```
Start coding or generate with AI.
# Example: Baseline inference with a 1B instruct model (zero-shot)
!pip install unsloth transformers datasets -q
from datasets import load_dataset
from unsloth import FastLanguageModel
import torch
# Load data (take 75%-agreement subset) and split
dataset = load_dataset("takala/financial_phrasebank", "sentences_75agree")
data = dataset["train"]
data = data.train_test_split(test_size=0.2, seed=42)
train_data = data["train"]
test_data = data["test"]
# Load base model in 4-bit (QLoRA) for speed
model name = "unsloth/Llama-3.2-1B-Instruct-bnb-4bit"
model, tokenizer = FastLanguageModel.from_pretrained(model_name, max_seq_length=2048, load_in_4bit=True)
FastLanguageModel.for_inference(model) # prepare for faster generation
# Example inference on one sample
sample = test_data[0]["sentence"]
prompt = f"{sample} Sentiment:"
inputs = tokenizer(prompt, return tensors="pt").to("cuda")
outs = model.generate(input_ids=inputs['input_ids'], max_new_tokens=3, temperature=0.2)
label = tokenizer.decode(outs[0], skip_special_tokens=True)
print("Sentence:", sample)
print("Predicted sentiment:", label)
→
                                                   - 52.3/52.3 kB 3.6 MB/s eta 0:00:00
                                                - 311.7/311.7 kB 13.6 MB/s eta 0:00:00
                                                 - 491.5/491.5 kB 30.2 MB/s eta 0:00:00
                                                - 511.9/511.9 kB 44.9 MB/s eta 0:00:00
                                                - 184.8/184.8 kB 18.6 MB/s eta 0:00:00
                                                - 117.2/117.2 MB 8.0 MB/s eta 0:00:00
                                                - 61.3/61.3 MB 13.4 MB/s eta 0:00:00
                                                 - 130.0/130.0 kB 12.0 MB/s eta 0:00:00
                                                 - 213.6/213.6 kB 20.2 MB/s eta 0:00:00
     Unsloth Zoo will now patch everything to make training faster!
                      8.88k/? [00:00<00:00, 711kB/s]
     README.md:
                              6.04k/? [00:00<00:00, 578kB/s]
     financial phrasebank.py:
     The repository for takala/financial_phrasebank contains custom code which must be executed to correctly load the dataset. You can inspec
     You can avoid this prompt in future by passing the argument `trust_remote_code=True`.
     Do you wish to run the custom code? [y/N] y
     FinancialPhraseBank-v1.0.zip: 100%
                                                                            682k/682k [00:00<00:00, 8.38MB/s]
     Generating train split: 100%
                                                                      3453/3453 [00:00<00:00, 42658.84 examples/s]
     ==((====))== Unsloth 2025.8.9: Fast Llama patching. Transformers: 4.55.4.
                   Tesla T4. Num GPUs = 1. Max memory: 14.741 GB. Platform: Linux.
        \\ /|
     0^0/ \_/ \
                   Torch: 2.8.0+cu126. CUDA: 7.5. CUDA Toolkit: 12.6. Triton: 3.4.0
                   Bfloat16 = FALSE. FA [Xformers = 0.0.32.post2. FA2 = False]
                   Free license: <a href="http://github.com/unslothai/unsloth">http://github.com/unslothai/unsloth</a>
     Unsloth: Fast downloading is enabled - ignore downloading bars which are red colored!
     model.safetensors: 100%
                                                                    1.03G/1.03G [00:08<00:00, 221MB/s]
     generation_config.json: 100%
                                                                       234/234 [00:00<00:00, 14.4kB/s]
     tokenizer_config.json:
                            54.7k/? [00:00<00:00, 5.27MB/s]
     tokenizer.json: 100%
                                                                17.2M/17.2M [00:00<00:00, 49.1MB/s]
     special_tokens_map.json: 100%
                                                                         454/454 [00:00<00:00, 37.5kB/s]
     The attention mask is not set and cannot be inferred from input because pad token is same as eos token. As a consequence, you may observ
     Sentence: It estimates the operating profit to further improve from the third quarter
     Predicted sentiment: It estimates the operating profit to further improve from the third quarter. Sentiment: positive. The
print(test_data[3])
 🚁 {'sentence': 'Our tools are specifically designed with the needs of both the business users and ICT experts in mind .', 'label': 1}
```

```
!pip install scikit-learn -q
from sklearn.metrics import accuracy_score, f1_score
# Label mapping
label_map = {"negative": 0, "neutral": 1, "positive": 2}
def normalize_pred(text):
    text = text.lower()
    if "pos" in text:
        return 2 # positive
    elif "neg" in text:
        return 0 # negative
    elif "neu" in text:
       return 1 # neutral
    else:
        return 1 # fallback to neutral
y_true = []
y_pred = []
for sample in test data:
    sent = sample["sentence"]
    gold = sample["label"] # already int (0/1/2)
    prompt = f"Sentence: {sent}\nSentiment:"
    inputs = tokenizer(prompt, return_tensors="pt").to("cuda")
    outputs = model.generate(
        input_ids=inputs["input_ids"],
        attention_mask=inputs["attention_mask"],
        max_new_tokens=3,
        temperature=0.2,
    pred_text = tokenizer.decode(outputs[0], skip_special_tokens=True)
    pred = normalize_pred(pred_text)
    y_true.append(gold)
    y_pred.append(pred)
# Compute metrics
acc = accuracy_score(y_true, y_pred)
f1 = f1_score(y_true, y_pred, average="macro")
print(f"Baseline Accuracy: {acc*100:.2f}%")
print(f"Baseline F1 (macro): {f1*100:.2f}%")
    Baseline Accuracy: 61.79%
     Baseline F1 (macro): 30.51%
from unsloth import FastLanguageModel
# Load base model (16-bit for LoRA training)
model, tokenizer = FastLanguageModel.from_pretrained(
    "unsloth/Llama-3.2-1B",
    max_seq_length=2048,
    load_in_4bit=False,
)
# Wrap with LoRA
model = FastLanguageModel.get_peft_model(
    model,
    r=16.
    target\_modules=["q\_proj","k\_proj","v\_proj","o\_proj","gate\_proj","up\_proj","down\_proj"],\\
    lora_alpha=16,
   lora_dropout=0.0,
    bias="none",
    use_gradient_checkpointing="unsloth",
)
model.print_trainable_parameters()
```

```
\Rightarrow ==((====))== Unsloth 2025.8.9: Fast Llama patching. Transformers: 4.55.4.
                    Tesla T4. Num GPUs = 1. Max memory: 14.741 GB. Platform: Linux.
                    Torch: 2.8.0+cu126. CUDA: 7.5. CUDA Toolkit: 12.6. Triton: 3.4.0
     0^0/ \_/ \
                    Bfloat16 = FALSE. FA [Xformers = 0.0.32.post2. FA2 = False]
                    Free license: <a href="http://github.com/unslothai/unsloth">http://github.com/unslothai/unsloth</a>
     Unsloth: Fast downloading is enabled - ignore downloading bars which are red colored!
     model.safetensors: 100%
                                                                      2.47G/2.47G [00:32<00:00, 262MB/s]
     generation_config.json: 100%
                                                                          230/230 [00:00<00:00, 15.0kB/s]
     tokenizer_config.json:
                             50.6k/? [00:00<00:00, 4.92MB/s]
                                                                            459/459 [00:00<00:00, 52.5kB/s]
     special_tokens_map.json: 100%
     tokenizer.json: 100%
                                                                   17.2M/17.2M [00:00<00:00, 31.5MB/s]
     Unsloth 2025.8.9 patched 16 layers with 16 QKV layers, 16 O layers and 16 MLP layers.
     trainable params: 11,272,192 || all params: 1,247,086,592 || trainable%: 0.9039
id2label = {0: "negative", 1: "neutral", 2: "positive"}
def formatting_func(example):
    texts = []
    sentences = example["sentence"]
    labels = example["label"]
    # Case 1: batch (lists)
    if isinstance(sentences, list):
        for sent, lab in zip(sentences, labels):
            texts.append(f"Sentence: {sent}\nSentiment: {id2label[lab]}")
    else:
        # Case 2: single sample
        texts.append(f"Sentence: {sentences}\nSentiment: {id2label[labels]}")
    return texts
from transformers import TrainingArguments
from unsloth.trainer import SFTTrainer
args = TrainingArguments(
    output_dir="outputs_lora_1b",
    num_train_epochs=3,
    per_device_train_batch_size=2,
    gradient_accumulation_steps=4,
    learning_rate=2e-4,
    fp16=True,
    logging_steps=50,
    save_strategy="no",
)
trainer = SFTTrainer(
    model=model,
    tokenizer=tokenizer,
    train_dataset=train_data,
    eval_dataset=test_data,
    formatting_func=formatting_func,
    max_seq_length=512,
    args=args,
)
trainer.train()
```

```
Unsloth: Tokenizing ["text"]: 100%
                                                                               2762/2762 [00:01<00:00, 2435.79 examples/s]
     Unsloth: Tokenizing ["text"]: 100%
                                                                               691/691 [00:00<00:00, 2955.41 examples/s]
     ==((====))== Unsloth - 2x faster free finetuning | Num GPUs used = 1
                    Num examples = 2,762 | Num Epochs = 3 | Total steps = 1,038
        \\ /
                    Batch size per device = 2 | Gradient accumulation steps = 4
     0^0/ \_/ \
                    Data Parallel GPUs = 1 | Total batch size (2 x 4 x 1) = 8
                    Trainable parameters = 11,272,192 of 1,247,086,592 (0.90% trained)
     /usr/local/lib/python3.12/dist-packages/notebook/notebookapp.py:191: SyntaxWarning: invalid escape sequence '\/'
       wandb: Logging into wandb.ai. (Learn how to deploy a W&B server locally: https://wandb.me/wandb-server)
     wandb: You can find your API key in your browser here: <a href="https://wandb.ai/authorize?ref=models">https://wandb.ai/authorize?ref=models</a>
     wandb: Paste an API key from your profile and hit enter: wandb: WARNING If you're specifying your api key in code, ensure this code is
     wandb: WARNING Consider setting the WANDB_API_KEY environment variable, or running `wandb login` from the command line.
     wandb: No netrc file found, creating one.
     wandb: Appending key for api.wandb.ai to your netrc file: /root/.netrc
     wandb: Currently logged in as: aravindyuvraj007 (aravindyuvraj007-vnrvjietofficial) to https://api.wandb.ai. Use `wandb login --relogi
     Tracking run with wandb version 0.21.1
     Run data is saved locally in /content/wandb/run-20250828_112757-19xaw7pe
     Syncing run easy-universe-2 to Weights & Biases (docs)
     View project at https://wandb.ai/aravindyuvraj007-vnrvjietofficial/huggingface
     View run at <a href="https://wandb.ai/aravindyuvraj007-vnrvjietofficial/huggingface/runs/19xaw7pe">https://wandb.ai/aravindyuvraj007-vnrvjietofficial/huggingface/runs/19xaw7pe</a>
                                               [ 362/1038 04:37 < 08:41, 1.30 it/s, Epoch 1.04/3]
      Step Training Loss
                  2 756500
        50
       100
                  2 333300
       150
                  2.237900
       200
                  2.260500
       250
                  2 180100
                  2.213300
       300
       350
                  2.137000
                                              [1038/1038 13:16, Epoch 3/3]
      Step Training Loss
                  2.756500
        50
       100
                  2.333300
                  2.237900
       150
       200
                  2.260500
       250
                  2.180100
       300
                  2.213300
       350
                  2.137000
                  1.888300
       400
       450
                  1.904700
from sklearn.metrics import accuracy_score, f1_score
y_true, y_pred = [], []
id2label = {0: "negative", 1: "neutral", 2: "positive"}
label2id = {v:k for k,v in id2label.items()}
for ex in test_data:
    prompt = f"Sentence: {ex['sentence']}\nSentiment:"
    inputs = tokenizer(prompt, return_tensors="pt").to(model.device)
    outputs = model.generate(**inputs, max_new_tokens=5)
    pred = tokenizer.decode(outputs[0], skip_special_tokens=True)
    # extract last token as sentiment guess
    guess = None
    for cand in id2label.values():
        if cand in pred.lower():
            guess = cand
            break
    if guess is None:
        guess = "neutral" # fallback
    y_true.append(ex["label"])
```

```
y_pred.append(label2id[guess])
# Compute metrics
acc = accuracy_score(y_true, y_pred)
f1 = f1_score(y_true, y_pred, average="macro")
print(f"Fine-tuned LoRA Accuracy: {acc*100:.2f}%")
print(f"Fine-tuned LoRA F1 (macro): {f1*100:.2f}%")
    Fine-tuned LoRA Accuracy: 90.74%
     Fine-tuned LoRA F1 (macro): 89.05%
Start coding or generate with AI.
# Test the fine-tuned model with a new prompt
new_prompt = "Sentence: I am not feeling good, I am feeling very not good and not good heart attack.\nSentiment:"
inputs = tokenizer(new_prompt, return_tensors="pt").to(model.device)
outputs = model.generate(**inputs, max_new_tokens=5)
generated_text = tokenizer.decode(outputs[0], skip_special_tokens=True)
print("Generated Sentiment:", generated_text)
    Generated Sentiment: Sentence: I am not feeling good, I am feeling very not good and not good heart attack.
     Sentiment: negative - negative Sentiment
Start coding or generate with AI.
```

Task

Set up the code to fine-tune a language model using QLoRA with the FastLanguageModel library. Load the model in 4-bit precision, wrap it with LoRA, define training arguments, and initialize the SFTTrainer. Do not run the training.

Load the model in 4-bit

Subtask:

 $Load\ the\ base\ model\ in\ 4-bit\ precision\ using\ Fast Language Model.from_pretrained\ .$

Reasoning: The subtask is to load the base model in 4-bit precision. This requires using the FastLanguageModel.from_pretrained method with the specified parameters.

```
from unsloth import FastLanguageModel
# Load base model in 4-bit for QLoRA fine-tuning
model, tokenizer = FastLanguageModel.from_pretrained(
    "unsloth/Llama-3.2-3B-bnb-4bit",
    max_seq_length=2048,
    load_in_4bit=True,
)
peft_model = FastLanguageModel.get_peft_model(
    model,
    r=16,
    target_modules=["q_proj","k_proj","v_proj","o_proj","gate_proj","up_proj","down_proj"],
    lora_alpha=16,
    lora_dropout=0.0,
    bias="none",
    use_gradient_checkpointing="unsloth"
peft_model.print_trainable_parameters()
    ==((====))== Unsloth 2025.8.9: Fast Llama patching. Transformers: 4.55.4.
                    Tesla T4. Num GPUs = 1. Max memory: 14.741 GB. Platform: Linux.
     0^0/ \_/
                    Torch: 2.8.0+cu126. CUDA: 7.5. CUDA Toolkit: 12.6. Triton: 3.4.0
                    Bfloat16 = FALSE. FA [Xformers = 0.0.32.post2. FA2 = False]
                    Free license: <a href="http://github.com/unslothai/unsloth">http://github.com/unslothai/unsloth</a>
```

```
Unsloth: Fast downloading is enabled - ignore downloading bars which are red colored! Unsloth 2025.8.9 patched 28 layers with 28 QKV layers, 28 O layers and 28 MLP layers.
      trainable params: 24,313,856 || all params: 3,237,063,680 || trainable%: 0.7511
from transformers import TrainingArguments
from unsloth.trainer import SFTTrainer
args = TrainingArguments(
    output_dir="outputs_lora_1b",
    num_train_epochs=3,
    per_device_train_batch_size=2,
    gradient_accumulation_steps=4,
    learning_rate=2e-4,
    fp16=True,
    logging_steps=50,
    save_strategy="no",
trainer = SFTTrainer(
    model=peft\_model,
    tokenizer=tokenizer,
    train_dataset=train_data,
    eval_dataset=test_data,
    formatting_func=formatting_func,
    max_seq_length=512,
```

trainer.train()

args=args,

```
Unsloth: Tokenizing ["text"]: 100%
                                                                            2762/2762 [00:00<00:00, 5458.54 examples/s]
     Unsloth: Tokenizing ["text"]: 100%
                                                                            691/691 [00:00<00:00, 4953.17 examples/s]
     ==((====))== Unsloth - 2x faster free finetuning | Num GPUs used = 1
                    Num examples = 2,762 | Num Epochs = 3 | Total steps = 1,038
        \\ /
     0^0/ \_/
                    Batch size per device = 2 | Gradient accumulation steps = 4
                   Data Parallel GPUs = 1 | Total batch size (2 x 4 x 1) = 8
                    Trainable parameters = 24,313,856 of 3,237,063,680 (0.75% trained)
                                             ■ [1038/1038 29:14, Epoch 3/3]
      Step Training Loss
        50
                  2.503700
       100
                  2 219600
       150
                  2.118500
                  2.134100
       200
       250
                  2.057000
       300
                  2.091300
       350
                  2.022600
       400
                  1.771900
                  1.780200
       450
       500
                  1.790400
       550
                  1.720600
       600
                  1.777300
       650
                  1.723300
       700
                  1.671700
       750
                  1.438500
       800
                  1.431600
       850
                  1.447000
                  1.402600
       900
                  1.383300
       950
                  1.385300
      1000
     TrainOutput(global_step=1038, training_loss=1.7802981264559061, metrics={'train_runtime': 1759.1777, 'train_samples_per_second': 4.71,
     'train_steps_per_second': 0.59, 'total_flos': 6197031974510592.0, 'train_loss': 1.7802981264559061})
from sklearn.metrics import accuracy_score, f1_score
y_true, y_pred = [], []
id2label = {0: "negative", 1: "neutral", 2: "positive"}
label2id = {v:k for k,v in id2label.items()}
for ex in test data:
    prompt = f"Sentence: {ex['sentence']}\nSentiment:"
    inputs = tokenizer(prompt, return_tensors="pt").to(model.device)
    outputs = peft model.generate(**inputs, max new tokens=5)
    pred = tokenizer.decode(outputs[0], skip_special_tokens=True)
    # extract last token as sentiment guess
    guess = None
    for cand in id2label.values():
        if cand in pred.lower():
            guess = cand
            break
    if guess is None:
        guess = "neutral" # fallback
    y_true.append(ex["label"])
    y_pred.append(label2id[guess])
# Compute metrics
acc = accuracy_score(y_true, y_pred)
f1 = f1_score(y_true, y_pred, average="macro")
print(f"Fine-tuned LoRA Accuracy: {acc*100:.2f}%")
```

print(f"Fine-tuned LoRA F1 (macro): {f1*100:.2f}%")

Fine-tuned LoRA Accuracy: 95.66% Fine-tuned LoRA F1 (macro): 94.98%

from peft import PromptTuningConfig, get_peft_model, TaskType, PromptTuningInit