Fine-tuning a language model from datasets import load dataset from transformers import AutoTokenizer, TrainingArguments, Trainer from transformers import AutoModelForSequenceClassification import numpy as np from evaluate import load import torch # Yelp Review data dataset = load dataset("yelp\_review\_full") # Tokenizer tokenizer = AutoTokenizer.from pretrained("bert-base-cased") In [4]: # Tokenization function def tokenize function(examples): return tokenizer(examples["text"], padding="max length", truncation=True, max length=512) # Tokenize the dataset tokenized\_datasets = dataset.map(tokenize\_function, batched=True) # Create small training and evaluation sets small\_train\_dataset = tokenized\_datasets["train"].shuffle(seed=42).select(range(1000)) small\_eval\_dataset = tokenized\_datasets["test"].shuffle(seed=42).select(range(1000)) # Load the pretrained BERT model model = AutoModelForSequenceClassification.from pretrained("bert-base-cased", num labels=5) Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-cased and are newly initialized: ['classifier.weight', 'classifier.bias'] You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference. # Metric - Accuracy accuracy\_metric = load("accuracy") def compute metrics(eval pred): logits, labels = eval pred predictions = np.argmax(logits, axis=-1) return accuracy metric.compute(predictions=predictions, references=labels) # Training arguments training args = TrainingArguments( output dir="./results", learning rate=2e-5, per device train batch size=8, per device eval batch\_size=8, num train epochs=3, weight decay=0.01, evaluation strategy="epoch", save strategy="epoch" # Initializing the Trainer trainer = Trainer( model=model, args=training args, train dataset=small train dataset, eval dataset=small eval dataset, compute metrics=compute metrics, In [8]: # Fine-tune the model trainer.train() [375/375 07:01, Epoch 3/3] **Epoch Training Loss Validation Loss Accuracy** 1.142848 0.531000 1 No log 0.592000 No log 0.958671 0.960508 0.599000 3 No log Out[8]: TrainOutput(global\_step=375, training\_loss=1.0517815755208333, metrics={'train runtime': 422.5052, 'train sampl es\_per\_second': 7.101, 'train\_steps\_per\_second': 0.888, 'total\_flos': 789354427392000.0, 'train\_loss': 1.051781 5755208333, 'epoch': 3.0}) In [9]: # Evaluate the model after training trainer.evaluate() [125/125 00:35] Out[9]: {'eval\_loss': 0.9605082869529724, 'eval\_accuracy': 0.599, 'eval runtime': 35.6936, 'eval\_samples\_per\_second': 28.016, 'eval\_steps\_per\_second': 3.502, 'epoch': 3.0} Inferencing with the fine-tuned language model reviews = [ "Let this review be your reason to visit. We were celebrating my birthday this evening, and I was so happy "First time having Ukrainian food! It was delicious, but we waited about 1h20min for our entrees. I think t "In the evening the establishment was full, but we were served quickly enough, the waiter was very nice and "Little bit disappointed. The food tastes good. Nice aromatic seasonings. Food processing time is heavily of "Today we were served rotten fish on potato pancakes. The fish smelled terrible. Never in 9 years in the Ur # The trained model is accessed from the trainer model = trainer.model # Tokenize the reviews tokenized reviews = tokenizer(reviews, padding=True, truncation=True, return tensors="pt") model = model.cuda() tokenized reviews = tokenized reviews.to('cuda') # Perform inference model.eval() # Set the model to evaluation mode with torch.no grad(): outputs = model(\*\*tokenized reviews) predictions = torch.argmax(outputs.logits, dim=1) # Convert predictions to list for easy viewing predicted\_ratings = predictions.cpu().tolist() # Print the predicted ratings for review, rating in zip(reviews, predicted\_ratings): print(f"Review: {review}\nPredicted Rating: {rating}\n") Review: Let this review be your reason to visit. We were celebrating my birthday this evening, and I was so hap py to share my favorite meals that remind me of home with my American friends. Everyone at the table loved the food. Excellent and attentive service complemented incredible food. I am so grateful for every person who works at Nene's. Predicted Rating: 4 Review: First time having Ukrainian food! It was delicious, but we waited about 1h20min for our entrees. I thin k that discourages me a bit to come back soon, despite the great food and atmosphere. I would still recommend t his place. Predicted Rating: 2 Review: In the evening the establishment was full, but we were served quickly enough, the waiter was very nice and quite attentive). Of all the dishes I liked the kharcho soup, very tasty). Pancakes with cottage cheese are tasty, but a little undercooked). Khachapuri is not tasty at all, as if it came from frozen. The dough is hard, there is not enough cheese. Draniki are half raw. Pkhali are not similar to pkhali. Predicted Rating: 2 Review: Little bit disappointed. The food tastes good. Nice aromatic seasonings. Food processing time is heavil y diversified Ajaruli Khachapuri was burned and cheese was hard. Might be it was warmed up second time in the o ven. Pic is included. Khinkali was good. Predicted Rating: 2 Review: Today we were served rotten fish on potato pancakes. The fish smelled terrible. Never in 9 years in the United States have I been served rotten fish. We were with a small child, I can't even imagine what would have happened to the child if he had eaten rotten fish. This would be our third time at the restaurant. Service is a lways great, food is mediocre. . . but, guys, rotten fish, seriously? I wanted to support this restaurant becau se the idea is amazing, but after today I can't. Predicted Rating: 0 Fine-tuning a vision transformer In [13]: import torch import numpy as np from datasets import load dataset, load metric from transformers import AutoImageProcessor from torchvision.transforms import RandomResizedCrop, Compose, Normalize, ToTensor from transformers import DefaultDataCollator, ViTForImageClassification, TrainingArguments, Trainer from evaluate import load In [14]: # Loading the Food101 dataset food = load\_dataset("food101", split="train[:5000]") food = food.train\_test\_split(test\_size=0.2) # Creating label dictionaries labels = food["train"].features["label"].names label2id, id2label = dict(), dict() for i, label in enumerate(labels): label2id[label] = str(i) id2label[str(i)] = label # Load the image processor for ViT checkpoint = "google/vit-base-patch16-224-in21k" image processor = AutoImageProcessor.from pretrained(checkpoint) # Image transformation normalize = Normalize (mean=image processor.image mean, std=image processor.image std) image processor.size["shortest edge"] if "shortest edge" in image processor.size else (image processor.size["height"], image processor.size["width"]) \_transforms = Compose([RandomResizedCrop(size), ToTensor(), normalize]) # Preprocessing function def transforms(examples): if "image" in examples: examples["pixel values"] = [ transforms(img.convert("RGB")) for img in examples["image"]] del examples["image"] return examples # Apply preprocessing food = food.with transform(transforms) data\_collator = DefaultDataCollator() # Define the model model = ViTForImageClassification.from\_pretrained( checkpoint, num\_labels=len(labels), label2id=label2id, id2label=id2label # Define Training Arguments vision\_training\_args = TrainingArguments( output\_dir="./vit\_food101\_results", num\_train\_epochs=3, per\_device\_train\_batch\_size=8, # Adjust based on your GPU memory per\_device\_eval\_batch\_size=8, # Adjust based on your GPU memory learning\_rate=5e-5, evaluation\_strategy="epoch", save\_strategy="epoch", remove\_unused\_columns=False, load\_best\_model\_at\_end=True, metric\_for\_best\_model="accuracy", # Metric - Accuracy accuracy metric = load("accuracy") def compute\_metrics(eval\_pred): logits, labels = eval\_pred predictions = np.argmax(logits, axis=-1) return accuracy\_metric.compute(predictions=predictions, references=labels) # Initialize Trainer vision\_trainer = Trainer( model=model, args=vision\_training\_args, train\_dataset=food["train"], eval\_dataset=food["test"], data\_collator=data\_collator, compute\_metrics=compute\_metrics, Some weights of ViTForImageClassification were not initialized from the model checkpoint at google/vit-base-pat ch16-224-in21k and are newly initialized: ['classifier.weight', 'classifier.bias'] You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference. In [17]: # Fine-tune the model vision trainer.train() [1500/1500 09:12, Epoch 3/3] **Epoch Training Loss Validation Loss Accuracy** 1.534100 0.601970 0.897000 0.375700 0.905000 0.370031 0.216000 0.323047 0.919000 Out[17]: TrainOutput(global step=1500, training loss=0.7086004994710287, metrics={'train runtime': 553.8309, 'train samp les\_per\_second': 21.667, 'train\_steps\_per\_second': 2.708, 'total\_flos': 9.307289843712e+17, 'train\_loss': 0.708 6004994710287, 'epoch': 3.0}) In [18]: # Evaluate the model after training vision trainer.evaluate() [125/125 00:17] Out[18]: {'eval\_loss': 0.31369879841804504, 'eval\_accuracy': 0.929, 'eval\_runtime': 17.5373, 'eval\_samples\_per\_second': 57.021, 'eval\_steps\_per\_second': 7.128, 'epoch': 3.0} Inference with the fine-tuned vision model import matplotlib.pyplot as plt from PIL import Image # Load the validation dataset ds = load dataset("food101", split="validation[:1000]") # Loading model fine\_tuned\_model = vision\_trainer.model fine\_tuned\_model = fine\_tuned\_model.cuda() # Selected indices for inference indices = [0, 299, 599, 899]# Preprocess and perform inference for idx in indices: # Original image image = ds[idx]["image"] plt.imshow(image) plt.axis("off") plt.show() # Preprocess the image processed\_image = \_transforms(image.convert("RGB")).unsqueeze(0).cuda() # Model inference fine tuned model.eval() with torch.no\_grad(): outputs = fine\_tuned\_model(processed\_image) prediction = torch.argmax(outputs.logits, dim=1) # Get the predicted class predicted\_class = id2label[str(prediction.item())] print(f"Image Index: {idx}, Predicted Class: {predicted\_class}") Image Index: 0, Predicted Class: beignets Image Index: 299, Predicted Class: prime\_rib Image Index: 599, Predicted Class: ramen Image Index: 899, Predicted Class: hamburger