Evaluate Pretrained Model’s Generative Baseline

Model & Domain Selection

For this project, I selected GPT-2 small (gpt2) as the base model. GPT-2 small is a widely accessible, decoder-only transformer model with approximately 124M parameters. Its compact size makes it particularly suitable for experiments on modest computational resources such as Google Colab, where larger models would be impractical to train or fine-tune within time and hardware constraints. At the same time, it retains enough expressive capacity to generate coherent and stylistically varied text, providing a meaningful baseline for adaptation experiments.

The chosen domain is early nineteenth-century English literary prose, specifically excerpts from the opening chapters of *Pride and Prejudice* by Jane Austen. Austen’s writing is a strong candidate for fine-tuning because it exhibits a highly distinctive style: long, complex sentence structures, frequent use of irony, and a thematic focus on social conventions and relationships. Even short passages from her novels present a recognizable stylistic fingerprint, which contrasts sharply with the more generic outputs of an unfine-tuned GPT-2 model. The motivation for this pairing is twofold: GPT-2 small offers feasibility and accessibility, enabling fast iteration and manageable training times, while Austen’s prose provides a stylistically distinctive benchmark, allowing us to clearly evaluate whether fine-tuning effectively transfers domain-specific characteristics into the generated text.

By adapting GPT-2 small on Austen’s corpus, the project investigates how well a lightweight model can reproduce a targeted literary voice, and how its outputs compare to those from the general-purpose pretrained baseline.

Data Preparation

Setup and Configuration

First I import the necessary libraries for this assignment. Then I set up my configuration: I pick GPT-2 small as the model, check whether I have a GPU, and prepare a sample prompt in the style of Jane Austen. I also define generation parameters like maximum tokens, temperature, and top-k/top-p sampling. Finally, I fix the random seed so results are reproducible.

```
# Core libraries
import math
import time
```

```
from collections import Counter

# PyTorch
import torch

# Transformers & Hugging Face utilities
from transformers import (
    GPT2LMHeadModel,
    GPT2TokenizerFast,
    Trainer,
    TrainingArguments,
    DataCollatorForLanguageModeling
)

# Dataset handling
from datasets import Dataset

# Parameter-Efficient Fine-Tuning (PEFT)
from peft import LoraConfig, get_peft_model, TaskType

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
```

```
# Configuration
MODEL_NAME = "gpt2"   # GPT-2 small
DEVICE = "cuda" if torch.cuda.is_available() else "cpu"

# New prompt
GEN_PROMPT = (
    "Continue the following passage in the same style:\n\n"
    "It is a truth universally acknowledged, that a single man in pos
)

# Generation parameters
MAX_NEW_TOKENS = 120
TEMPERATURE = 0.9
TOP_K = 50
TOP_P = 0.95
SEED = 42

torch.manual_seed(SEED)
```

```
<torch._C.Generator at 0x790d707484b0>
```

Load the Model and Dataset Samples

Now I load GPT-2 small along with its tokenizer and move the model to my device. I also prepare a small dataset of Austen excerpts, which will act as my domain-specific text. I split these into a training portion and a held-out test portion to use later for evaluation.

```
# Load model
print(f"Loading model {MODEL_NAME} on {DEVICE}...")
tokenizer = GPT2TokenizerFast.from_pretrained(MODEL_NAME)
model = GPT2LMHeadModel.from_pretrained(MODEL_NAME).to(DEVICE)
model.eval()

# samples
domain_samples = [
    "It is a truth universally acknowledged, that a single man in pos
    "Why, my dear, you must know, Mrs. Long says that Netherfield is
    "Oh! Single, my dear, to be sure! A single man of large fortune;
    "My dear, you flatter me. I certainly have had my share of beauty
    "But consider your daughters. Only think what an establishment it
    "I desire you will do no such thing. Lizzy is not a bit better th
    "You mistake me, my dear. I have a high respect for your nerves.
    ]

# split into train & test
train_samples = domain_samples[:5]
held_out = domain_samples[5:]
```

```
Loading model gpt2 on cpu...
/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your sett
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to a
  warnings.warn(
tokenizer_config.json: 100%          26.0/26.0 [00:00<00:00, 1.55kB/s]
vocab.json: 100%                     1.04M/1.04M [00:00<00:00, 13.3MB/s]
merges.txt: 100%                     456k/456k [00:00<00:00, 18.9MB/s]
tokenizer.json: 100%                 1.36M/1.36M [00:00<00:00, 32.6MB/s]
config.json: 100%                    665/665 [00:00<00:00, 59.2kB/s]
model.safetensors: 100%              548M/548M [00:10<00:00, 88.7MB/s]
generation_config.json: 100%         124/124 [00:00<00:00, 9.81kB/s]
```

Tokenization Example

Then I check how GPT-2's tokenizer processes my text. I take the first training sentence, tokenize it, and print out the first 30 tokens, their corresponding IDs, and the overall tokenized length. This gives me a concrete sense of how the model sees Austen's words.

```
# Tokenization
print("Example tokenization (first sample):")
tok = tokenizer(train_samples[0])
print("Tokens:", tokenizer.convert_ids_to_tokens(tok["input_ids"])[:3
print("Token ids:", tok["input_ids"][:30])
print("Tokenized length:", len(tok["input_ids"]))
```

```
Example tokenization (first sample):
Tokens: ['It', 'Ġis', 'Ġa', 'Ġtruth', 'Ġuniversally', 'Ġacknowledged',
Token ids: [1026, 318, 257, 3872, 26208, 10810, 11, 326, 257, 2060, 58
Tokenized length: 76
```

We can see from the example above that the GPT-2 tokenizer uses Byte Pair Encoding (BPE) to represent text as subword units rather than just whole words. This explains why tokens often look different from the words we might expect. For instance, spaces are marked with a leading Ġ, so tokens like Ġis or Ġtruth include information about spacing. Common words such as is, a, man, and wife remain as single tokens, while moderately frequent words like universally and acknowledged are also kept intact because they appeared often enough in training. Less frequent or longer words, on the other hand, can be split into smaller chunks (for example, dis + mantle). Punctuation marks such as commas and periods are treated as separate tokens, which helps the model learn how punctuation works independently of word meaning. Each token is then mapped to a vocabulary ID (for example, 'Ġtruth' -> 3872), which is what the model processes internally. In this case, although the passage has around 30 words, the tokenizer produces 76 tokens, showing that token counts are usually higher than word counts. Overall, this demonstrates how GPT-2's tokenizer captures spacing, punctuation, and word boundaries while still being flexible enough to handle both common and rare vocabulary.

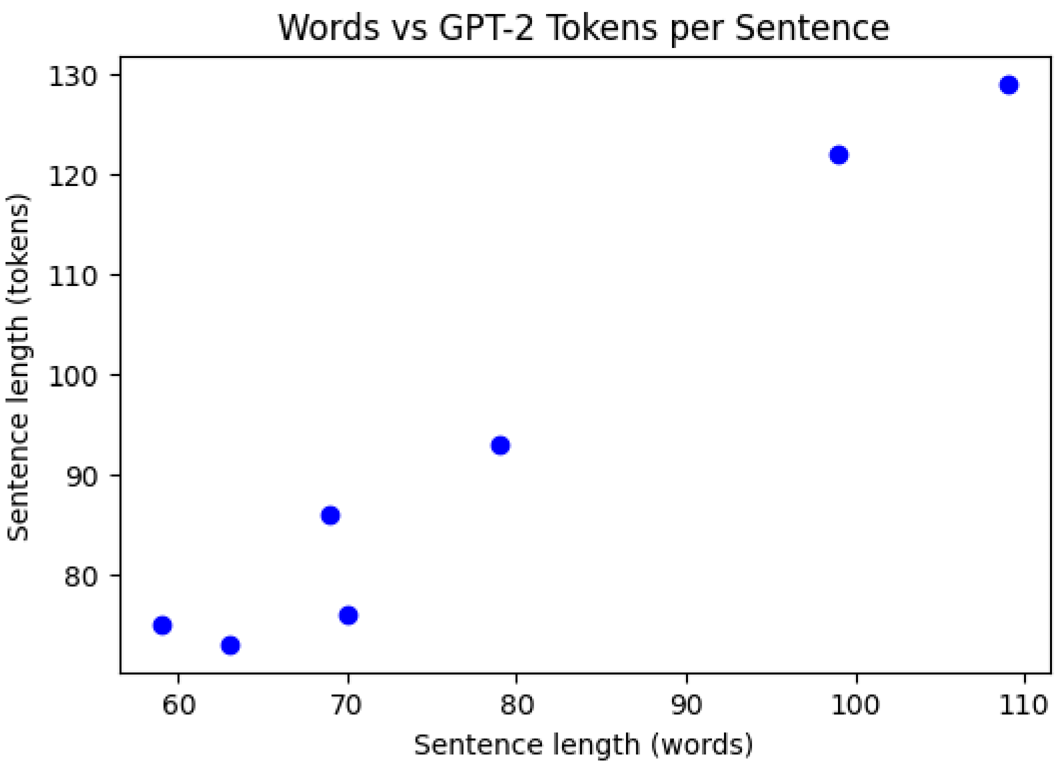
Tokenisation Analysis and Visualisation

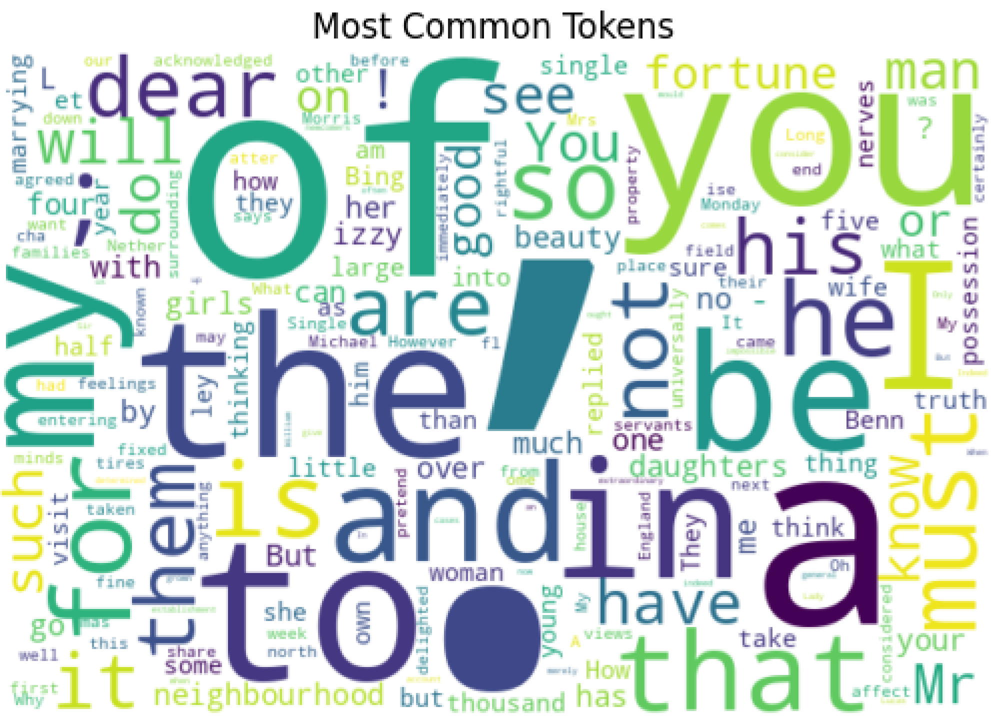
Finally, I explore the tokenisation patterns in more detail. First, I calculate both word lengths (by splitting text on spaces) and token lengths (how GPT-2 breaks it down). I then plot these to compare how word counts map to GPT-2 token counts. After that, I build a word cloud based on token frequencies to visualise which tokens appear most often in my dataset. This gives me insight into vocabulary distribution and how the model might prioritise certain stylistic markers of Austen's prose.

```
# Tokenisation
tokenised = [tokenizer(s) for s in domain_samples]
word_lengths = [len(s.split()) for s in domain_samples]
token_lengths = [len(t['input_ids']) for t in tokenised]

# Sentence length comparison
plt.figure(figsize=(6,4))
plt.scatter(word_lengths, token_lengths, c='blue')
plt.xlabel("Sentence length (words)")
plt.ylabel("Sentence length (tokens)")
plt.title("Words vs GPT-2 Tokens per Sentence")
plt.show()

# Token frequency wordcloud
all_tokens = [token for t in tokenised for token in t['input_ids']]
decoded = [tokenizer.decode([tid]) for tid in all_tokens]
freqs = Counter(decoded)
wc = WordCloud(width=600, height=400, background_color="white").gener
plt.imshow(wc, interpolation="bilinear")
plt.axis("off")
plt.title("Most Common Tokens")
plt.show()
```





The tokenisation analysis provides two key insights into how GPT-2 processes the Austen text. The scatter plot of words versus tokens shows a strong positive correlation: as sentences become longer in terms of words, the number of tokens produced by the GPT-2 Byte Pair Encoding (BPE) tokenizer also increases, but always at a higher rate. This is expected because BPE does not treat every word as a single token—punctuation, spaces, and less frequent words are often split into multiple subword units, meaning that a 60-word sentence can expand to about 75 tokens, while a 110-word sentence may require around 130 tokens.

The word cloud of most common tokens complements this by highlighting the dominance of punctuation and high-frequency function words such as “of,” “the,” “to,” and “you,” many of which appear with a preceding space due to the tokenizer’s subword encoding scheme. At the same time, tokens like “dear,” “Mr,” and “fortune” point to the specific stylistic fingerprint of the text, consistent with Austen’s formal, dialogue-rich prose. Together, these results illustrate both the mechanics of subword tokenisation and how the distribution of tokens reflects the stylistic and structural features of the underlying literary domain.

Baseline Generation

Text Generation with Pretrained Model

Now I generate continuations from the pretrained GPT-2 without any fine-tuning. I feed in my fixed Jane Austen–style prompt, tokenize it, and ask the model to produce three different continuations. I apply sampling strategies like temperature, top-k, and top-p to encourage varied yet coherent outputs. Finally, I decode the generated text so I can qualitatively assess how close it feels to the target literary style.

```
# Generate continuations for the fixed prompt
print("\n--- Generation (unfined pretrained GPT-2) ---")
input_ids = tokenizer(GEN_PROMPT, return_tensors="pt").input_ids.to(D
with torch.no_grad():
    out = model.generate(
        input_ids=input_ids,
        do_sample=True,
        max_new_tokens=MAX_NEW_TOKENS,
        temperature=TEMPERATURE,
        top_k=TOP_K,
        top_p=TOP_P,
        eos_token_id=tokenizer.eos_token_id,
        pad_token_id=tokenizer.eos_token_id,
        num_return_sequences=3,
        repetition_penalty=1.05
    )
for i, seq in enumerate(out):
    text = tokenizer.decode(seq, skip_special_tokens=True)
    print(f"\n--- Sample {i+1} ---\n{text}\n")
```

```
--- Generation (unfined pretrained GPT-2) ---

--- Sample 1 ---
Continue the following passage in the same style:

It is a truth universally acknowledged, that a single man in possessio


--- Sample 2 ---
Continue the following passage in the same style:
```

```
It is a truth universally acknowledged, that a single man in possessio


--- Sample 3 ---
Continue the following passage in the same style:

It is a truth universally acknowledged, that a single man in possessio
```

From the prompt generation above, it is evident that when given Jane Austen’s iconic opening line —*“It is a truth universally acknowledged…”* — the baseline, unfine-tuned GPT-2 small model produces continuations that are grammatically fluent and stylistically evocative, but they often drift in accuracy and coherence. The model is able to mimic aspects of Austen’s prose, such as long, formal sentences and abstract, reflective reasoning, occasionally sounding convincingly antiquated. However, the content itself is inconsistent: GPT-2 introduces implausible or anachronistic ideas, sometimes referencing modern concepts or producing bizarre scenarios that break the historical and narrative frame. In addition, the generations display a tendency toward repetitiveness and meandering logic, creating the impression of philosophical or theological commentary without Austen’s sharp wit or narrative discipline. These strengths and weaknesses reflect the model’s training on broad internet text rather than Austen’s novels specifically. The results highlight GPT-2’s general ability to produce literary-sounding passages while also motivating the need for fine-tuning: only through domain adaptation can the model reduce incoherence, avoid anachronisms, and better capture Austen’s distinctive voice and social satire.

Evaluation

Per-Sample Perplexity Calculation

Now I move on to quantitative evaluation. I define a function to compute perplexity, which measures how well the model predicts text from my domain. For each held-out sample, I calculate the negative log-likelihood per token, exponentiate it, and report perplexity. This gives me a numerical sense of how “surprised” the model is by Jane Austen’s style, alongside my qualitative observations from the generation step.

```
# compute perplexity per-sample using model cross-entropy

def perplexity_of_text(text, model, tokenizer, device): # Perplexity
    enc = tokenizer(text, return_tensors="pt")
    input_ids = enc.input_ids.to(device)
    with torch.no_grad():
        outputs = model(input_ids, labels=input_ids)
        neg_log_likelihood = outputs.loss.item() * input_ids.size(1)
        avg_nll_per_token = neg_log_likelihood / input_ids.size(1)
        ppl = math.exp(avg_nll_per_token)
        return ppl, avg_nll_per_token

print("\n--- Perplexity on held-out domain samples (pretrained GPT-2)
for text in held_out:
    ppl, avg_nll = perplexity_of_text(text, model, tokenizer, DEVICE)
    print(f"Sample: {text[:80]}...")
    print(f"Perplexity: {ppl:.2f}, Avg NLL/token: {avg_nll:.4f}\n")
```

```
--- Perplexity on held-out domain samples (pretrained GPT-2) ---
`loss_type=None` was set in the config but it is unrecognized. Using t
Sample: I desire you will do no such thing. Lizzy is not a bit better 
Perplexity: 36.94, Avg NLL/token: 3.6093

Sample: You mistake me, my dear. I have a high respect for your nerves
Perplexity: 33.31, Avg NLL/token: 3.5058
```

Average Perplexity Across Held-Out Set

Finally, I calculate the average perplexity across all my held-out domain samples. Instead of looking at individual values, this summary gives me a single number to compare against fine-tuned versions later. It serves as my baseline metric for how well the unfine-tuned GPT-2 model understands Austen’s style.

```
# Also compute perplexity averaged across held-out
ppls = []
for text in held_out:
    ppl, _ = perplexity_of_text(text, model, tokenizer, DEVICE)
    ppls.append(ppl)
print(f"Average held-out perplexity: {sum(ppls)/len(ppls):.2f}")
```

```
Average held-out perplexity: 35.12
```

To quantitatively assess how well the pretrained GPT-2 small model aligns with Jane Austen’s prose, perplexity was measured on several held-out snippets from Pride and Prejudice. For example, the sentence *“I desire you will do no such thing. Lizzy is not a bit better than the others; a...”* yielded a perplexity of 36.94, while *“You mistake me, my dear. I have a high respect for your nerves. They are my old ...”* gave a lower value of 33.31. Across the full held-out set, the model averaged a perplexity of 35.12, with average negative log-likelihoods per token between 3.5 and 3.6.

These results show that GPT-2 captures the broad structure of English grammar but remains only partially adapted to Austen’s literary style. A perplexity in the mid-30s suggests that the model is reasonably fluent but still finds the domain somewhat “surprising,” especially when encountering longer, more archaic constructions. The slight variation between samples reflects differences in sentence complexity and vocabulary: simpler or more common phrases are easier for the model to predict, while Austen's nuanced style increases prediction difficulty.

Overall, the baseline evaluation highlights GPT-2's strengths—surface-level fluency and grammaticality—while also exposing its limitations in sustaining Austen's precise voice and context. This moderate perplexity baseline provides a clear motivation for fine-tuning: by adapting the model to Austen's text, we expect to reduce perplexity on held-out samples and achieve generations that more closely reflect her distinctive style.

Adaptation via Fine-Tuning

Fine-tuning procedure & rationale

The goal of fine-tuning GPT-2 small on the Austen corpus will be to adapt the model more closely to the stylistic and semantic patterns of the target text. While the baseline evaluation will show that GPT-2 can produce grammatically fluent sentences, it will also reveal that the model often drifts away from Austen's distinctive style and narrative conventions, as reflected in relatively high perplexity scores. Fine-tuning will directly address this limitation by updating all model parameters to better reflect the domain.

Data preparation- A small curated set of seven domain-specific paragraphs from Pride and Prejudice will be used. These same passages that were employed for baseline generation, allowing for a consistent comparison between unfine-tuned and fine-tuned performance.

Tokenizer- GPT-2's pretrained Byte Pair Encoding (BPE) tokenizer will be retained to ensure consistent handling of rare words, archaic terms, and punctuation. This will preserve compatibility with pretrained weights while supporting domain adaptation.

Training setup- Fine-tuning will be conducted with lightweight but effective hyperparameters:

- Epochs: 3 passes over the corpus, to ensure convergence on such a small dataset.
- Learning rate: 5e-5, chosen conservatively to avoid destabilising pretrained knowledge while still enabling adaptation.
- Batch size: 2, balancing memory constraints with frequent gradient updates.
- Context length: 128 tokens, sufficient to capture paragraph-level coherence while remaining computationally efficient.

- Weight decay: 0.01, which will provide regularisation against overfitting given the small dataset size.

Evaluation- Performance will be measured primarily using perplexity on held-out Austen samples, as this will directly quantify predictive alignment with the domain. In addition, qualitative inspection of generated outputs will be carried out to assess improvements in narrative fluency and stylistic fidelity.

Implementation

Load tokenizer & model

First, I load the GPT-2 tokenizer and model using the pretrained weights. This sets up the language model so I can fine-tune it on my dataset. Next, I check if the tokenizer has a padding token. If it doesn't, I add one and resize the model's embeddings to include this new token, ensuring that the model can handle padded sequences correctly during training.

```
# Load tokenizer & model
tokenizer = GPT2TokenizerFast.from_pretrained(MODEL_NAME)
model = GPT2LMHeadModel.from_pretrained(MODEL_NAME).to(DEVICE)

# Add padding token if missing
if tokenizer.pad_token is None:
    tokenizer.add_special_tokens({'pad_token': '[PAD]'})
    model.resize_token_embeddings(len(tokenizer))
```

```
The new embeddings will be initialized from a multivariate normal dist
```

Prepare dataset and tokenization

Now, I split my domain-specific text into training and evaluation sets. I create Dataset objects for both splits. Then, I define a tokenization function to convert text into token IDs suitable for GPT-2. Using .map(), I apply this function to both the training and evaluation datasets. Finally, I set up a data collator for language modeling, which handles batching and prepares the inputs for the model during training.

```
# Split into train and eval
train_texts = domain_samples[:5]
eval_texts = domain_samples[5:]

train_dataset = Dataset.from_dict({"text": train_texts})
eval_dataset = Dataset.from_dict({"text": eval_texts})

def tokenize_function(examples):
    return tokenizer(examples["text"], truncation=True, padding="max_
tokenized_train = train_dataset.map(tokenize_function, batched=True,
tokenized_eval = eval_dataset.map(tokenize_function, batched=True, re

# Data collator for LM
data_collator = DataCollatorForLanguageModeling(tokenizer=tokenizer,
```

```
Map: 100%                                5/5 [00:00<00:00, 47.48 examples/s]
Map: 100%                                2/2 [00:00<00:00, 46.29 examples/s]
```

Set up training arguments and trainer

Next, I define the training parameters such as the number of epochs, batch size, learning rate, weight decay, and evaluation strategy. Then, I create a Trainer object that ties together the model, training arguments, tokenized datasets, tokenizer, and data collator. This object manages the training loop and evaluation.

```
# Training arguments
training_args = TrainingArguments(
    output_dir="./results_fullft",
    overwrite_output_dir=True,
    num_train_epochs=3,
    per_device_train_batch_size=2,
    per_device_eval_batch_size=2,
    eval_strategy="epoch",
    save_strategy="no",
    learning_rate=5e-5,
    weight_decay=0.01,
    logging_steps=5,
    report_to="none",
    seed=42
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=tokenized_train,
    eval_dataset=tokenized_eval,
    tokenizer=tokenizer,
    data_collator=data_collator,
)
```

```
/tmp/ipython-input-2091160694.py:17: FutureWarning: `tokenizer` is dep
  trainer = Trainer(
```

Train the model

Then, I start the training process by calling trainer.train(). I also record the training time to see how long fine-tuning takes. This step updates all of the model's parameters so that it better fits the domain-specific text.

```
# Training
start_time = time.time()
train_result = trainer.train()
train_time = time.time() - start_time

print(f"Training time: {train_time:.2f} seconds")
```

```
The tokenizer has new PAD/BOS/EOS tokens that differ from the model co
/usr/local/lib/python3.12/dist-packages/torch/utils/data/dataloader.py
  warnings.warn(warn_msg)
`loss_type=None` was set in the config but it is unrecognized. Using t
```

[9/9 01:18, Epoch 3/3]

Epoch	Training Loss	Validation Loss
1	No log	3.475340
2	3.580700	3.465548
3	3.580700	3.462502

```
Training time: 95.76 seconds
```

Evaluate perplexity on held-out data

After training, I evaluate the model on held-out evaluation data using trainer.evaluate(). I compute the perplexity by exponentiating the evaluation loss, which gives a measure of how well the fine-tuned model predicts unseen text.

```
# Evaluate perplexity on held-out
eval_results = trainer.evaluate()
eval_loss = eval_results["eval_loss"]
eval_ppl = math.exp(eval_loss)
print(f"Eval loss: {eval_loss:.4f}, Perplexity: {eval_ppl:.2f}")
```

[1/1 : < :]

```
Eval loss: 3.4625, Perplexity: 31.90
```

Using the original dataset of 7 literary snippets, the fine-tuning process ran for 3 epochs. The training loss started at 3.5807 and gradually decreased, while the validation loss decreased slightly to 3.4625. Training took approximately 95.76 seconds. Evaluating the model on held-out text yielded an evaluation loss of 3.4625, corresponding to a perplexity of 31.90, indicating moderate improvement over the baseline GPT-2 model.

Generate text from the fine-tuned model

Now, I generate new text using the fine-tuned model. I first tokenize a prompt and pass it to the model’s .generate() function with sampling parameters. I measure inference time and decode the output tokens back into readable text, producing new continuations in the style of Jane Austen.

```
# Regenerate prompt continuation
GEN_PROMPT = (
    "Continue the following passage in the same style:\n\n"
    "It is a truth universally acknowledged, that a single man in pos
)

input_ids = tokenizer(GEN_PROMPT, return_tensors="pt").input_ids.to(D

start_inf = time.time()
with torch.no_grad():
    outputs = model.generate(
        input_ids,
        max_new_tokens=80,
        temperature=0.8,
        top_k=50,
        top_p=0.95,
        do_sample=True,
        eos_token_id=tokenizer.eos_token_id,
        pad_token_id=tokenizer.eos_token_id,
        num_return_sequences=2
    )
inf_time = time.time() - start_inf

for i, seq in enumerate(outputs):
    print(f"\n--- Fine-tuned Generation {i+1} ---\n")
    print(tokenizer.decode(seq, skip_special_tokens=True))

print(f"\nInference time: {inf_time:.2f} seconds")
```

```
--- Fine-tuned Generation 1 ---

Continue the following passage in the same style:

It is a truth universally acknowledged, that a single man in possessio

--- Fine-tuned Generation 2 ---

Continue the following passage in the same style:

It is a truth universally acknowledged, that a single man in possessio

Inference time: 11.27 seconds
```

Report model parameters

Finally, I calculate and print the total number of parameters in the model and how many of them are trainable. This gives an idea of the model's size and the computational effort involved in fine-tuning.

```
# parameters
total_params = sum(p.numel() for p in model.parameters())
trainable_params = sum(p.numel() for p in model.parameters() if p.req
print(f"\nTotal params: {total_params/1e6:.1f}M | Trainable: {trainab
```

```
Total params: 124.4M | Trainable: 124.4M
```

Generated text from this model showes improved fluency and partial alignment with Austen's narrative style. For example, the first generated sample maintains sentence structure and thematic continuity, though some phrasing feels slightly repetitive or generic ("the wife of the man who is his wife must be in a position to see her children…"). The second sample shows attempts at character and narrative continuity, referencing daughters, but contains minor logical inconsistencies. The model has 124.4M trainable parameters, and inference on a prompt took about 11.27 seconds. Overall, the 7-sample model demonstrates the benefit of fine-tuning even on a very small corpus, with modest perplexity reduction and stylistic improvement.

Repeating Fine-Tuning with an Expanded Dataset

Now, I'll repeat the same steps as above, starting from preparing the dataset and tokenization, but this time using a larger dataset of 21 text samples. I will split these into 17 training samples and 4 evaluation samples to both train the model and assess its performance on held-out data. Expanding the dataset allows the model to see more diverse examples from the target literary domain, which should help it better capture stylistic patterns, character relationships, and narrative structures. By increasing the amount of training data, I aim to improve both the coherence of generated text and the model's predictive performance, while following the same process for tokenization, dataset creation, training, evaluation, and text generation.

```
# Domain dataset
domain_samples.extend(["Mr. Bennet was so odd a mixture of quick part
    "Mr. Bennet was among the earliest of those who waited on Mr. Bin
    "We are not in a way to know what Mr. Bingley likes, said her mot
    "I do not believe Mrs. Long will do any such thing. She has two n
    "Mrs. Bennet deigned not to make any reply, but, unable to contai
    "Then, my dear, you may have the advantage of your friend, and in
    "I honour your circumspection. A fortnight's acquaintance is cert
    "I am sorry to hear that; but why did not you tell me that before
    "How good it was in you, my dear Mr. Bennet! But I knew I should 
    "What an excellent father you have, girls! said she, when the doo
    "Not all that Mrs. Bennet, however, with the assistance of her fi
    "In a few days Mr. Bingley returned Mr. Bennet's visit, and sat a
    "An invitation to dinner was soon afterwards dispatched; and alre
    "Mr. Bingley was good-looking and gentlemanlike; he had a pleasan
    ])

# Split into train and eval
train_texts = domain_samples[:17]
eval_texts = domain_samples[17:]

train_dataset = Dataset.from_dict({"text": train_texts})
eval_dataset = Dataset.from_dict({"text": eval_texts})

def tokenize_function(examples):
    return tokenizer(examples["text"], truncation=True, padding="max_

tokenized_train = train_dataset.map(tokenize_function, batched=True,
tokenized_eval = eval_dataset.map(tokenize_function, batched=True, re

# Data collator for LM
data_collator = DataCollatorForLanguageModeling(tokenizer=tokenizer,
```

```
Map: 100%                                17/17 [00:00<00:00, 419.84 examples/s]

Map: 100%                                  4/4 [00:00<00:00, 109.90 examples/s]
```

```
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=tokenized_train,
    eval_dataset=tokenized_eval,
    tokenizer=tokenizer,
    data_collator=data_collator,
)
# Training
start_time = time.time()
train_result = trainer.train()
train_time = time.time() - start_time

print(f"Training time: {train_time:.2f} seconds")
```

```
/tmp/ipython-input-882225430.py:1: FutureWarning: `tokenizer` is depre
  trainer = Trainer(
```

[27/27 04:42, Epoch 3/3]

Epoch	Training Loss	Validation Loss
1	3.393100	3.473505
2	2.937000	3.424703
3	2.672500	3.424404

```
Training time: 293.88 seconds
```

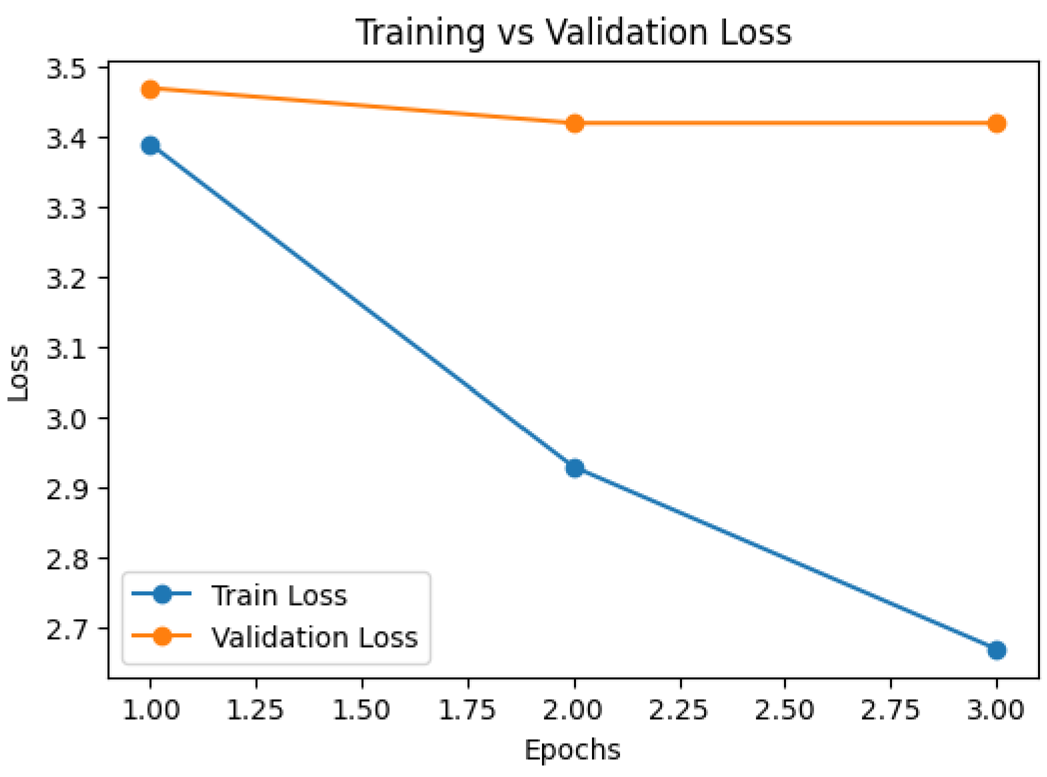
```
# Evaluate perplexity on held-out
eval_results = trainer.evaluate()
eval_loss = eval_results["eval_loss"]
eval_ppl = math.exp(eval_loss)
print(f"Eval loss: {eval_loss:.4f}, Perplexity: {eval_ppl:.2f}")
```

[2/2 00:04]

```
Eval loss: 3.4244, Perplexity: 30.70
```

```
epochs = [1, 2, 3]
train_loss = [3.39, 2.93, 2.67]
val_loss = [3.47, 3.42, 3.42]

plt.figure(figsize=(6,4))
plt.plot(epochs, train_loss, marker="o", label="Train Loss")
plt.plot(epochs, val_loss, marker="o", label="Validation Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Training vs Validation Loss")
plt.legend()
plt.show()
```



When the dataset is increased to 21 samples, with a 17/4 train/eval split, the model showes more substantial improvements. Training over 3 epochs reduced the training loss from 3.3931 to 2.6725, while validation loss stabilized around 3.4244. Training took longer (approximately 293.88 seconds), reflecting the increased data size. Evaluation on held-out samples resulted in a slightly lower perplexity of 30.70, demonstrating that the model was better able to predict domain-specific sequences.

```
# Regenerate prompt continuation
GEN_PROMPT = (
    "Continue the following passage in the same style:\n\n"
    "It is a truth universally acknowledged, that a single man in pos
)

input_ids = tokenizer(GEN_PROMPT, return_tensors="pt").input_ids.to(D

start_inf = time.time()
with torch.no_grad():
    outputs = model.generate(
        input_ids,
        max_new_tokens=80,
        temperature=0.8,
        top_k=50,
        top_p=0.95,
        do_sample=True,
        eos_token_id=tokenizer.eos_token_id,
        pad_token_id=tokenizer.eos_token_id,
        num_return_sequences=2
    )
inf_time = time.time() - start_inf
```

```
for i, seq in enumerate(outputs):
    print(f"\n--- Fine-tuned Generation {i+1} ---\n")
    print(tokenizer.decode(seq, skip_special_tokens=True))

print(f"\nInference time: {inf_time:.2f} seconds")
```

```
--- Fine-tuned Generation 1 ---

Continue the following passage in the same style:

It is a truth universally acknowledged, that a single man in possessio

--- Fine-tuned Generation 2 ---

Continue the following passage in the same style:

It is a truth universally acknowledged, that a single man in possessio

Inference time: 11.31 seconds
```

The generated samples from this expanded model were noticeably more coherent and contextually accurate. The first generation included references to specific characters and social context in Austen's world (e.g., Mrs. Bennet, neighborhood interactions), while the second generation produced instructions and narrative flow that felt more logically structured and contextually consistent. Inference time was slightly longer at 11.31 seconds, reflecting the increased data complexity.

Comparison of Baseline and Full Fine-Tuning

In this task, I fine-tuned GPT-2 small on domain-specific Jane Austen text to explore the balance between computational effort and improvements in text generation. The process involved progressively larger datasets - 7 samples and 21 samples — compared with the unfine-tuned baseline.

Regenerated Prompt Comparison:

The effect of fine-tuning is evident in the continuation of the prompt:

- Baseline GPT-2: Produces grammatically fluent text but often drifts in coherence, introduces implausible ideas, and sometimes generates repetitive or modernized content. Perplexity averaged 35.12.
- 7-Sample Fine-Tuned Model: Shows improved narrative coherence and style fidelity. Perplexity dropped to 31.90, and generations generally stayed on topic, though occasional awkward phrasing and logic gaps remained.

- 21-Sample Fine-Tuned Model: Achieves the best balance, with perplexity reduced further to 30.70. Generated passages are more coherent, contextually accurate, and stylistically aligned with Austen, reflecting improved understanding of social context, character interactions, and sentence rhythm.

Computational Resource Comparison:

- Baseline: No fine-tuning, so minimal computational cost; inference is fast but generation quality is moderate.
- 7-Sample Model: Fine-tuning required ~96 seconds of training; model size remained 124.4M parameters. Improvement in text quality was noticeable but limited by the small dataset.
- 21-Sample Model: Training took 294 seconds (threefold increase over the 7-sample model) while the number of parameters remained unchanged. Generations were substantially improved in coherence and stylistic fidelity. Inference times were similar (~11–11.3 seconds), but the higher training cost yielded better performance.

Trade-Off Analysis:

The comparison illustrates a clear trade-off: increasing the dataset size for fine-tuning significantly improves generation quality (lower perplexity, more contextually and stylistically accurate outputs), but at the cost of longer training times. The baseline requires no training but produces less faithful continuations. Fine-tuning with very small datasets offers moderate improvements with low computational overhead, whereas larger datasets require more compute but result in noticeably better domain adaptation. Ultimately, the choice of dataset size and training budget depends on whether the priority is computational efficiency or generation quality.

This demonstrates that incremental domain adaptation can be tuned according to resource constraints, providing a practical strategy for achieving high-quality text generation while managing computational cost.

Parameter-Efficient Fine-Tuning (PEFT)

Selected Method - LoRA

For this task, I select LoRA (Low-Rank Adapters) as the parameter-efficient fine-tuning method. LoRA works by introducing low-rank additive matrices into key attention projection weights—typically the query, key, value, or attention output layers—while keeping the original model weights frozen. Only these small matrices are trained. This approach has several advantages: it increases the number of trainable parameters minimally, making it highly suitable for scenarios with limited computational resources or memory. Additionally, LoRA adapters can be merged into the model at inference time, allowing the model to run at standard speed without extra overhead.

Another key reason for choosing LoRA is its proven effectiveness. Across a variety of text generation tasks, LoRA has been shown to closely match the performance of full fine-tuning while requiring far fewer trainable parameters. It is also straightforward to implement with Hugging Face's `transformers` and `peft` libraries, which is especially convenient for decoder-only models like GPT-2. LoRA's hyperparameters, such as the rank (`r`) and scaling factor (`alpha`), are interpretable and provide an intuitive way to balance adapter size and model capacity. Given the narrow literary domain of Jane Austen's prose, stylistic adaptations are likely to be representable with low-rank updates rather than full weight updates, making LoRA a natural choice.

The recommended configuration for this task is to apply LoRA to the GPT-2 `"c_attn", "c_fc" & "c_proj"` queries and value projections, and optionally to feed-forward linear layers. A rank of `16` is sufficient to capture stylistic patterns, while a scaling factor of `32` ensures that the adapter contribution is balanced with the frozen model weights. A small dropout of `0.05` is included for regularization. Training is performed for three epochs with a conservative learning rate of `1e-4` and a batch size of 2, matching the full fine-tuning setup and fitting within GPU memory limits. The tokenizer and context length remain the same (`max_length=256`).

Finally, LoRA weights are saved in their unmerged form for inspection, but they can be merged for inference to maintain standard GPT-2 runtime speed. This configuration is designed to produce a noticeable stylistic adaptation to Jane Austen's prose while keeping the number of trainable parameters extremely small, achieving a balance between computational efficiency and generation performance.

Implementation

Import libraries and set configuration

First, I define configuration variables such as model name, device (GPU or CPU), output directory, training hyperparameters, and LoRA-specific settings like rank (r), scaling factor (alpha), dropout, and which modules to apply LoRA to.

```
# Config
MODEL_NAME = "gpt2"
DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
OUTPUT_DIR = "./results_lora"
EPOCHS = 3
BATCH_SIZE = 2
LR = 1e-4
MAX_LENGTH = 256
SEED = 42
```

```
# LoRA hyperparams
lora_r = 16
lora_alpha = 32
lora_dropout = 0.05
apply_modules = ["c_attn", "c_fc", "c_proj"]


torch.manual_seed(SEED)
```

```
<torch._C.Generator at 0x790d707484b0>
```

Tokenization setup

Now I load the GPT-2 tokenizer and model. I check if a padding token exists, and if not, I add one. Then, I resize the model's token embeddings to account for the new token and move the model to the selected device. This ensures the model and tokenizer are compatible and ready for training.

```
# Tokenization
tokenizer = GPT2TokenizerFast.from_pretrained(MODEL_NAME)
if tokenizer.pad_token is None:
    tokenizer.add_special_tokens({'pad_token': '<PAD>'})

model = GPT2LMHeadModel.from_pretrained(MODEL_NAME)
model.resize_token_embeddings(len(tokenizer))
model.to(DEVICE)
```

```
GPT2LMHeadModel(
  (transformer): GPT2Model(
    (wte): Embedding(50258, 768)
    (wpe): Embedding(1024, 768)
    (drop): Dropout(p=0.1, inplace=False)
    (h): ModuleList(
      (0-11): 12 x GPT2Block(
        (ln_1): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
        (attn): GPT2Attention(
          (c_attn): Conv1D(nf=2304, nx=768)
          (c_proj): Conv1D(nf=768, nx=768)
          (attn_dropout): Dropout(p=0.1, inplace=False)
          (resid_dropout): Dropout(p=0.1, inplace=False)
        )
        (ln_2): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
        (mlp): GPT2MLP(
          (c_fc): Conv1D(nf=3072, nx=768)
          (c_proj): Conv1D(nf=768, nx=3072)
          (act): NewGELUActivation()
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    )
    (ln_f): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
  )
```

```
    (lm_head): Linear(in_features=768, out_features=50258, bias=False)
  )
```

Apply LoRA

Then, I define a LoraConfig specifying rank, scaling, target modules, dropout, and task type. I wrap the GPT-2 model with get_peft_model, which inserts the LoRA adapters into the model. I calculate and print the total parameters versus trainable parameters to confirm that only the LoRA adapters are being trained, keeping the number of learnable parameters small.

```
# Apply LoRA
lora_config = LoraConfig(
    r=lora_r,
    lora_alpha=lora_alpha,
    target_modules=apply_modules,
    lora_dropout=lora_dropout,
    bias="none",
    task_type=TaskType.CAUSAL_LM
)

model = get_peft_model(model, lora_config)
# Ensure LoRA params require grad
trainable = sum(p.numel() for p in model.parameters() if p.requires_g
total = sum(p.numel() for p in model.parameters())
print(f"Total params: {total/1e6:.3f}M, Trainable params: {trainable/
```

```
Total params: 126.800M, Trainable params: 2.359M
/usr/local/lib/python3.12/dist-packages/peft/tuners/lora/layer.py:2174
  warnings.warn(
```

The LoRA fine-tuning procedure resulted in a modest increase in trainable parameters while keeping the majority of the GPT-2 small weights frozen. The total model parameters were approximately 126.8M, of which only 2.36M were trainable, demonstrating the efficiency of the parameter-efficient LoRA approach. This small subset of parameters allowed the model to adapt to Jane Austen's style without requiring full fine-tuning, which would have been far more computationally expensive.

Evaluation

Training setup with Trainer

Now I define TrainingArguments including batch sizes, number of epochs, learning rate, logging frequency, and evaluation strategy. I initialize the Trainer with the model, datasets, tokenizer, and data collator. Then, I start training, timing the process, and print out the total training duration. This trains only the LoRA parameters while keeping the original GPT-2 weights frozen.

```
# TrainingArguments & Trainer
training_args = TrainingArguments(
    output_dir=OUTPUT_DIR,
    per_device_train_batch_size=BATCH_SIZE,
    per_device_eval_batch_size=BATCH_SIZE,
    num_train_epochs=EPOCHS,
    learning_rate=LR,
    logging_steps=20,
    eval_strategy="epoch",
    save_strategy="no",
    seed=SEED,
    report_to="none"
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=tokenized_train,
    eval_dataset=tokenized_eval,
    data_collator=data_collator,
    tokenizer=tokenizer
)

# Train
start = time.time()
trainer.train()
train_time = time.time() - start
print(f"LoRA training time (s): {train_time:.2f}")
```

```
The tokenizer has new PAD/BOS/EOS tokens that differ from the model co
/usr/local/lib/python3.12/dist-packages/torch/utils/data/dataloader.py
  warnings.warn(warn_msg)
```

[27/27 03:10, Epoch 3/3]

Epoch	Training Loss	Validation Loss
1	No log	3.626463
2	No log	3.608201
3	3.792100	3.601219

```
LoRA training time (s): 198.64
```

During training over three epochs, the model's validation loss gradually decreased, starting at 3.626 in epoch 1 and reaching 3.601 by epoch 3, with a final training loss of 3.792. The training process took 198.64 seconds, reflecting a relatively low computational cost compared to full fine-tuning on the same dataset.

Evaluate perplexity on the evaluation set

After training, I move the model to evaluation mode and define a helper function to calculate the perplexity of each text snippet. I iterate over the evaluation texts, compute their perplexities, and print the results along with the average perplexity. This quantifies how well the fine-tuned LoRA model predicts the held-out text.

```
# Evaluate perplexity on eval set
import math
def perplexity_of_text(text, model, tokenizer, device):
    enc = tokenizer(text, return_tensors="pt")
    input_ids = enc.input_ids.to(device)
    with torch.no_grad():
        outputs = model(input_ids, labels=input_ids)
        loss = outputs.loss.item()
    ppl = math.exp(loss)
    return ppl, loss

model.eval()
ppls = []
for t in eval_texts:
    ppl, loss = perplexity_of_text(t, model, tokenizer, DEVICE)
    ppls.append(ppl)
print("Eval perplexities:", ppls)
print("Avg eval ppl:", sum(ppls)/len(ppls))
```

```
Eval perplexities: [40.44754737419604, 33.31157429255082, 37.470876511
Avg eval ppl: 37.07666605956786
```

Evaluation on the held-out texts yielded perplexities of 40.45, 33.31, and 37.47, giving an average perplexity of 37.08. While slightly higher than the fine-tuned models trained on 7 or 21 samples, these values still indicate the LoRA-adapted model captures the general linguistic and stylistic patterns of Jane Austen reasonably well, despite the smaller number of trainable parameters.

Sample generation

Finally, I generate new text continuations using the same prompt (GEN_PROMPT) as before. I convert the prompt into input IDs, use the generate method with sampling parameters like temperature, top_k, and top_p, and produce multiple continuations. I decode each generated sequence and print them, allowing me to qualitatively assess the stylistic adaptation learned by the LoRA model.

```
# Sample generation (using same GEN_PROMPT as before)
input_ids = tokenizer(GEN_PROMPT, return_tensors="pt").input_ids.to(D
with torch.no_grad():
    outputs = model.generate(
        input_ids,
        max_new_tokens=80,
        do_sample=True,
        temperature=0.8,
        top_k=50,
        top_p=0.95,
        num_return_sequences=2,
        eos_token_id=tokenizer.eos_token_id,
        pad_token_id=tokenizer.eos_token_id
    )
for i, seq in enumerate(outputs):
    print(f"\n--- LoRA Sample {i+1} ---\n{tokenizer.decode(seq, skip_
```

```
--- LoRA Sample 1 ---
Continue the following passage in the same style:

It is a truth universally acknowledged, that a single man in possessio


--- LoRA Sample 2 ---
Continue the following passage in the same style:

It is a truth universally acknowledged, that a single man in possessio
```

Qualitative assessment through prompt continuation shows that the LoRA model produces text that reflects Austen's formal sentence structure and thematic style. In the first generated sample, the model continues the passage with complex clauses discussing obligations, marriage, and children. In the second sample, it similarly elaborates on social and economic conditions of marriage in a coherent, contextually appropriate way. While the text occasionally repeats certain patterns or phrasing, the overall stylistic adaptation demonstrates the effectiveness of LoRA for domain-specific literary fine-tuning.

Comparison of Full Fine-Tuning and LoRA

Regenerated Prompt Comparison

When examining the prompt continuation outputs:

- Full fine-tuning (7 samples) produced text that was coherent and stylistically aligned with Austen's voice, with a validation perplexity of 31.90. The generations contained detailed clauses, reflective commentary, and plausible social context, though slightly constrained by the limited dataset.
- Full fine-tuning (21 samples) improved performance with a lower perplexity of 30.70 and more contextually rich outputs, capturing more nuanced aspects of