i've been good. i'm in school right now.

In [ ]:
```
chatbot_df.shape
```

Out[ ]:
```
(3725, 2)
```

EDA

EDA was performed by following a similar procedure to the one described by Singh (n.d.).

References:

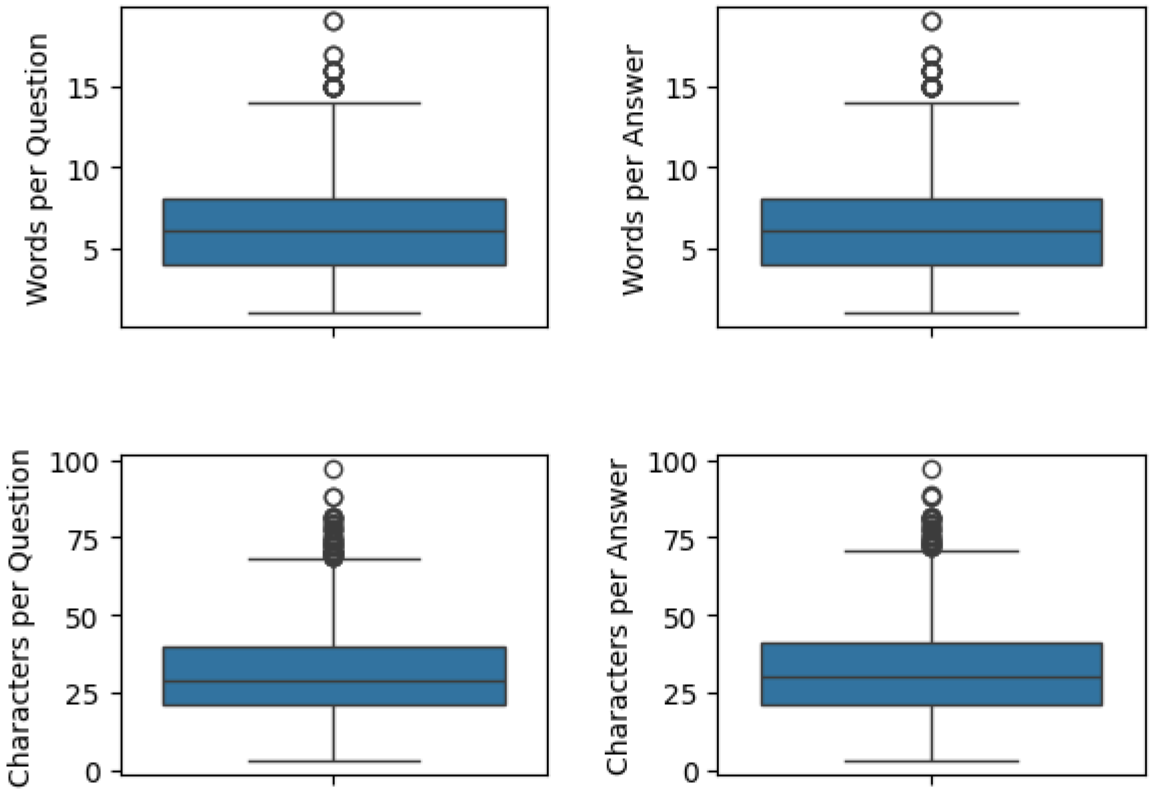
Singh, H. (n.d.). Complete Guide to EDA on Text Data. Kaggle. https://www.kaggle.com/code/harshsingh2209/complete-guide-to-eda-on-text-data

In [ ]:
```
# Function to count the number of words in a sentence
def count_words(text):
    words = text.split() # extract the words from text
    num_words = len(words) # count the number of words
    return num_words

# Function to count the number of characters in a sentence
def count_characters(text):
    num_char = len(text) # count the number of chatacters
    return num_char

num_words_question = chatbot_df['question'].apply(count_words)
num_words_answer = chatbot_df['answer'].apply(count_words)
num_char_question = chatbot_df['question'].apply(count_characters)
num_char_answer = chatbot_df['answer'].apply(count_characters)
```

```
plt.subplot(2, 2, 1)
sns.boxplot(y = num_words_question)
plt.ylabel('Words per Question')
plt.subplot(2, 2, 2)
sns.boxplot(y = num_words_answer)
plt.ylabel('Words per Answer')
plt.subplot(2, 2, 3)
sns.boxplot(y = num_char_question)
plt.ylabel('Characters per Question')
plt.subplot(2, 2, 4)
sns.boxplot(y = num_char_answer)
plt.ylabel('Characters per Answer')
plt.subplots_adjust(left = 0.1, bottom = 0.1, right = 0.9, top = 0.9, wspace = 0.4, hspace = 0.4)
plt.show()
```



In [ ]:
```
# Identify the most frequent words in the question/answer columns

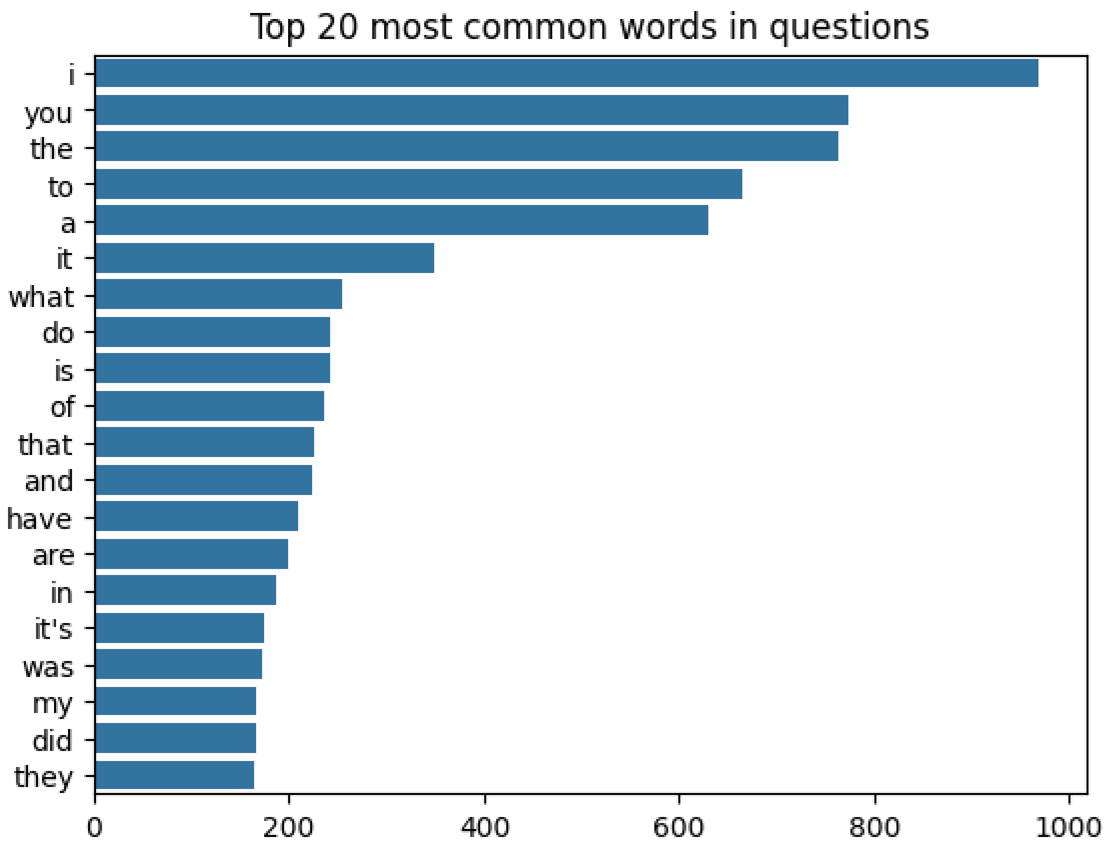
# Function to get the list of words in a sentence
def list_words(text):
    words = text.split() # extract the words from text
    return words

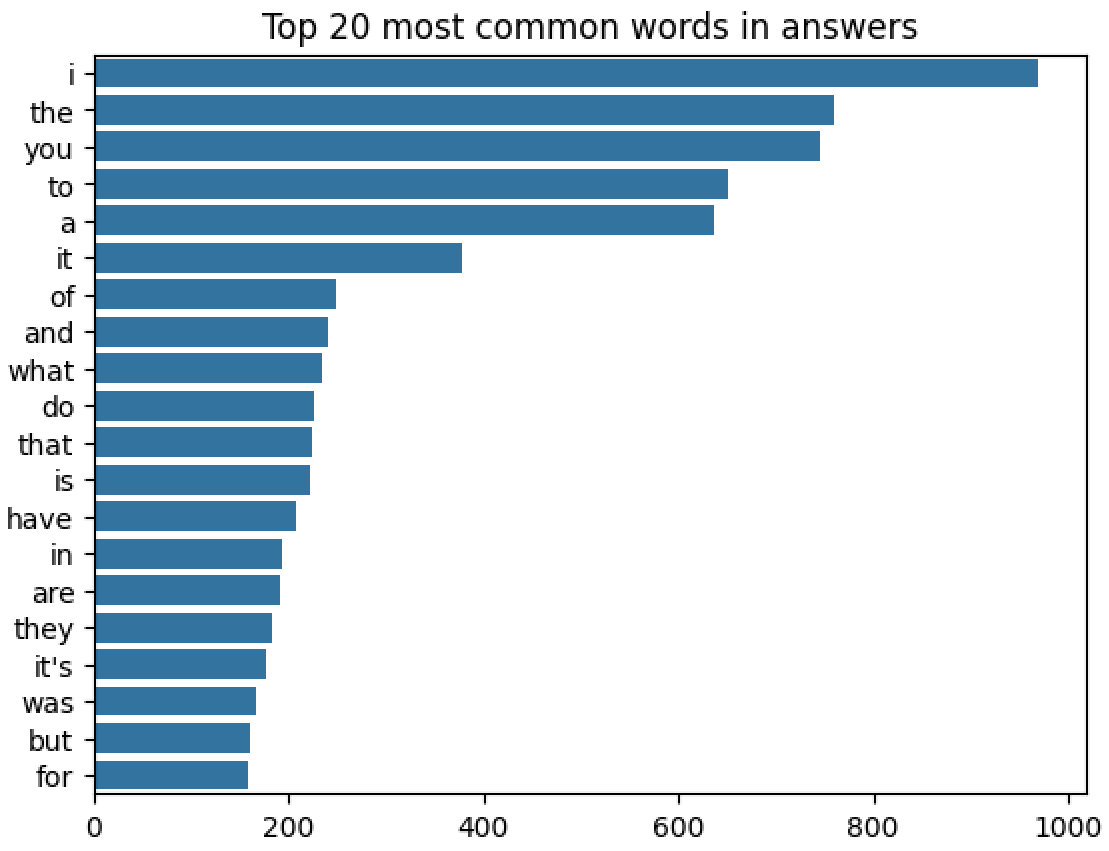
# Function to get the top 20 most common words and their counts
def words_freq(mostcommon):
    words = []
    counts = []
    for word, count in mostcommon:
        words.append(word)
        counts.append(count)
    return words, counts

words_question = chatbot_df['question'].apply(list_words)
words_answer = chatbot_df['answer'].apply(list_words)
corpus_question = []
for jj in range(len(words_question)):
    corpus_question += words_question[jj] # all the words in all the questions
corpus_answer = []
for jj in range(len(words_answer)):
    corpus_answer += words_answer[jj] # all the words in all the answers
mostcommon_words_question = Counter(corpus_question).most_common(20) # 20 most common words in all the questions
mostcommon_words_answer = Counter(corpus_answer).most_common(20) # 20 most common words in all the answers
words_question, counts_question = words_freq(mostcommon_words_question) # top 20 most common words and their counts
words_answer, counts_answer = words_freq(mostcommon_words_answer) # top 20 most common words and their counts in ansu

sns.barplot(x = counts_question, y = words_question)
plt.title('Top 20 most common words in questions')
plt.show()

sns.barplot(x = counts_answer, y = words_answer)
plt.title('Top 20 most common words in answers')
plt.show()
```


Top 20 most common words in questions
i
you
the
to
a
it
what
do
is
of
that
and
have
are
in
it's
was
my
did
they
0
200
400
600
800
1000



Preprocessing

In order to replace contractions, we adopted the same procedure described in Replace apostrophe/short words in python (n.d.).

References:

Replace apostrophe/short words in python. (n.d.). Stack Overflow. Retrieved July 24, 2024, from https://owl.purdue.edu/owl/research_and_citation/apa_style/apa_formatting_and_style_guide/reference_list_electronic_sources.html

In [ ]:
```
# List of common contractions
contractions = {
"ain't": "am not / are not",
"aren't": "are not / am not",
"can't": "cannot",
"can't've": "cannot have",
"'cause": "because",
"could've": "could have",
"couldn't": "could not",
"couldn't've": "could not have",
"didn't": "did not",
"doesn't": "does not",
"don't": "do not",
"hadn't": "had not",
"hadn't've": "had not have",
"hasn't": "has not",
"haven't": "have not",
"he'd": "he had / he would",
"he'd've": "he would have",
"he'll": "he shall / he will",
"he'll've": "he shall have / he will have",
"he's": "he has / he is",
"how'd": "how did",
"how'd'y": "how do you",
"how'll": "how will",
"how's": "how has / how is",
"i'd": "I had / I would",
"i'd've": "I would have",
"i'll": "I shall / I will",
"i'll've": "I shall have / I will have",
"i'm": "I am",
"i've": "I have",
"isn't": "is not",
"it'd": "it had / it would",
"it'd've": "it would have",
"it'll": "it shall / it will",
"it'll've": "it shall have / it will have",
"it's": "it has / it is",
"let's": "let us",
"ma'am": "madam",
"mayn't": "may not",
"might've": "might have",
"mightn't": "might not",
"mightn't've": "might not have",
"must've": "must have",
"mustn't": "must not",
"mustn't've": "must not have",
"needn't": "need not",
"needn't've": "need not have",
"o'clock": "of the clock",
"oughtn't": "ought not",
"oughtn't've": "ought not have",
"shan't": "shall not",
"sha'n't": "shall not",
"shan't've": "shall not have",
"she'd": "she had / she would",
"she'd've": "she would have",
"she'll": "she shall / she will",
"she'll've": "she shall have / she will have",
"she's": "she has / she is",
"should've": "should have",
"shouldn't": "should not",
"shouldn't've": "should not have",
"so've": "so have",
"so's": "so as / so is",
"that'd": "that would / that had",
"that'd've": "that would have",
"that's": "that has / that is",
"there'd": "there had / there would",
"there'd've": "there would have",
"there's": "there has / there is",
"they'd": "they had / they would",
"they'd've": "they would have",
"they'll": "they shall / they will",
"they'll've": "they shall have / they will have",
"they're": "they are",
"they've": "they have",
"to've": "to have",
"wasn't": "was not",
"we'd": "we had / we would",
"we'd've": "we would have",
"we'll": "we will",
"we'll've": "we will have",
"we're": "we are",
"we've": "we have",
"weren't": "were not",
"what'll": "what shall / what will",
"what'll've": "what shall have / what will have",
"what're": "what are",
"what's": "what has / what is",
"what've": "what have",
"when's": "when has / when is",
"when've": "when have",
"where'd": "where did",
"where's": "where has / where is",
"where've": "where have",
"who'll": "who shall / who will",
"who'll've": "who shall have / who will have",
"who's": "who has / who is",
"who've": "who have",
"why's": "why has / why is",
"why've": "why have",
"will've": "will have",
"won't": "will not",
"won't've": "will not have",
"would've": "would have",
"wouldn't": "would not",
"wouldn't've": "would not have",
"y'all": "you all",
"y'all'd": "you all would",
"y'all'd've": "you all would have",
"y'all're": "you all are",
"y'all've": "you all have",
"you'd": "you had / you would",
"you'd've": "you would have",
"you'll": "you shall / you will",
"you'll've": "you shall have / you will have",
"you're": "you are",
"you've": "you have"
}

# Function to replace contractions, remove punctuation and apply lowercase
def clear_text(text):
    for word in text.split(): # remove contractions and apply lowercase
        if word.lower() in contractions:
            text = text.replace(word, contractions[word.lower()])
    text = re.sub(r'[^\w\s]', '', text) # remove punctuation
    return text

chatbot_df['question'] = chatbot_df['question'].apply(clear_text)
```

```
chatbot_df['answer'] = chatbot_df['answer'].apply(clear_text)
chatbot_df.head()
```

Out[ ]:

	question	answer
0	hi how are you doing	I am fine how about yourself
1	I am fine how about yourself	I am pretty good thanks for asking
2	I am pretty good thanks for asking	no problem so how have you been
3	no problem so how have you been	I have been great what about you
4	I have been great what about you	I have been good I am in school right now

In [ ]:

```
# Tokenization
chatbot_df['token_question'] = chatbot_df['question'].apply(nltk.word_tokenize)
chatbot_df['token_answer'] = chatbot_df['answer'].apply(nltk.word_tokenize)
chatbot_df.head()
```

Out[ ]:

	question	answer	token_question	token_answer
0	hi how are you doing	I am fine how about yourself	[hi, how, are, you, doing]	[I, am, fine, how, about, yourself]
1	I am fine how about yourself	I am pretty good thanks for asking	[I, am, fine, how, about, yourself]	[I, am, pretty, good, thanks, for, asking]
2	I am pretty good thanks for asking	no problem so how have you been	[I, am, pretty, good, thanks, for, asking]	[no, problem, so, how, have, you, been]
3	no problem so how have you been	I have been great what about you	[no, problem, so, how, have, you, been]	[I, have, been, great, what, about, you]
4	I have been great what about you	I have been good I am in school right now	[I, have, been, great, what, about, you]	[I, have, been, good, I, am, in, school, right...

In [ ]:

```
# Lemmatization

# Function to obtain the right positional tagging prior to Lemmatization
# Same function presented in Python – Lemmatization Approaches with Examples (n.d.)
def right_pos_tagging(tag):
    if tag.startswith('J'):
        return wordnet.ADJ
    elif tag.startswith('V'):
        return wordnet.VERB
    elif tag.startswith('N'):
        return wordnet.NOUN
    elif tag.startswith('R'):
        return wordnet.ADV
    else:
        return None

# Obtain the right positional tagging prior to Lemmatization
# Positional tags were modified as suggested by Python – Lemmatization Approaches with Examples (n.d.)

tokens = chatbot_df['token_question']
new_tag_tokens = []
for jj in range(len(tokens)):
    tokens_jj = tokens[jj] # tokens at the jjth row
    tag_tokens_jj = nltk.pos_tag(tokens_jj) # POS tags for the generic tokens_jj
    new_tag_tokens.append(list(map(lambda x: (x[0], right_pos_tagging(x[1])), tag_tokens_jj))) # modified POS tags fo
tagged_token_question = new_tag_tokens

tokens = chatbot_df['token_answer']
new_tag_tokens = []
for jj in range(len(tokens)):
    tokens_jj = tokens[jj] # tokens at the jjth row
    tag_tokens_jj = nltk.pos_tag(tokens_jj) # POS tags for the generic tokens_jj
    new_tag_tokens.append(list(map(lambda x: (x[0], right_pos_tagging(x[1])), tag_tokens_jj))) # modified POS tags fo
tagged_token_answer = new_tag_tokens

# Implement Lemmatization on the tokens
# A procedure similar to the one described in Python – Lemmatization Approaches with Examples (n.d.) and by Kumar (20

wnl = WordNetLemmatizer()
Lemmatization = []
for jj in range(len(tagged_token_question)):
    lemmatized_question = []
# Same lines of codes used in Python – Lemmatization Approaches with Examples (n.d.)
    for word, tag in tagged_token_question[jj]:
        if tag is None:
            lemmatized_question.append(word)
        else:
            lemmatized_question.append(wnl.lemmatize(word, tag))
    Lemmatization.append(lemmatized_question)
chatbot_df['lem_question'] = Lemmatization

Lemmatization = []
for jj in range(len(tagged_token_answer)):
    lemmatized_answer = []
# Same lines of codes used in Python - Lemmatization Approaches with Examples (n.d.)
    for word, tag in tagged_token_answer[jj]:
        if tag is None:
            lemmatized_answer.append(word)
        else:
            lemmatized_answer.append(wnl.lemmatize(word, tag))
    Lemmatization.append(lemmatized_answer)
chatbot_df['lem_answer'] = Lemmatization

chatbot_df.head()

# References
# Kumar, R. (2021, August 6). Natural Language Processing | Text Preprocessing | Spacy vs NLTK. Medium. https://mediu
# Python - Lemmatization Approaches with Examples. (n.d.). Geeks for Geeks.  https://www.geeksforgeeks.org/python-lem
```

Out[ ]:

	question	answer	token_question	token_answer	lem_question	lem_answer
0	hi how are you doing	I am fine how about yourself	[hi, how, are, you, doing]	[I, am, fine, how, about, yourself]	[hi, how, be, you, do]	[I, be, fine, how, about, yourself]
1	I am fine how about yourself	I am pretty good thanks for asking	[I, am, fine, how, about, yourself]	[I, am, pretty, good, thanks, for, asking]	[I, be, fine, how, about, yourself]	[I, be, pretty, good, thanks, for, ask]
2	I am pretty good thanks for asking	no problem so how have you been	[I, am, pretty, good, thanks, for, asking]	[no, problem, so, how, have, you, been]	[I, be, pretty, good, thanks, for, ask]	[no, problem, so, how, have, you, be]
3	no problem so how have you been	I have been great what about you	[no, problem, so, how, have, you, been]	[I, have, been, great, what, about, you]	[no, problem, so, how, have, you, be]	[I, have, be, great, what, about, you]
4	I have been great what about you	I have been good I am in school right now	[I, have, been, great, what, about, you]	[I, have, been, good, I, am, in, school, right...	[I, have, be, great, what, about, you]	[I, have, be, good, I, be, in, school, right, ...

T5 Fine Tuning

This section was created based on a combination of the following references.

References: https://www.kaggle.com/code/ajinkyabhandare2002/fine-tune-flan-t5-base-for-chat-with-peft-lora

Import tokenizer and model

In [ ]:
```
model_name = 'google/flan-t5-base'
model = AutoModelForSeq2SeqLM.from_pretrained(model_name, torch_dtype = torch.bfloat16)
tokenizer = AutoTokenizer.from_pretrained(model_name)
```

In [ ]:
```
# Check number of parameters to train
def model_parameters(model):
    trainable_model_params = 0
    all_model_params = 0
    for _, param in model.named_parameters():
        all_model_params += param.numel()
        if param.requires_grad:
            trainable_model_params += param.numel()
    return f"trainable model parameters: {trainable_model_params}\nall model parameters: {all_model_params}\npercenta

print(model_parameters(model))
```

```
trainable model parameters: 247577856
all model parameters: 247577856
percentage of trainable model parameters: 100.00%
```

Preprocess Data for Retrain

In [ ]:
```
chatbot_df=chatbot_df.drop(columns=['token_question','token_answer','lem_question','lem_answer'])
```

In [ ]:
```
train_data, temp_data = train_test_split(chatbot_df, test_size=0.2, random_state=42)
val_data, test_data = train_test_split(temp_data, test_size=0.5, random_state=42)
train_dataset = Dataset.from_pandas(train_data)
val_dataset = Dataset.from_pandas(val_data)
test_dataset = Dataset.from_pandas(test_data)
```

In [ ]:
```
from datasets import DatasetDict
working_dataset = DatasetDict({
    "train": train_dataset,
    "validation": val_dataset,
    "test": test_dataset,
})
```

In [ ]:
```
working_dataset
```

Out[ ]:
```
DatasetDict({
    train: Dataset({
        features: ['question', 'answer', '__index_level_0__'],
        num_rows: 2980
    })
    validation: Dataset({
        features: ['question', 'answer', '__index_level_0__'],
        num_rows: 372
    })
    test: Dataset({
        features: ['question', 'answer', '__index_level_0__'],
        num_rows: 373
    })
})
```

In [ ]:
```
working_dataset["train"] = working_dataset["train"].remove_columns("__index_level_0__")
working_dataset["validation"] = working_dataset["validation"].remove_columns("__index_level_0__")
working_dataset["test"] = working_dataset["test"].remove_columns("__index_level_0__")
working_dataset
```

Out[ ]:
```
DatasetDict({
    train: Dataset({
        features: ['question', 'answer'],
        num_rows: 2980
    })
    validation: Dataset({
        features: ['question', 'answer'],
        num_rows: 372
    })
    test: Dataset({
        features: ['question', 'answer'],
        num_rows: 373
    })
})
```

In [ ]:
```
def tokenize_function(example):
    # start_prompt = 'Answer the following question.\n\n'
    # end_prompt = '\n\nSummary: '
    # prompt = [start_prompt + question + end_prompt for question in example["question"]]
    example['input_ids'] = tokenizer(example['question'], padding='max_length', truncation=True, return_tensors="pt")
    example['labels'] = tokenizer(example["answer"], padding='max_length', truncation=True, return_tensors="pt").inpu

    return example

# The dataset actually contains 3 diff splits: train, validation, test.
# The tokenize_function code is handling all data across all splits in batches.
tokenized_datasets = working_dataset.map(tokenize_function, batched=True)
tokenized_datasets = tokenized_datasets.remove_columns(['question', 'answer'])
```

```
Map: 100%|██████████| 2980/2980 [00:00<00:00, 5327.93 examples/s]
Map: 100%|██████████| 372/372 [00:00<00:00, 6009.08 examples/s]
Map: 100%|██████████| 373/373 [00:00<00:00, 6893.48 examples/s]
```

In [ ]:
```
tokenized_datasets
```

Out[ ]:
```
DatasetDict({
    train: Dataset({
        features: ['input_ids', 'labels'],
        num_rows: 2980
    })
    validation: Dataset({
        features: ['input_ids', 'labels'],
        num_rows: 372
    })
    test: Dataset({
        features: ['input_ids', 'labels'],
        num_rows: 373
    })
})
```

In [ ]:
```
print(f"Shapes of the datasets:")
print(f"Dataset: {tokenized_datasets.shape}")
print(tokenized_datasets)
```

```
Shapes of the datasets:
Dataset: {'train': (2980, 2), 'validation': (372, 2), 'test': (373, 2)}
DatasetDict({
    train: Dataset({
        features: ['input_ids', 'labels'],
        num_rows: 2980
    })
    validation: Dataset({
        features: ['input_ids', 'labels'],
        num_rows: 372
    })
    test: Dataset({
        features: ['input_ids', 'labels'],
        num_rows: 373
    })
})
```

Setup the PEFT/LoRA model for Fine-Tuning

In [ ]:
```
lora_config = LoraConfig(
    r=8, # Rank
    lora_alpha=8,
    target_modules=["q", "v"],
    lora_dropout=0.05,
    bias="none",
    task_type=TaskType.SEQ_2_SEQ_LM # FLAN-T5
)
```

Add LoRA adapter layers/prameters to the LLM model to be trained

In [ ]:
```
peft_model = get_peft_model(model, lora_config)
print(model_parameters(peft_model))
```

```
bin c:\Users\Paul\anaconda3\envs\torch\lib\site-packages\bitsandbytes\libbitsandbytes_cuda118.dll
trainable model parameters: 884736
all model parameters: 248462592
percentage of trainable model parameters: 0.36%
```

Train PEFT Adapter

In [ ]:
```
# Define Trianing Arguements
output_dir = f'./peft-conversation-training'

peft_training_args = TrainingArguments(
    output_dir=output_dir,
    auto_find_batch_size=True,
    learning_rate=1e-3, # Higher learning rate than full fine-tuning.
    num_train_epochs=5,
    save_steps=100,
    save_strategy='steps',
    evaluation_strategy='steps',
    eval_steps=10,
)

peft_trainer = Trainer(
    model=peft_model,
    args=peft_training_args,
    train_dataset=tokenized_datasets["train"],
    eval_dataset = tokenized_datasets['validation']
)
```

```
c:\Users\Paul\anaconda3\envs\torch\lib\site-packages\transformers\training_args.py:1525: FutureWarning: `evaluation_s
trategy` is deprecated and will be removed in version 4.46 of 🤗 Transformers. Use `eval_strategy` instead
  warnings.warn(
```

Train the model

In [ ]:

```
try:
    peft_trainer.train()
except OutOfMemoryError:
    print("Training interrupted due to OOM. Saving model checkpoint...")
    peft_model_path="./peft-conversation-checkpoint-local"
    peft_trainer.model.save_pretrained(peft_model_path)
    tokenizer.save_pretrained(peft_model_path)
    print("Checkpoint saved. You can resume training from here.")
```

```
  1%|          | 10/1865 [00:02<05:55,  5.21it/s]
  1%|          | 11/1865 [00:05<35:46,  1.16s/it]
{'eval_loss': 30.860214233398438, 'eval_runtime': 3.1556, 'eval_samples_per_second': 117.886, 'eval_steps_per_secon
d': 14.894, 'epoch': 0.03}

  1%|          | 21/1865 [00:11<39:59,  1.30s/it]
{'eval_loss': 14.452284812927246, 'eval_runtime': 3.6103, 'eval_samples_per_second': 103.039, 'eval_steps_per_secon
d': 13.018, 'epoch': 0.05}

  2%|▏         | 31/1865 [00:16<35:48,  1.17s/it]
{'eval_loss': 4.510080814361572, 'eval_runtime': 3.1676, 'eval_samples_per_second': 117.44, 'eval_steps_per_second':
14.838, 'epoch': 0.08}

  2%|▏         | 41/1865 [00:21<35:20,  1.16s/it]
{'eval_loss': 4.096774101257324, 'eval_runtime': 3.1505, 'eval_samples_per_second': 118.075, 'eval_steps_per_second':
14.918, 'epoch': 0.11}

  3%|▎         | 51/1865 [00:26<35:10,  1.16s/it]
{'eval_loss': 2.7189180850982666, 'eval_runtime': 3.1536, 'eval_samples_per_second': 117.962, 'eval_steps_per_secon
d': 14.904, 'epoch': 0.13}

  3%|▎         | 61/1865 [00:31<38:45,  1.29s/it]
{'eval_loss': 1.0347782373428345, 'eval_runtime': 3.5698, 'eval_samples_per_second': 104.208, 'eval_steps_per_secon
d': 13.166, 'epoch': 0.16}
```

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  4%|▌         | 71/1865 [00:36<34:48,  1.16s/it]
{'eval_loss': 0.5599378347396851, 'eval_runtime': 3.1425, 'eval_samples_per_second': 118.377, 'eval_steps_per_secon
d': 14.956, 'epoch': 0.19}

  4%|▌         | 81/1865 [00:41<34:31,  1.16s/it]
{'eval_loss': 0.33358535170555115, 'eval_runtime': 3.1468, 'eval_samples_per_second': 118.214, 'eval_steps_per_secon
d': 14.936, 'epoch': 0.21}

  5%|▌         | 91/1865 [00:46<34:17,  1.16s/it]
{'eval_loss': 0.2514490783214569, 'eval_runtime': 3.1435, 'eval_samples_per_second': 118.34, 'eval_steps_per_second':
14.952, 'epoch': 0.24}

  5%|▌         | 100/1865 [00:51<06:41,  4.40it/s]
{'eval_loss': 0.1840347796678543, 'eval_runtime': 3.1439, 'eval_samples_per_second': 118.326, 'eval_steps_per_secon
d': 14.95, 'epoch': 0.27}

  6%|▌         | 111/1865 [00:57<34:00,  1.16s/it]
{'eval_loss': 0.16665616631507874, 'eval_runtime': 3.1478, 'eval_samples_per_second': 118.177, 'eval_steps_per_secon
d': 14.931, 'epoch': 0.29}

  6%|▋         | 121/1865 [01:02<33:37,  1.16s/it]
{'eval_loss': 0.1538243442773819, 'eval_runtime': 3.1331, 'eval_samples_per_second': 118.731, 'eval_steps_per_secon
d': 15.001, 'epoch': 0.32}

  7%|▋         | 131/1865 [01:07<33:29,  1.16s/it]
{'eval_loss': 0.14440524578094482, 'eval_runtime': 3.1422, 'eval_samples_per_second': 118.39, 'eval_steps_per_secon
d': 14.958, 'epoch': 0.35}

  8%|▊         | 141/1865 [01:12<33:15,  1.16s/it]
{'eval_loss': 0.13718077540397644, 'eval_runtime': 3.1381, 'eval_samples_per_second': 118.544, 'eval_steps_per_secon
d': 14.977, 'epoch': 0.38}

  8%|▊         | 151/1865 [01:17<33:01,  1.16s/it]
{'eval_loss': 0.13080687820911407, 'eval_runtime': 3.1309, 'eval_samples_per_second': 118.817, 'eval_steps_per_secon
d': 15.012, 'epoch': 0.4}

  9%|▊         | 161/1865 [01:22<32:56,  1.16s/it]
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{'eval_loss': 0.1274886578321457, 'eval_runtime': 3.1428, 'eval_samples_per_second': 118.367, 'eval_steps_per_secon
d': 14.955, 'epoch': 0.43}

  9%|█         | 171/1865 [01:27<32:44,  1.16s/it]
{'eval_loss': 0.12263734638690948, 'eval_runtime': 3.1424, 'eval_samples_per_second': 118.381, 'eval_steps_per_secon
d': 14.957, 'epoch': 0.46}

 10%|█         | 180/1865 [01:32<06:22,  4.40it/s]
{'eval_loss': 0.11838982999324799, 'eval_runtime': 3.5633, 'eval_samples_per_second': 104.399, 'eval_steps_per_secon
d': 13.19, 'epoch': 0.48}

 10%|█         | 191/1865 [01:37<32:24,  1.16s/it]
{'eval_loss': 0.11515036970376968, 'eval_runtime': 3.1372, 'eval_samples_per_second': 118.578, 'eval_steps_per_secon
d': 14.982, 'epoch': 0.51}

 11%|█         | 200/1865 [01:42<06:17,  4.41it/s]
{'eval_loss': 0.11255670338869095, 'eval_runtime': 3.1597, 'eval_samples_per_second': 117.734, 'eval_steps_per_secon
d': 14.875, 'epoch': 0.54}

 11%|█         | 210/1865 [01:47<06:20,  4.35it/s]
{'eval_loss': 0.10888146609067917, 'eval_runtime': 3.1586, 'eval_samples_per_second': 117.772, 'eval_steps_per_secon
d': 14.88, 'epoch': 0.56}

 12%|█         | 221/1865 [01:53<31:43,  1.16s/it]
{'eval_loss': 0.10646631568670273, 'eval_runtime': 3.1392, 'eval_samples_per_second': 118.5, 'eval_steps_per_second':
14.972, 'epoch': 0.59}

 12%|█         | 231/1865 [01:58<31:26,  1.15s/it]
{'eval_loss': 0.1039881557226181, 'eval_runtime': 3.1258, 'eval_samples_per_second': 119.008, 'eval_steps_per_secon
d': 15.036, 'epoch': 0.62}

 13%|█         | 241/1865 [02:03<31:19,  1.16s/it]
{'eval_loss': 0.10217154026031494, 'eval_runtime': 3.1362, 'eval_samples_per_second': 118.615, 'eval_steps_per_secon
d': 14.986, 'epoch': 0.64}

 13%|█         | 251/1865 [02:08<31:09,  1.16s/it]
{'eval_loss': 0.0994623675942421, 'eval_runtime': 3.1405, 'eval_samples_per_second': 118.452, 'eval_steps_per_secon
d': 14.966, 'epoch': 0.67}
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 14%|█▍        | 261/1865 [02:13<31:00,  1.16s/it]
{'eval_loss': 0.09701045602560043, 'eval_runtime': 3.1432, 'eval_samples_per_second': 118.35, 'eval_steps_per_secon
d': 14.953, 'epoch': 0.7}

 15%|█▍        | 271/1865 [02:18<30:54,  1.16s/it]
{'eval_loss': 0.09564012289047241, 'eval_runtime': 3.1535, 'eval_samples_per_second': 117.965, 'eval_steps_per_secon
d': 14.904, 'epoch': 0.72}

 15%|█▌        | 281/1865 [02:23<30:37,  1.16s/it]
{'eval_loss': 0.09327221661806107, 'eval_runtime': 3.1428, 'eval_samples_per_second': 118.366, 'eval_steps_per_secon
d': 14.955, 'epoch': 0.75}

 16%|█▌        | 291/1865 [02:28<30:27,  1.16s/it]
{'eval_loss': 0.09321446716785431, 'eval_runtime': 3.1481, 'eval_samples_per_second': 118.166, 'eval_steps_per_secon
d': 14.93, 'epoch': 0.78}

 16%|█▌        | 300/1865 [02:33<05:55,  4.40it/s]
{'eval_loss': 0.09120358526706696, 'eval_runtime': 3.1441, 'eval_samples_per_second': 118.315, 'eval_steps_per_secon
d': 14.948, 'epoch': 0.8}

 17%|█▋        | 311/1865 [02:38<30:07,  1.16s/it]
{'eval_loss': 0.08915070444345474, 'eval_runtime': 3.148, 'eval_samples_per_second': 118.169, 'eval_steps_per_secon
d': 14.93, 'epoch': 0.83}

 17%|█▋        | 321/1865 [02:43<30:01,  1.17s/it]
{'eval_loss': 0.08911395072937012, 'eval_runtime': 3.1618, 'eval_samples_per_second': 117.656, 'eval_steps_per_secon
d': 14.865, 'epoch': 0.86}

 18%|█▊        | 331/1865 [02:48<29:43,  1.16s/it]
{'eval_loss': 0.08748109638690948, 'eval_runtime': 3.1512, 'eval_samples_per_second': 118.052, 'eval_steps_per_secon
d': 14.915, 'epoch': 0.88}

 18%|█▊        | 341/1865 [02:53<29:30,  1.16s/it]
{'eval_loss': 0.0862787738442421, 'eval_runtime': 3.1497, 'eval_samples_per_second': 118.105, 'eval_steps_per_secon
d': 14.922, 'epoch': 0.91}

 19%|█▉        | 350/1865 [02:58<05:45,  4.39it/s]
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{'eval_loss': 0.08584299683570862, 'eval_runtime': 3.1394, 'eval_samples_per_second': 118.494, 'eval_steps_per_secon
d': 14.971, 'epoch': 0.94}

 19%|██        | 361/1865 [03:03<29:02,  1.16s/it]
{'eval_loss': 0.08338584005832672, 'eval_runtime': 3.139, 'eval_samples_per_second': 118.511, 'eval_steps_per_secon
d': 14.973, 'epoch': 0.97}

 20%|██        | 370/1865 [03:08<05:39,  4.40it/s]
{'eval_loss': 0.08290805667638779, 'eval_runtime': 3.3862, 'eval_samples_per_second': 109.857, 'eval_steps_per_secon
d': 13.88, 'epoch': 0.99}

 20%|█        | 381/1865 [03:14<31:50,  1.29s/it]
{'eval_loss': 0.08205749839544296, 'eval_runtime': 3.5065, 'eval_samples_per_second': 106.089, 'eval_steps_per_secon
d': 13.404, 'epoch': 1.02}

 21%|█        | 391/1865 [03:19<28:32,  1.16s/it]
{'eval_loss': 0.08042464405298233, 'eval_runtime': 3.1366, 'eval_samples_per_second': 118.6, 'eval_steps_per_second':
14.984, 'epoch': 1.05}

 21%|██        | 400/1865 [03:24<05:31,  4.42it/s]
{'eval_loss': 0.07961084693670273, 'eval_runtime': 3.1192, 'eval_samples_per_second': 119.262, 'eval_steps_per_secon
d': 15.068, 'epoch': 1.07}

 22%|██        | 410/1865 [03:29<05:32,  4.37it/s]
{'eval_loss': 0.0802408829331398, 'eval_runtime': 3.0914, 'eval_samples_per_second': 120.335, 'eval_steps_per_secon
d': 15.204, 'epoch': 1.1}

 23%|██        | 421/1865 [03:35<27:45,  1.15s/it]
{'eval_loss': 0.07775222510099411, 'eval_runtime': 3.1211, 'eval_samples_per_second': 119.19, 'eval_steps_per_secon
d': 15.059, 'epoch': 1.13}

 23%|██        | 431/1865 [03:40<27:22,  1.15s/it]
{'eval_loss': 0.07681766897439957, 'eval_runtime': 3.1029, 'eval_samples_per_second': 119.887, 'eval_steps_per_secon
d': 15.147, 'epoch': 1.15}

 24%|██        | 441/1865 [03:45<27:32,  1.16s/it]
{'eval_loss': 0.0776052176952362, 'eval_runtime': 3.154, 'eval_samples_per_second': 117.944, 'eval_steps_per_second':
14.902, 'epoch': 1.18}
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 24%|██▍       | 451/1865 [03:50<27:07,  1.15s/it]
{'eval_loss': 0.07609836757183075, 'eval_runtime': 3.1235, 'eval_samples_per_second': 119.098, 'eval_steps_per_secon
d': 15.047, 'epoch': 1.21}

 25%|██▍       | 461/1865 [03:55<27:02,  1.16s/it]
{'eval_loss': 0.07625062763690948, 'eval_runtime': 3.1318, 'eval_samples_per_second': 118.781, 'eval_steps_per_secon
d': 15.007, 'epoch': 1.23}

 25%|██▌       | 471/1865 [04:00<26:41,  1.15s/it]
{'eval_loss': 0.07512180507183075, 'eval_runtime': 3.1189, 'eval_samples_per_second': 119.271, 'eval_steps_per_secon
d': 15.069, 'epoch': 1.26}

 26%|██▌       | 481/1865 [04:05<26:15,  1.14s/it]
{'eval_loss': 0.07464402914047241, 'eval_runtime': 3.0789, 'eval_samples_per_second': 120.824, 'eval_steps_per_secon
d': 15.265, 'epoch': 1.29}

 26%|██▋       | 491/1865 [04:10<26:20,  1.15s/it]
{'eval_loss': 0.07493279874324799, 'eval_runtime': 3.136, 'eval_samples_per_second': 118.624, 'eval_steps_per_secon
d': 14.987, 'epoch': 1.31}
 27%|██▋       | 500/1865 [04:11<04:59,  4.56it/s]
{'loss': 1.6373, 'grad_norm': 0.07249174267053604, 'learning_rate': 0.0007319034852546918, 'epoch': 1.34}

 27%|██▋       | 500/1865 [04:14<04:59,  4.56it/s]
{'eval_loss': 0.0734049454331398, 'eval_runtime': 3.1305, 'eval_samples_per_second': 118.831, 'eval_steps_per_secon
d': 15.014, 'epoch': 1.34}

 27%|██▋       | 511/1865 [04:20<26:12,  1.16s/it]
{'eval_loss': 0.07353095710277557, 'eval_runtime': 3.1432, 'eval_samples_per_second': 118.352, 'eval_steps_per_secon
d': 14.953, 'epoch': 1.37}

 28%|██▊       | 521/1865 [04:25<26:37,  1.19s/it]
{'eval_loss': 0.07254914194345474, 'eval_runtime': 3.2222, 'eval_samples_per_second': 115.449, 'eval_steps_per_secon
d': 14.586, 'epoch': 1.39}

 28%|██▊       | 531/1865 [04:30<26:04,  1.17s/it]
{'eval_loss': 0.07197685539722443, 'eval_runtime': 3.1853, 'eval_samples_per_second': 116.786, 'eval_steps_per_secon
d': 14.755, 'epoch': 1.42}
```

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 29%|██▉       | 541/1865 [04:35<25:45,  1.17s/it]
{'eval_loss': 0.0715988352894783, 'eval_runtime': 3.1645, 'eval_samples_per_second': 117.553, 'eval_steps_per_secon
d': 14.852, 'epoch': 1.45}

 30%|██▉       | 551/1865 [04:40<25:11,  1.15s/it]
{'eval_loss': 0.07134681940078735, 'eval_runtime': 3.1136, 'eval_samples_per_second': 119.474, 'eval_steps_per_secon
d': 15.095, 'epoch': 1.47}

 30%|███       | 561/1865 [04:45<24:54,  1.15s/it]
{'eval_loss': 0.0711420550942421, 'eval_runtime': 3.1238, 'eval_samples_per_second': 119.087, 'eval_steps_per_secon
d': 15.046, 'epoch': 1.5}

 31%|███       | 571/1865 [04:50<24:46,  1.15s/it]
{'eval_loss': 0.07077453285455704, 'eval_runtime': 3.1249, 'eval_samples_per_second': 119.045, 'eval_steps_per_secon
d': 15.041, 'epoch': 1.53}

 31%|███       | 581/1865 [04:55<24:46,  1.16s/it]
{'eval_loss': 0.06965620815753937, 'eval_runtime': 3.155, 'eval_samples_per_second': 117.908, 'eval_steps_per_secon
d': 14.897, 'epoch': 1.55}

 32%|███▏      | 591/1865 [05:00<24:31,  1.15s/it]
{'eval_loss': 0.06988197565078735, 'eval_runtime': 3.1339, 'eval_samples_per_second': 118.703, 'eval_steps_per_secon
d': 14.997, 'epoch': 1.58}

 32%|███▏      | 600/1865 [05:05<04:45,  4.42it/s]
{'eval_loss': 0.06925718486309052, 'eval_runtime': 3.1055, 'eval_samples_per_second': 119.786, 'eval_steps_per_secon
d': 15.134, 'epoch': 1.61}

 33%|███▎      | 611/1865 [05:10<24:07,  1.15s/it]
{'eval_loss': 0.06922043114900589, 'eval_runtime': 3.1206, 'eval_samples_per_second': 119.208, 'eval_steps_per_secon
d': 15.061, 'epoch': 1.64}

 33%|███▎      | 621/1865 [05:15<23:36,  1.14s/it]
{'eval_loss': 0.06869539618492126, 'eval_runtime': 3.0973, 'eval_samples_per_second': 120.106, 'eval_steps_per_secon
d': 15.175, 'epoch': 1.66}

 34%|███▍      | 631/1865 [05:20<23:35,  1.15s/it]
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{'eval_loss': 0.0683436244726181, 'eval_runtime': 3.1211, 'eval_samples_per_second': 119.187, 'eval_steps_per_secon
d': 15.059, 'epoch': 1.69}

 34%|███▍      | 641/1865 [05:25<23:12,  1.14s/it]
{'eval_loss': 0.06796559691429138, 'eval_runtime': 3.0717, 'eval_samples_per_second': 121.106, 'eval_steps_per_secon
d': 15.301, 'epoch': 1.72}

 35%|███▍      | 651/1865 [05:30<23:02,  1.14s/it]
{'eval_loss': 0.06760332733392715, 'eval_runtime': 3.0862, 'eval_samples_per_second': 120.535, 'eval_steps_per_secon
d': 15.229, 'epoch': 1.74}

 35%|███▌     | 661/1865 [05:35<22:51,  1.14s/it]
{'eval_loss': 0.06821761280298233, 'eval_runtime': 3.0976, 'eval_samples_per_second': 120.092, 'eval_steps_per_secon
d': 15.173, 'epoch': 1.77}

 36%|███▌     | 671/1865 [05:40<22:50,  1.15s/it]
{'eval_loss': 0.06681577861309052, 'eval_runtime': 3.1167, 'eval_samples_per_second': 119.359, 'eval_steps_per_secon
d': 15.08, 'epoch': 1.8}

 37%|███▋      | 681/1865 [05:45<23:15,  1.18s/it]
{'eval_loss': 0.06684202700853348, 'eval_runtime': 3.2144, 'eval_samples_per_second': 115.73, 'eval_steps_per_secon
d': 14.622, 'epoch': 1.82}

 37%|███▋      | 691/1865 [05:50<22:42,  1.16s/it]
{'eval_loss': 0.06701003760099411, 'eval_runtime': 3.1479, 'eval_samples_per_second': 118.173, 'eval_steps_per_secon
d': 14.93, 'epoch': 1.85}

 38%|███▊      | 700/1865 [05:55<04:23,  4.42it/s]
{'eval_loss': 0.06670551747083664, 'eval_runtime': 3.1369, 'eval_samples_per_second': 118.588, 'eval_steps_per_secon
d': 14.983, 'epoch': 1.88}

 38%|███▊      | 711/1865 [06:00<22:48,  1.19s/it]
{'eval_loss': 0.06666351854801178, 'eval_runtime': 3.2274, 'eval_samples_per_second': 115.262, 'eval_steps_per_secon
d': 14.563, 'epoch': 1.9}

 39%|███▊      | 721/1865 [06:05<22:00,  1.15s/it]
{'eval_loss': 0.06557144969701767, 'eval_runtime': 3.1177, 'eval_samples_per_second': 119.318, 'eval_steps_per_secon
d': 15.075, 'epoch': 1.93}
```

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 39%|███▏      | 731/1865 [06:10<21:51,  1.16s/it]
{'eval_loss': 0.06646400690078735, 'eval_runtime': 3.1507, 'eval_samples_per_second': 118.07, 'eval_steps_per_secon
d': 14.917, 'epoch': 1.96}

 40%|███▏      | 741/1865 [06:15<21:38,  1.15s/it]
{'eval_loss': 0.06565020233392715, 'eval_runtime': 3.1346, 'eval_samples_per_second': 118.674, 'eval_steps_per_secon
d': 14.994, 'epoch': 1.98}

 40%|████      | 751/1865 [06:20<21:11,  1.14s/it]
{'eval_loss': 0.06534568220376968, 'eval_runtime': 3.0999, 'eval_samples_per_second': 120.002, 'eval_steps_per_secon
d': 15.162, 'epoch': 2.01}

 41%|████      | 761/1865 [06:25<20:55,  1.14s/it]
{'eval_loss': 0.0649729073047638, 'eval_runtime': 3.0918, 'eval_samples_per_second': 120.319, 'eval_steps_per_secon
d': 15.202, 'epoch': 2.04}

 41%|████▏     | 771/1865 [06:31<24:36,  1.35s/it]
{'eval_loss': 0.06561870127916336, 'eval_runtime': 3.7772, 'eval_samples_per_second': 98.486, 'eval_steps_per_secon
d': 12.443, 'epoch': 2.06}

 42%|████▏     | 781/1865 [06:36<21:20,  1.18s/it]
{'eval_loss': 0.06476814299821854, 'eval_runtime': 3.1965, 'eval_samples_per_second': 116.379, 'eval_steps_per_secon
d': 14.704, 'epoch': 2.09}

 42%|████▏     | 790/1865 [06:41<03:57,  4.52it/s]
{'eval_loss': 0.0649571567773819, 'eval_runtime': 3.1845, 'eval_samples_per_second': 116.815, 'eval_steps_per_secon
d': 14.759, 'epoch': 2.12}

 43%|████▎     | 800/1865 [06:46<04:09,  4.27it/s]
{'eval_loss': 0.06444787234067917, 'eval_runtime': 3.2269, 'eval_samples_per_second': 115.28, 'eval_steps_per_secon
d': 14.565, 'epoch': 2.14}

 43%|████▎     | 811/1865 [06:51<20:49,  1.19s/it]
{'eval_loss': 0.06427986174821854, 'eval_runtime': 3.2121, 'eval_samples_per_second': 115.813, 'eval_steps_per_secon
d': 14.632, 'epoch': 2.17}

 44%|████▍     | 821/1865 [06:56<20:19,  1.17s/it]
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{'eval_loss': 0.06420110911130905, 'eval_runtime': 3.11, 'eval_samples_per_second': 119.614, 'eval_steps_per_second':
15.113, 'epoch': 2.2}

 45%|████▍     | 831/1865 [07:01<19:38,  1.14s/it]
{'eval_loss': 0.06432186812162399, 'eval_runtime': 3.0931, 'eval_samples_per_second': 120.266, 'eval_steps_per_secon
d': 15.195, 'epoch': 2.23}

 45%|████▌     | 841/1865 [07:06<19:30,  1.14s/it]
{'eval_loss': 0.06439536809921265, 'eval_runtime': 3.103, 'eval_samples_per_second': 119.885, 'eval_steps_per_secon
d': 15.147, 'epoch': 2.25}

 46%|████▌     | 851/1865 [07:11<19:18,  1.14s/it]
{'eval_loss': 0.06362882256507874, 'eval_runtime': 3.0985, 'eval_samples_per_second': 120.06, 'eval_steps_per_secon
d': 15.169, 'epoch': 2.28}

 46%|████▌     | 861/1865 [07:16<19:09,  1.14s/it]
{'eval_loss': 0.06394384056329727, 'eval_runtime': 3.1175, 'eval_samples_per_second': 119.326, 'eval_steps_per_secon
d': 15.076, 'epoch': 2.31}

 47%|████▋     | 871/1865 [07:21<19:06,  1.15s/it]
{'eval_loss': 0.06408035010099411, 'eval_runtime': 3.1478, 'eval_samples_per_second': 118.178, 'eval_steps_per_secon
d': 14.931, 'epoch': 2.33}

 47%|████▋     | 880/1865 [07:26<03:38,  4.51it/s]
{'eval_loss': 0.06355531513690948, 'eval_runtime': 3.1621, 'eval_samples_per_second': 117.644, 'eval_steps_per_secon
d': 14.864, 'epoch': 2.36}

 48%|████▊     | 891/1865 [07:31<18:46,  1.16s/it]
{'eval_loss': 0.06349756568670273, 'eval_runtime': 3.1363, 'eval_samples_per_second': 118.611, 'eval_steps_per_secon
d': 14.986, 'epoch': 2.39}

 48%|████▊     | 900/1865 [07:36<03:29,  4.61it/s]
{'eval_loss': 0.06337680667638779, 'eval_runtime': 3.1118, 'eval_samples_per_second': 119.545, 'eval_steps_per_secon
d': 15.104, 'epoch': 2.41}

 49%|████▉     | 911/1865 [07:41<18:29,  1.16s/it]
{'eval_loss': 0.06334005296230316, 'eval_runtime': 3.1486, 'eval_samples_per_second': 118.146, 'eval_steps_per_secon
d': 14.927, 'epoch': 2.44}
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 49%|████▋     | 921/1865 [07:46<18:11,  1.16s/it]
{'eval_loss': 0.0629725307226181, 'eval_runtime': 3.1474, 'eval_samples_per_second': 118.194, 'eval_steps_per_secon
d': 14.933, 'epoch': 2.47}

 50%|████▉     | 931/1865 [07:51<17:55,  1.15s/it]
{'eval_loss': 0.06289377808570862, 'eval_runtime': 3.1327, 'eval_samples_per_second': 118.747, 'eval_steps_per_secon
d': 15.003, 'epoch': 2.49}

 50%|█████     | 941/1865 [07:56<17:48,  1.16s/it]
{'eval_loss': 0.0631667897105217, 'eval_runtime': 3.1346, 'eval_samples_per_second': 118.675, 'eval_steps_per_secon
d': 14.994, 'epoch': 2.52}

 51%|█████     | 951/1865 [08:01<17:35,  1.15s/it]
{'eval_loss': 0.06275201588869095, 'eval_runtime': 3.1367, 'eval_samples_per_second': 118.597, 'eval_steps_per_secon
d': 14.984, 'epoch': 2.55}

 52%|█████▏    | 961/1865 [08:06<17:25,  1.16s/it]
{'eval_loss': 0.06255775690078735, 'eval_runtime': 3.1397, 'eval_samples_per_second': 118.481, 'eval_steps_per_secon
d': 14.969, 'epoch': 2.57}

 52%|█████▏    | 971/1865 [08:11<17:21,  1.16s/it]
{'eval_loss': 0.06283076852560043, 'eval_runtime': 3.1586, 'eval_samples_per_second': 117.774, 'eval_steps_per_secon
d': 14.88, 'epoch': 2.6}

 53%|█████▎    | 980/1865 [08:16<03:18,  4.46it/s]
{'eval_loss': 0.06289902329444885, 'eval_runtime': 3.1331, 'eval_samples_per_second': 118.733, 'eval_steps_per_secon
d': 15.001, 'epoch': 2.63}

 53%|█████▎    | 991/1865 [08:21<16:53,  1.16s/it]
{'eval_loss': 0.06371808052062988, 'eval_runtime': 3.1439, 'eval_samples_per_second': 118.324, 'eval_steps_per_secon
d': 14.95, 'epoch': 2.65}
 54%|█████▎    | 1000/1865 [08:23<03:15,  4.43it/s]
{'loss': 0.0888, 'grad_norm': 0.06895048171281815, 'learning_rate': 0.00046380697050938335, 'epoch': 2.68}

 54%|█████▎    | 1000/1865 [08:26<03:15,  4.43it/s]
{'eval_loss': 0.06247112154960632, 'eval_runtime': 3.1341, 'eval_samples_per_second': 118.695, 'eval_steps_per_secon
d': 14.996, 'epoch': 2.68}
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 54%|█████▍    | 1011/1865 [08:32<16:33,  1.16s/it]
{'eval_loss': 0.06292002648115158, 'eval_runtime': 3.1485, 'eval_samples_per_second': 118.152, 'eval_steps_per_secon
d': 14.928, 'epoch': 2.71}

 55%|█████▍    | 1020/1865 [08:36<03:11,  4.42it/s]
{'eval_loss': 0.06193558871746063, 'eval_runtime': 3.1539, 'eval_samples_per_second': 117.95, 'eval_steps_per_secon
d': 14.902, 'epoch': 2.73}

 55%|█████▌    | 1031/1865 [08:42<16:03,  1.16s/it]
{'eval_loss': 0.06236349046230316, 'eval_runtime': 3.1324, 'eval_samples_per_second': 118.757, 'eval_steps_per_secon
d': 15.004, 'epoch': 2.76}

 56%|█████▌    | 1041/1865 [08:47<15:56,  1.16s/it]
{'eval_loss': 0.062022220343351364, 'eval_runtime': 3.1458, 'eval_samples_per_second': 118.254, 'eval_steps_per_secon
d': 14.941, 'epoch': 2.79}

 56%|█████▋    | 1051/1865 [08:52<15:46,  1.16s/it]
{'eval_loss': 0.06223485618829727, 'eval_runtime': 3.1529, 'eval_samples_per_second': 117.986, 'eval_steps_per_secon
d': 14.907, 'epoch': 2.82}

 57%|█████▋    | 1061/1865 [08:57<15:33,  1.16s/it]
{'eval_loss': 0.06181482970714569, 'eval_runtime': 3.1482, 'eval_samples_per_second': 118.163, 'eval_steps_per_secon
d': 14.929, 'epoch': 2.84}

 57%|█████▋    | 1071/1865 [09:02<15:20,  1.16s/it]
{'eval_loss': 0.06191721186041832, 'eval_runtime': 3.1405, 'eval_samples_per_second': 118.453, 'eval_steps_per_secon
d': 14.966, 'epoch': 2.87}

 58%|█████▊    | 1081/1865 [09:07<15:10,  1.16s/it]
{'eval_loss': 0.061615318059921265, 'eval_runtime': 3.1487, 'eval_samples_per_second': 118.146, 'eval_steps_per_secon
d': 14.927, 'epoch': 2.9}

 58%|█████▊    | 1091/1865 [09:12<15:00,  1.16s/it]
{'eval_loss': 0.06182270497083664, 'eval_runtime': 3.1543, 'eval_samples_per_second': 117.933, 'eval_steps_per_secon
d': 14.9, 'epoch': 2.92}

 59%|█████▉    | 1100/1865 [09:17<02:53,  4.40it/s]
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{'eval_loss': 0.06146305799484253, 'eval_runtime': 3.1463, 'eval_samples_per_second': 118.234, 'eval_steps_per_secon
d': 14.938, 'epoch': 2.95}

 60%|██████     | 1111/1865 [09:22<14:36,  1.16s/it]
{'eval_loss': 0.0617518275976181, 'eval_runtime': 3.143, 'eval_samples_per_second': 118.357, 'eval_steps_per_second':
14.954, 'epoch': 2.98}

 60%|██████     | 1121/1865 [09:27<14:16,  1.15s/it]
{'eval_loss': 0.061581190675497055, 'eval_runtime': 3.1535, 'eval_samples_per_second': 117.963, 'eval_steps_per_secon
d': 14.904, 'epoch': 3.0}

 61%|██████     | 1131/1865 [09:32<14:16,  1.17s/it]
{'eval_loss': 0.061342302709817886, 'eval_runtime': 3.1654, 'eval_samples_per_second': 117.521, 'eval_steps_per_secon
d': 14.848, 'epoch': 3.03}

 61%|██████     | 1141/1865 [09:37<13:57,  1.16s/it]
{'eval_loss': 0.06129767373204231, 'eval_runtime': 3.1319, 'eval_samples_per_second': 118.779, 'eval_steps_per_secon
d': 15.007, 'epoch': 3.06}

 62%|██████▏    | 1151/1865 [09:42<13:49,  1.16s/it]
{'eval_loss': 0.06148406118154526, 'eval_runtime': 3.1509, 'eval_samples_per_second': 118.06, 'eval_steps_per_secon
d': 14.916, 'epoch': 3.08}

 62%|██████▏    | 1161/1865 [09:47<13:39,  1.16s/it]
{'eval_loss': 0.06157331541180611, 'eval_runtime': 3.1553, 'eval_samples_per_second': 117.899, 'eval_steps_per_secon
d': 14.896, 'epoch': 3.11}

 63%|██████▎    | 1171/1865 [09:52<13:30,  1.17s/it]
{'eval_loss': 0.06095639988780022, 'eval_runtime': 3.1642, 'eval_samples_per_second': 117.565, 'eval_steps_per_secon
d': 14.854, 'epoch': 3.14}

 63%|██████▎    | 1181/1865 [09:57<13:14,  1.16s/it]
{'eval_loss': 0.06116903945803642, 'eval_runtime': 3.1497, 'eval_samples_per_second': 118.106, 'eval_steps_per_secon
d': 14.922, 'epoch': 3.16}

 64%|██████▍    | 1191/1865 [10:02<13:04,  1.16s/it]
{'eval_loss': 0.06092489883303642, 'eval_runtime': 3.1533, 'eval_samples_per_second': 117.971, 'eval_steps_per_secon
d': 14.905, 'epoch': 3.19}
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 64%|██████▍   | 1200/1865 [10:07<02:31,  4.39it/s]
{'eval_loss': 0.060990527272224426, 'eval_runtime': 3.1583, 'eval_samples_per_second': 117.785, 'eval_steps_per_secon
d': 14.881, 'epoch': 3.22}

 65%|██████▍   | 1211/1865 [10:13<12:43,  1.17s/it]
{'eval_loss': 0.06089864671230316, 'eval_runtime': 3.1593, 'eval_samples_per_second': 117.749, 'eval_steps_per_secon
d': 14.877, 'epoch': 3.24}

 65%|██████▌   | 1221/1865 [10:18<12:27,  1.16s/it]
{'eval_loss': 0.060612503439188004, 'eval_runtime': 3.1453, 'eval_samples_per_second': 118.271, 'eval_steps_per_secon
d': 14.943, 'epoch': 3.27}

 66%|██████▌   | 1231/1865 [10:23<12:21,  1.17s/it]
{'eval_loss': 0.0606440044939518, 'eval_runtime': 3.1714, 'eval_samples_per_second': 117.298, 'eval_steps_per_secon
d': 14.82, 'epoch': 3.3}

 67%|██████▋   | 1241/1865 [10:28<12:07,  1.17s/it]
{'eval_loss': 0.06070176139473915, 'eval_runtime': 3.1617, 'eval_samples_per_second': 117.659, 'eval_steps_per_secon
d': 14.866, 'epoch': 3.32}

 67%|██████▋   | 1251/1865 [10:33<11:56,  1.17s/it]
{'eval_loss': 0.06057312712073326, 'eval_runtime': 3.1614, 'eval_samples_per_second': 117.668, 'eval_steps_per_secon
d': 14.867, 'epoch': 3.35}

 68%|██████▊   | 1261/1865 [10:38<11:44,  1.17s/it]
{'eval_loss': 0.060515373945236206, 'eval_runtime': 3.1634, 'eval_samples_per_second': 117.593, 'eval_steps_per_secon
d': 14.857, 'epoch': 3.38}

 68%|██████▊   | 1271/1865 [10:43<11:32,  1.17s/it]
{'eval_loss': 0.060686007142066956, 'eval_runtime': 3.1601, 'eval_samples_per_second': 117.719, 'eval_steps_per_secon
d': 14.873, 'epoch': 3.4}

 69%|██████▊   | 1281/1865 [10:48<11:21,  1.17s/it]
{'eval_loss': 0.06065713241696358, 'eval_runtime': 3.1646, 'eval_samples_per_second': 117.549, 'eval_steps_per_secon
d': 14.852, 'epoch': 3.43}

 69%|██████▉   | 1291/1865 [10:53<11:09,  1.17s/it]
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{'eval_loss': 0.06052849814295769, 'eval_runtime': 3.1598, 'eval_samples_per_second': 117.728, 'eval_steps_per_secon
d': 14.874, 'epoch': 3.46}

 70%|███████▌  | 1300/1865 [10:58<02:09,  4.37it/s]
{'eval_loss': 0.06049437075853348, 'eval_runtime': 3.153, 'eval_samples_per_second': 117.984, 'eval_steps_per_secon
d': 14.907, 'epoch': 3.49}

 70%|███████   | 1311/1865 [11:04<10:45,  1.17s/it]
{'eval_loss': 0.06041036546230316, 'eval_runtime': 3.1549, 'eval_samples_per_second': 117.912, 'eval_steps_per_secon
d': 14.898, 'epoch': 3.51}

 71%|███████   | 1321/1865 [11:09<10:33,  1.17s/it]
{'eval_loss': 0.06034473702311516, 'eval_runtime': 3.1586, 'eval_samples_per_second': 117.775, 'eval_steps_per_secon
d': 14.88, 'epoch': 3.54}

 71%|███████▏  | 1331/1865 [11:14<10:25,  1.17s/it]
{'eval_loss': 0.06049174815416336, 'eval_runtime': 3.1793, 'eval_samples_per_second': 117.006, 'eval_steps_per_secon
d': 14.783, 'epoch': 3.57}

 72%|███████▏  | 1341/1865 [11:19<10:09,  1.16s/it]
{'eval_loss': 0.06027385592460632, 'eval_runtime': 3.1525, 'eval_samples_per_second': 118.003, 'eval_steps_per_secon
d': 14.909, 'epoch': 3.59}

 72%|███████▏  | 1351/1865 [11:24<09:57,  1.16s/it]
{'eval_loss': 0.060386739671230316, 'eval_runtime': 3.1509, 'eval_samples_per_second': 118.062, 'eval_steps_per_secon
d': 14.916, 'epoch': 3.62}

 73%|███████▎  | 1361/1865 [11:29<09:45,  1.16s/it]
{'eval_loss': 0.06023447960615158, 'eval_runtime': 3.1534, 'eval_samples_per_second': 117.967, 'eval_steps_per_secon
d': 14.904, 'epoch': 3.65}

 74%|███████▎  | 1371/1865 [11:34<09:57,  1.21s/it]
{'eval_loss': 0.06025548279285431, 'eval_runtime': 3.1619, 'eval_samples_per_second': 117.651, 'eval_steps_per_secon
d': 14.865, 'epoch': 3.67}

 74%|███████▍  | 1381/1865 [11:39<09:24,  1.17s/it]
{'eval_loss': 0.06031585857272148, 'eval_runtime': 3.1625, 'eval_samples_per_second': 117.627, 'eval_steps_per_secon
d': 14.861, 'epoch': 3.7}
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 75%|███████▌  | 1391/1865 [11:44<09:11,  1.16s/it]
{'eval_loss': 0.0602213554084301, 'eval_runtime': 3.1567, 'eval_samples_per_second': 117.846, 'eval_steps_per_secon
d': 14.889, 'epoch': 3.73}

 75%|███████▌  | 1400/1865 [11:49<01:45,  4.39it/s]
{'eval_loss': 0.060142599046230316, 'eval_runtime': 3.1484, 'eval_samples_per_second': 118.154, 'eval_steps_per_secon
d': 14.928, 'epoch': 3.75}

 76%|███████▌  | 1411/1865 [11:55<08:50,  1.17s/it]
{'eval_loss': 0.05994571000337601, 'eval_runtime': 3.1597, 'eval_samples_per_second': 117.731, 'eval_steps_per_secon
d': 14.875, 'epoch': 3.78}

 76%|███████▌  | 1421/1865 [12:00<08:38,  1.17s/it]
{'eval_loss': 0.06015310063958168, 'eval_runtime': 3.1601, 'eval_samples_per_second': 117.717, 'eval_steps_per_secon
d': 14.873, 'epoch': 3.81}

 77%|███████▋  | 1431/1865 [12:05<08:25,  1.16s/it]
{'eval_loss': 0.06013735011219978, 'eval_runtime': 3.1552, 'eval_samples_per_second': 117.901, 'eval_steps_per_secon
d': 14.896, 'epoch': 3.83}

 77%|███████▋  | 1440/1865 [12:10<01:36,  4.40it/s]
{'eval_loss': 0.05998246371746063, 'eval_runtime': 3.1542, 'eval_samples_per_second': 117.937, 'eval_steps_per_secon
d': 14.901, 'epoch': 3.86}

 78%|███████▊  | 1451/1865 [12:15<08:00,  1.16s/it]
{'eval_loss': 0.059974588453769684, 'eval_runtime': 3.1464, 'eval_samples_per_second': 118.231, 'eval_steps_per_secon
d': 14.938, 'epoch': 3.89}

 78%|███████▊  | 1461/1865 [12:20<07:50,  1.17s/it]
{'eval_loss': 0.05992733687162399, 'eval_runtime': 3.1653, 'eval_samples_per_second': 117.526, 'eval_steps_per_secon
d': 14.849, 'epoch': 3.91}

 79%|███████▉  | 1471/1865 [12:25<07:40,  1.17s/it]
{'eval_loss': 0.05984333157539368, 'eval_runtime': 3.1685, 'eval_samples_per_second': 117.405, 'eval_steps_per_secon
d': 14.833, 'epoch': 3.94}

 79%|███████▉  | 1481/1865 [12:30<07:28,  1.17s/it]
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{'eval_loss': 0.0599115826189518, 'eval_runtime': 3.1615, 'eval_samples_per_second': 117.666, 'eval_steps_per_secon
d': 14.866, 'epoch': 3.97}

 80%|████████  | 1491/1865 [12:35<07:14,  1.16s/it]
{'eval_loss': 0.05967269465327263, 'eval_runtime': 3.1466, 'eval_samples_per_second': 118.224, 'eval_steps_per_secon
d': 14.937, 'epoch': 3.99}
 80%|████████  | 1500/1865 [12:37<01:27,  4.16it/s]
{'loss': 0.0785, 'grad_norm': 0.04232126846909523, 'learning_rate': 0.00019571045576407506, 'epoch': 4.02}

 80%|████████  | 1500/1865 [12:40<01:27,  4.16it/s]
{'eval_loss': 0.05969894677400589, 'eval_runtime': 3.1481, 'eval_samples_per_second': 118.165, 'eval_steps_per_secon
d': 14.929, 'epoch': 4.02}

 81%|████████  | 1510/1865 [12:45<01:22,  4.32it/s]
{'eval_loss': 0.05979344993829727, 'eval_runtime': 3.1578, 'eval_samples_per_second': 117.804, 'eval_steps_per_secon
d': 14.884, 'epoch': 4.05}

 82%|████████▏ | 1521/1865 [12:50<06:41,  1.17s/it]
{'eval_loss': 0.05973832309246063, 'eval_runtime': 3.163, 'eval_samples_per_second': 117.61, 'eval_steps_per_second':
14.859, 'epoch': 4.08}

 82%|████████▏ | 1531/1865 [12:55<06:29,  1.16s/it]
{'eval_loss': 0.05989058315753937, 'eval_runtime': 3.1556, 'eval_samples_per_second': 117.884, 'eval_steps_per_secon
d': 14.894, 'epoch': 4.1}

 83%|████████▎ | 1540/1865 [13:00<01:14,  4.38it/s]
{'eval_loss': 0.05983807891607284‌5, 'eval_runtime': 3.1586, 'eval_samples_per_second': 117.772, 'eval_steps_per_secon
d': 14.88, 'epoch': 4.13}

 83%|████████▎ | 1551/1865 [13:06<06:06,  1.17s/it]
{'eval_loss': 0.059572938829660416, 'eval_runtime': 3.1631, 'eval_samples_per_second': 117.605, 'eval_steps_per_secon
d': 14.859, 'epoch': 4.16}

 84%|████████▎ | 1560/1865 [13:10<01:09,  4.40it/s]
{'eval_loss': 0.05951518565416336, 'eval_runtime': 3.1498, 'eval_samples_per_second': 118.103, 'eval_steps_per_secon
d': 14.922, 'epoch': 4.18}

 84%|████████▍ | 1571/1865 [13:16<05:42,  1.17s/it]
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{'eval_loss': 0.05953618511557579, 'eval_runtime': 3.1603, 'eval_samples_per_second': 117.709, 'eval_steps_per_secon
d': 14.872, 'epoch': 4.21}

 85%|████████▍ | 1581/1865 [13:21<05:30,  1.16s/it]
{'eval_loss': 0.059546686708927155, 'eval_runtime': 3.1552, 'eval_samples_per_second': 117.9, 'eval_steps_per_secon
d': 14.896, 'epoch': 4.24}

 85%|████████▌ | 1591/1865 [13:26<05:19,  1.16s/it]
{'eval_loss': 0.05962543934583664, 'eval_runtime': 3.1591, 'eval_samples_per_second': 117.757, 'eval_steps_per_secon
d': 14.878, 'epoch': 4.26}

 86%|████████▌ | 1600/1865 [13:31<01:00,  4.37it/s]
{'eval_loss': 0.05946793034672737, 'eval_runtime': 3.1572, 'eval_samples_per_second': 117.824, 'eval_steps_per_secon
d': 14.886, 'epoch': 4.29}

 86%|████████▋ | 1611/1865 [13:36<04:56,  1.17s/it]
{'eval_loss': 0.059328798204660416, 'eval_runtime': 3.155, 'eval_samples_per_second': 117.906, 'eval_steps_per_secon
d': 14.897, 'epoch': 4.32}

 87%|████████▋ | 1620/1865 [13:41<00:55,  4.38it/s]
{'eval_loss': 0.059478431940078735, 'eval_runtime': 3.1527, 'eval_samples_per_second': 117.996, 'eval_steps_per_secon
d': 14.908, 'epoch': 4.34}

 87%|████████▋ | 1631/1865 [13:46<04:33,  1.17s/it]
{'eval_loss': 0.059633318334817886, 'eval_runtime': 3.1661, 'eval_samples_per_second': 117.493, 'eval_steps_per_secon
d': 14.845, 'epoch': 4.37}

 88%|████████▊ | 1641/1865 [13:51<04:20,  1.16s/it]
{'eval_loss': 0.05948368087410927, 'eval_runtime': 3.1519, 'eval_samples_per_second': 118.025, 'eval_steps_per_secon
d': 14.912, 'epoch': 4.4}

 89%|████████▊ | 1651/1865 [13:56<04:07,  1.16s/it]
{'eval_loss': 0.059504684060811996, 'eval_runtime': 3.1386, 'eval_samples_per_second': 118.523, 'eval_steps_per_secon
d': 14.975, 'epoch': 4.42}

 89%|████████▉ | 1661/1865 [14:01<03:57,  1.16s/it]
{'eval_loss': 0.05947580561041832, 'eval_runtime': 3.1523, 'eval_samples_per_second': 118.008, 'eval_steps_per_secon
d': 14.91, 'epoch': 4.45}
```

```
 90%|████████▉ | 1671/1865 [14:06<03:45,  1.16s/it]
{'eval_loss': 0.05935505032539368, 'eval_runtime': 3.1525, 'eval_samples_per_second': 118.002, 'eval_steps_per_secon
d': 14.909, 'epoch': 4.48}

 90%|█████████ | 1681/1865 [14:12<03:34,  1.17s/it]
{'eval_loss': 0.059234291315078735, 'eval_runtime': 3.1612, 'eval_samples_per_second': 117.675, 'eval_steps_per_secon
d': 14.868, 'epoch': 4.5}

 91%|█████████ | 1691/1865 [14:17<03:22,  1.16s/it]
{'eval_loss': 0.05947580561041832, 'eval_runtime': 3.1528, 'eval_samples_per_second': 117.989, 'eval_steps_per_secon
d': 14.907, 'epoch': 4.53}

 91%|█████████ | 1700/1865 [14:21<00:37,  4.40it/s]
{'eval_loss': 0.05953618511557579, 'eval_runtime': 3.151, 'eval_samples_per_second': 118.057, 'eval_steps_per_secon
d': 14.916, 'epoch': 4.56}

 92%|█████████▏| 1711/1865 [14:27<02:59,  1.16s/it]
{'eval_loss': 0.05943642929196358, 'eval_runtime': 3.16, 'eval_samples_per_second': 117.72, 'eval_steps_per_second':
14.873, 'epoch': 4.58}

 92%|█████████▏| 1721/1865 [14:32<02:48,  1.17s/it]
{'eval_loss': 0.05929729342460632, 'eval_runtime': 3.1699, 'eval_samples_per_second': 117.355, 'eval_steps_per_secon
d': 14.827, 'epoch': 4.61}

 93%|█████████▎| 1731/1865 [14:37<02:36,  1.17s/it]
{'eval_loss': 0.05927629396319389, 'eval_runtime': 3.1641, 'eval_samples_per_second': 117.571, 'eval_steps_per_secon
d': 14.854, 'epoch': 4.64}

 93%|█████████▎| 1741/1865 [14:42<02:24,  1.17s/it]
{'eval_loss': 0.05921328812837601, 'eval_runtime': 3.1629, 'eval_samples_per_second': 117.613, 'eval_steps_per_secon
d': 14.86, 'epoch': 4.66}

 94%|█████████▍| 1751/1865 [14:47<02:12,  1.16s/it]
{'eval_loss': 0.05922378972172737, 'eval_runtime': 3.1465, 'eval_samples_per_second': 118.227, 'eval_steps_per_secon
d': 14.937, 'epoch': 4.69}

 94%|█████████▍| 1761/1865 [14:52<02:01,  1.17s/it]
```

```
{'eval_loss': 0.059315670281648636, 'eval_runtime': 3.1629, 'eval_samples_per_second': 117.615, 'eval_steps_per_secon
d': 14.86, 'epoch': 4.72}

 95%|█████████▍| 1771/1865 [14:57<01:49,  1.16s/it]
{'eval_loss': 0.05932092294096947, 'eval_runtime': 3.1534, 'eval_samples_per_second': 117.968, 'eval_steps_per_secon
d': 14.905, 'epoch': 4.75}

 95%|█████████▌| 1780/1865 [15:02<00:19,  4.38it/s]
{'eval_loss': 0.05931304767727852, 'eval_runtime': 3.1666, 'eval_samples_per_second': 117.477, 'eval_steps_per_secon
d': 14.842, 'epoch': 4.77}

 96%|█████████▌| 1791/1865 [15:07<01:26,  1.17s/it]
{'eval_loss': 0.05930516868829727, 'eval_runtime': 3.1578, 'eval_samples_per_second': 117.803, 'eval_steps_per_secon
d': 14.884, 'epoch': 4.8}

 97%|█████████▋| 1800/1865 [15:12<00:14,  4.39it/s]
{'eval_loss': 0.059389177709817886, 'eval_runtime': 3.1528, 'eval_samples_per_second': 117.989, 'eval_steps_per_secon
d': 14.907, 'epoch': 4.83}

 97%|█████████▋| 1811/1865 [15:18<01:02,  1.17s/it]
{'eval_loss': 0.059315670281648636, 'eval_runtime': 3.1538, 'eval_samples_per_second': 117.951, 'eval_steps_per_secon
d': 14.902, 'epoch': 4.85}

 98%|█████████▊| 1821/1865 [15:23<00:51,  1.16s/it]
{'eval_loss': 0.05927892029285431, 'eval_runtime': 3.1529, 'eval_samples_per_second': 117.985, 'eval_steps_per_secon
d': 14.907, 'epoch': 4.88}

 98%|█████████▊| 1831/1865 [15:28<00:39,  1.16s/it]
{'eval_loss': 0.05930516868829727, 'eval_runtime': 3.1419, 'eval_samples_per_second': 118.401, 'eval_steps_per_secon
d': 14.959, 'epoch': 4.91}

 99%|█████████▊| 1841/1865 [15:33<00:27,  1.16s/it]
{'eval_loss': 0.059289418160915375, 'eval_runtime': 3.1462, 'eval_samples_per_second': 118.238, 'eval_steps_per_secon
d': 14.939, 'epoch': 4.93}

 99%|█████████▉| 1851/1865 [15:38<00:16,  1.17s/it]
{'eval_loss': 0.05931304767727852, 'eval_runtime': 3.1648, 'eval_samples_per_second': 117.542, 'eval_steps_per_secon
d': 14.851, 'epoch': 4.96}
```

```
100%|█████████▉| 1861/1865 [15:43<00:04,  1.16s/it]
{'eval_loss': 0.05931304767727852, 'eval_runtime': 3.1507, 'eval_samples_per_second': 118.07, 'eval_steps_per_secon
d': 14.917, 'epoch': 4.99}
100%|██████████| 1865/1865 [15:44<00:00,  1.97it/s]
{'train_runtime': 944.3468, 'train_samples_per_second': 15.778, 'train_steps_per_second': 1.975, 'train_loss': 0.4984
449616705764, 'epoch': 5.0}
```

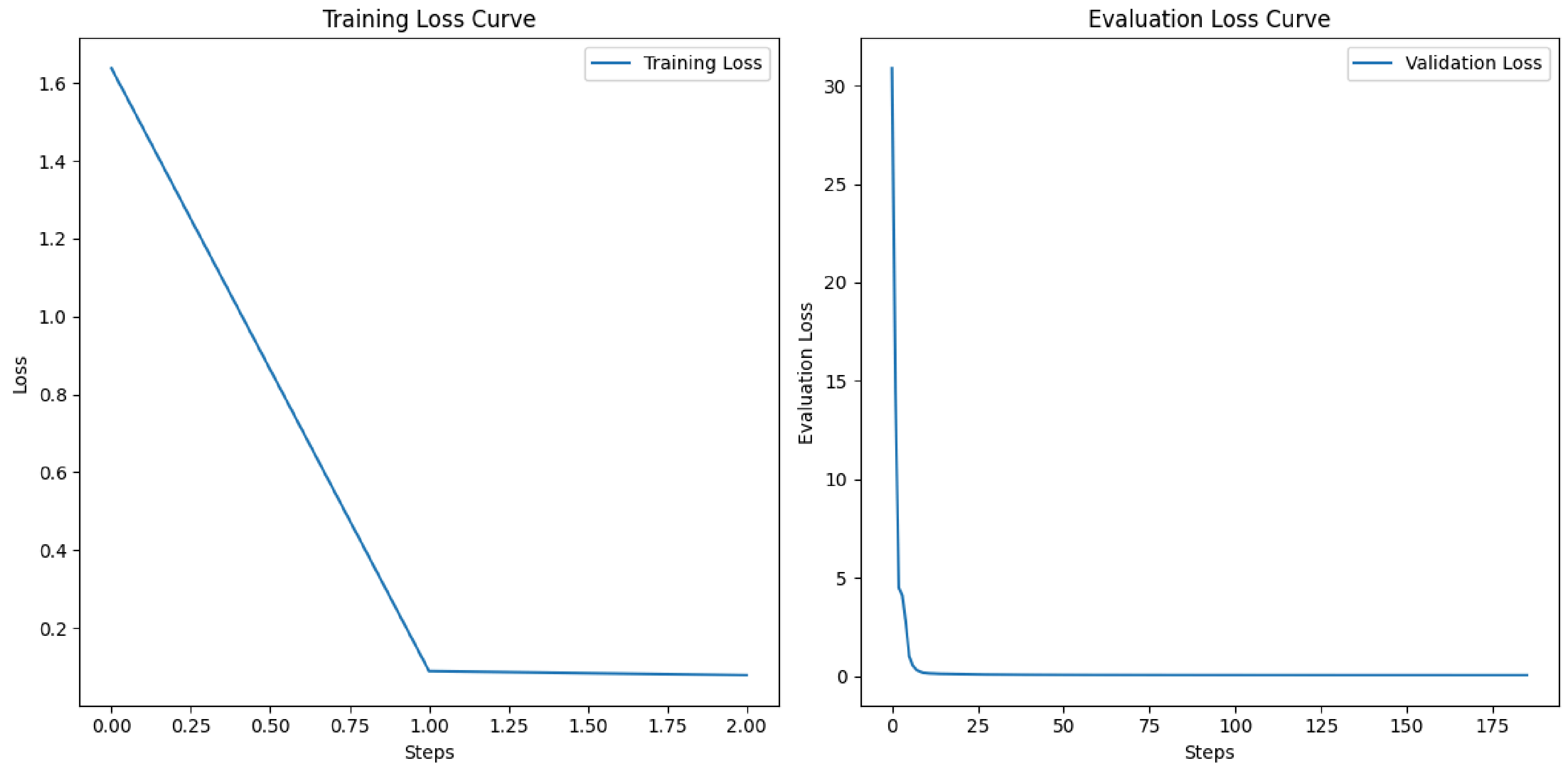
In [ ]:
```python
# Evaluate using the validation dataset
peft_trainer.evaluate(tokenized_datasets['validation'])
```

```
100%|██████████| 47/47 [00:03<00:00, 15.16it/s]
```

Out[ ]:
```
{'eval_loss': 0.05931829661130905,
 'eval_runtime': 3.1482,
 'eval_samples_per_second': 118.162,
 'eval_steps_per_second': 14.929,
 'epoch': 5.0}
```

In [ ]:
```python
# Path to the log file
import json
log_file_path = f"{output_dir}/checkpoint-1865/trainer_state.json"

# Load the log file
with open(log_file_path, "r") as log_file:
    logs = json.load(log_file)

# Extract the training losses
training_losses = [entry["loss"] for entry in logs["log_history"] if "loss" in entry]
# Extract validation loss from log history
validation_loss = [entry['eval_loss'] for entry in logs["log_history"] if "eval_loss" in entry]

# Plot the learning curve
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))

ax1.plot(training_losses, label="Training Loss")
ax1.set_xlabel("Steps")
ax1.set_ylabel("Loss")
ax1.set_title("Training Loss Curve")
ax1.legend()

ax2.plot(validation_loss, label="Validation Loss")
```

```
ax2.set_xlabel("Steps")
ax2.set_ylabel("Evaluation Loss")
ax2.set_title("Evaluation Loss Curve")
ax2.legend()

plt.tight_layout()

plt.show()
```



Save the fine-tuned model

In [ ]:
```
peft_model_path="./peft-conversation-checkpoint-local"

peft_trainer.model.save_pretrained(peft_model_path)
tokenizer.save_pretrained(peft_model_path)
```

```
Out[ ]: ('./peft-conversation-checkpoint-local\\tokenizer_config.json',
         './peft-conversation-checkpoint-local\\special_tokens_map.json',
         './peft-conversation-checkpoint-local\\tokenizer.json')
```

Adding an adapter to the original flan-t5 model

```
In [ ]: from peft import PeftModel

        peft_model_base = AutoModelForSeq2SeqLM.from_pretrained("google/flan-t5-base", torch_dtype=torch.bfloat16)
        tokenizer = AutoTokenizer.from_pretrained("google/flan-t5-base")

        peft_model = PeftModel.from_pretrained(peft_model_base,
                                               'peft-conversation-checkpoint-local',
                                               torch_dtype=torch.bfloat16,
                                               is_trainable=False)
```

```
In [ ]: print(model_parameters(peft_model))
```

```
trainable model parameters: 0
all model parameters: 248462592
percentage of trainable model parameters: 0.00%
```

```
In [ ]: def insert_prompt(prompt):
            input_ids = tokenizer(prompt, return_tensors="pt").input_ids

            peft_model_outputs = peft_model.generate(input_ids=input_ids, generation_config=GenerationConfig(max_new_tokens=
            peft_model_text_output = tokenizer.decode(peft_model_outputs[0], skip_special_tokens=True)

            return peft_model_text_output
```

```
In [ ]: prompt = "where is paris?"

        print(f'question:\n{prompt}')
        print(f'PEFT MODEL: {insert_prompt(prompt)}')
```

```
question:
where is paris?
PEFT MODEL: France
```

```
In [ ]: prompt = "What is the capital of california?"
```

```
print(f'question:\n{prompt}')
print(f'PEFT MODEL: {insert_prompt(prompt)}')
```

```
question:
What is the capital of california?
PEFT MODEL: San Francisco
```

In [ ]:
```
prompt = "What is the capital of Italy"

print(f'question:\n{prompt}')
print(f'PEFT MODEL: {insert_prompt(prompt)}')
```

```
question:
What is the capital of Italy
PEFT MODEL: Rome
```

In [ ]:
```
prompt = "What is the best drink for a hangover?"

print(f'question:\n{prompt}')
print(f'PEFT MODEL: {insert_prompt(prompt)}')
```

```
question:
What is the best drink for a hangover?
PEFT MODEL: a stout
```

In [ ]:
```
prompt = "What is the probability that two apples will fall at the same time?"

print(f'question:\n{prompt}')
print(f'PEFT MODEL: {insert_prompt(prompt)}')
```

```
question:
What is the probability that two apples will fall at the same time?
PEFT MODEL: 1 / 2
```