# Starter Notebook

Install and import required libraries

```
!pip install transformers datasets evaluate accelerate peft trl
bitsandbytes
!pip install nvidia-ml-py3
!pip install scikit-learn
Requirement already satisfied: transformers in
/usr/local/lib/python3.11/dist-packages (4.51.3)
Collecting datasets
  Downloading datasets-3.5.0-py3-none-any.whl.metadata (19 kB)
Collecting evaluate
  Downloading evaluate-0.4.3-py3-none-any.whl.metadata (9.2 kB)
Requirement already satisfied: accelerate in
/usr/local/lib/python3.11/dist-packages (1.5.2)
Requirement already satisfied: peft in /usr/local/lib/python3.11/dist-
packages (0.14.0)
Collecting trl
  Downloading trl-0.16.1-py3-none-any.whl.metadata (12 kB)
Collecting bitsandbytes
  Downloading bitsandbytes-0.45.5-py3-none-
manylinux 2 24 x86 64.whl.metadata (5.0 kB)
Requirement already satisfied: filelock in
/usr/local/lib/python3.11/dist-packages (from transformers) (3.18.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.30.0 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.30.2)
Requirement already satisfied: numpy>=1.17 in
/usr/local/lib/python3.11/dist-packages (from transformers) (2.0.2)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from transformers) (24.2)
Requirement already satisfied: pyyaml>=5.1 in
/usr/local/lib/python3.11/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.11/dist-packages (from transformers)
(2024.11.6)
Requirement already satisfied: requests in
/usr/local/lib/python3.11/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: tokenizers<0.22,>=0.21 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.21.1)
Requirement already satisfied: safetensors>=0.4.3 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.5.3)
Requirement already satisfied: tgdm>=4.27 in
/usr/local/lib/python3.11/dist-packages (from transformers) (4.67.1)
Requirement already satisfied: pyarrow>=15.0.0 in
/usr/local/lib/python3.11/dist-packages (from datasets) (18.1.0)
```

```
Collecting dill<0.3.9,>=0.3.0 (from datasets)
  Downloading dill-0.3.8-py3-none-any.whl.metadata (10 kB)
Requirement already satisfied: pandas in
/usr/local/lib/python3.11/dist-packages (from datasets) (2.2.2)
Collecting xxhash (from datasets)
  Downloading xxhash-3.5.0-cp311-cp311-
manylinux 2 17 x86 64.manylinux2014 x86 64.whl.metadata (12 kB)
Collecting multiprocess<0.70.17 (from datasets)
  Downloading multiprocess-0.70.16-py311-none-any.whl.metadata (7.2
kB)
Collecting fsspec<=2024.12.0,>=2023.1.0 (from
fsspec[http]<=2024.12.0,>=2023.1.0->datasets)
  Downloading fsspec-2024.12.0-py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: aiohttp in
/usr/local/lib/python3.11/dist-packages (from datasets) (3.11.15)
Requirement already satisfied: psutil in
/usr/local/lib/python3.11/dist-packages (from accelerate) (5.9.5)
Requirement already satisfied: torch>=2.0.0 in
/usr/local/lib/python3.11/dist-packages (from accelerate)
(2.6.0+cu124)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-
packages (from trl) (13.9.4)
Requirement already satisfied: aiohappyeyeballs>=2.3.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets)
(2.6.1)
Requirement already satisfied: aiosignal>=1.1.2 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets)
(1.3.2)
Requirement already satisfied: attrs>=17.3.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets)
(25.3.0)
Requirement already satisfied: frozenlist>=1.1.1 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets)
(1.5.0)
Requirement already satisfied: multidict<7.0,>=4.5 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets)
Requirement already satisfied: propcache>=0.2.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets)
Requirement already satisfied: varl<2.0,>=1.17.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets)
(1.19.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/usr/local/lib/python3.11/dist-packages (from huggingface-
hub<1.0,>=0.30.0->transformers) (4.13.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.11/dist-packages (from requests->transformers)
(3.4.1)
```

```
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.11/dist-packages (from requests->transformers)
(3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.11/dist-packages (from requests->transformers)
(2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.11/dist-packages (from requests->transformers)
(2025.1.31)
Requirement already satisfied: networkx in
/usr/local/lib/python3.11/dist-packages (from torch>=2.0.0-
>accelerate) (3.4.2)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.11/dist-packages (from torch>=2.0.0-
>accelerate) (3.1.6)
Collecting nvidia-cuda-nvrtc-cu12==12.4.127 (from torch>=2.0.0-
>accelerate)
  Downloading nvidia_cuda_nvrtc_cu12-12.4.127-py3-none-
manylinux2014 x86 64.whl.metadata (1.5 kB)
Collecting nvidia-cuda-runtime-cu12==12.4.127 (from torch>=2.0.0-
>accelerate)
  Downloading nvidia cuda runtime cu12-12.4.127-py3-none-
manylinux2014 x86 64.whl.metadata (1.5 kB)
Collecting nvidia-cuda-cupti-cu12==12.4.127 (from torch>=2.0.0-
>accelerate)
  Downloading nvidia cuda cupti cu12-12.4.127-py3-none-
manylinux2014 x86 64.whl.metadata (1.6 kB)
Collecting nvidia-cudnn-cu12==9.1.0.70 (from torch>=2.0.0->accelerate)
  Downloading nvidia cudnn cu12-9.1.0.70-py3-none-
manylinux2014 x86 64.whl.metadata (1.6 kB)
Collecting nvidia-cublas-cu12==12.4.5.8 (from torch>=2.0.0-
>accelerate)
  Downloading nvidia cublas cu12-12.4.5.8-py3-none-
manylinux2014 x86 64.whl.metadata (1.5 kB)
Collecting nvidia-cufft-cu12==11.2.1.3 (from torch>=2.0.0->accelerate)
  Downloading nvidia cufft cu12-11.2.1.3-py3-none-
manylinux2014 x86 64.whl.metadata (1.5 kB)
Collecting nvidia-curand-cu12==10.3.5.147 (from torch>=2.0.0-
>accelerate)
  Downloading nvidia curand cu12-10.3.5.147-py3-none-
manylinux2014 x86 64.whl.metadata (1.5 kB)
Collecting nvidia-cusolver-cu12==11.6.1.9 (from torch>=2.0.0-
>accelerate)
  Downloading nvidia cusolver cu12-11.6.1.9-py3-none-
manylinux2014 x86 64.whl.metadata (1.6 kB)
Collecting nvidia-cusparse-cu12==12.3.1.170 (from torch>=2.0.0-
>accelerate)
  Downloading nvidia cusparse cu12-12.3.1.170-py3-none-
manylinux2014 x86 64.whl.metadata (1.6 kB)
```

```
Requirement already satisfied: nvidia-cusparselt-cu12==0.6.2 in
/usr/local/lib/python3.11/dist-packages (from torch>=2.0.0-
>accelerate) (0.6.2)
Requirement already satisfied: nvidia-nccl-cu12==2.21.5 in
/usr/local/lib/python3.11/dist-packages (from torch>=2.0.0-
>accelerate) (2.21.5)
Requirement already satisfied: nvidia-nvtx-cu12==12.4.127 in
/usr/local/lib/python3.11/dist-packages (from torch>=2.0.0-
>accelerate) (12.4.127)
Collecting nvidia-nvjitlink-cu12==12.4.127 (from torch>=2.0.0-
>accelerate)
  Downloading nvidia nvjitlink cu12-12.4.127-py3-none-
manylinux2014 x86 64.whl.metadata (1.5 kB)
Requirement already satisfied: triton==3.2.0 in
/usr/local/lib/python3.11/dist-packages (from torch>=2.0.0-
>accelerate) (3.2.0)
Requirement already satisfied: sympy==1.13.1 in
/usr/local/lib/python3.11/dist-packages (from torch>=2.0.0-
>accelerate) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.11/dist-packages (from sympy==1.13.1-
>torch>=2.0.0->accelerate) (1.3.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas->datasets)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.11/dist-packages (from pandas->datasets)
(2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.11/dist-packages (from pandas->datasets)
(2025.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.11/dist-packages (from rich->trl) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/usr/local/lib/python3.11/dist-packages (from rich->trl) (2.18.0)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0-
>rich->trl) (0.1.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2-
>pandas->datasets) (1.17.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.11/dist-packages (from jinja2->torch>=2.0.0-
>accelerate) (3.0.2)
Downloading datasets-3.5.0-py3-none-any.whl (491 kB)
                                      491.2/491.2 kB 15.1 MB/s eta
0:00:00
                                        - 84.0/84.0 kB 5.2 MB/s eta
0:00:00
```

```
- 336.4/336.4 kB 25.6 MB/s eta
0:00:00
anylinux 2 24 x86 64.whl (76.1 MB)
                                       - 76.1/76.1 MB 10.8 MB/s eta
0:00:00
                                        - 116.3/116.3 kB 6.2 MB/s eta
0:00:00
                                        - 183.9/183.9 kB 13.1 MB/s eta
0:00:00
ultiprocess-0.70.16-py311-none-any.whl (143 kB)
                                       143.5/143.5 kB 10.1 MB/s eta
0:00:00
anylinux2014_x86 64.whl (363.4 MB)

    363.4/363.4 MB 2.7 MB/s eta

0:00:00
anylinux2014_x86_64.whl (13.8 MB)
                                       — 13.8/13.8 MB 30.2 MB/s eta
0:00:00
anylinux2014 x86 64.whl (24.6 MB)
                                        - 24.6/24.6 MB 40.1 MB/s eta
0:00:00
e cu12-12.4.127-py3-none-manylinux2014 x86 64.whl (883 kB)
                                     --- 883.7/883.7 kB 31.5 MB/s eta
anylinux2014 x86 64.whl (664.8 MB)
                                        - 664.8/664.8 MB 3.0 MB/s eta
0:00:00
anylinux2014 x86 64.whl (211.5 MB)
                                        - 211.5/211.5 MB 5.4 MB/s eta
0:00:00
anylinux2014_x86_64.whl (56.3 MB)
                                        - 56.3/56.3 MB 13.1 MB/s eta
0:00:00
anylinux2014 x86 64.whl (127.9 MB)
                                        - 127.9/127.9 MB 7.5 MB/s eta
0:00:00
anylinux2014 x86 64.whl (207.5 MB)
                                        - 207.5/207.5 MB 5.2 MB/s eta
0:00:00
anylinux2014 x86 64.whl (21.1 MB)
                                      -- 21.1/21.1 MB 81.0 MB/s eta
anylinux 2 17 x86 64.manylinux2014 x86 64.whl (194 kB)
                                      — 194.8/194.8 kB 17.9 MB/s eta
0:00:00
e-cu12, nvidia-cuda-nvrtc-cu12, nvidia-cuda-cupti-cu12, nvidia-cublas-
cu12, fsspec, dill, nvidia-cusparse-cu12, nvidia-cudnn-cu12,
multiprocess, nvidia-cusolver-cu12, datasets, evaluate, bitsandbytes,
trl
```

```
Attempting uninstall: nvidia-nvjitlink-cu12
    Found existing installation: nvidia-nvjitlink-cu12 12.5.82
    Uninstalling nvidia-nvjitlink-cu12-12.5.82:
      Successfully uninstalled nvidia-nvjitlink-cu12-12.5.82
  Attempting uninstall: nvidia-curand-cu12
    Found existing installation: nvidia-curand-cu12 10.3.6.82
    Uninstalling nvidia-curand-cu12-10.3.6.82:
      Successfully uninstalled nvidia-curand-cu12-10.3.6.82
  Attempting uninstall: nvidia-cufft-cu12
    Found existing installation: nvidia-cufft-cu12 11.2.3.61
    Uninstalling nvidia-cufft-cu12-11.2.3.61:
      Successfully uninstalled nvidia-cufft-cu12-11.2.3.61
  Attempting uninstall: nvidia-cuda-runtime-cu12
    Found existing installation: nvidia-cuda-runtime-cul2 12.5.82
    Uninstalling nvidia-cuda-runtime-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-runtime-cu12-12.5.82
  Attempting uninstall: nvidia-cuda-nvrtc-cu12
    Found existing installation: nvidia-cuda-nvrtc-cu12 12.5.82
    Uninstalling nvidia-cuda-nvrtc-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-nvrtc-cu12-12.5.82
  Attempting uninstall: nvidia-cuda-cupti-cu12
    Found existing installation: nvidia-cuda-cupti-cul2 12.5.82
    Uninstalling nvidia-cuda-cupti-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-cupti-cu12-12.5.82
  Attempting uninstall: nvidia-cublas-cu12
    Found existing installation: nvidia-cublas-cu12 12.5.3.2
    Uninstalling nvidia-cublas-cu12-12.5.3.2:
      Successfully uninstalled nvidia-cublas-cu12-12.5.3.2
  Attempting uninstall: fsspec
    Found existing installation: fsspec 2025.3.2
    Uninstalling fsspec-2025.3.2:
      Successfully uninstalled fsspec-2025.3.2
  Attempting uninstall: nvidia-cusparse-cu12
    Found existing installation: nvidia-cusparse-cul2 12.5.1.3
    Uninstalling nvidia-cusparse-cu12-12.5.1.3:
      Successfully uninstalled nvidia-cusparse-cu12-12.5.1.3
  Attempting uninstall: nvidia-cudnn-cu12
    Found existing installation: nvidia-cudnn-cu12 9.3.0.75
    Uninstalling nvidia-cudnn-cu12-9.3.0.75:
      Successfully uninstalled nvidia-cudnn-cu12-9.3.0.75
  Attempting uninstall: nvidia-cusolver-cu12
    Found existing installation: nvidia-cusolver-cu12 11.6.3.83
    Uninstalling nvidia-cusolver-cu12-11.6.3.83:
      Successfully uninstalled nvidia-cusolver-cu12-11.6.3.83
ERROR: pip's dependency resolver does not currently take into account
all the packages that are installed. This behaviour is the source of
the following dependency conflicts.
gcsfs 2025.3.2 requires fsspec==2025.3.2, but you have fsspec
2024.12.0 which is incompatible.
```

```
Successfully installed bitsandbytes-0.45.5 datasets-3.5.0 dill-0.3.8
evaluate-0.4.3 fsspec-2024.12.0 multiprocess-0.70.16 nvidia-cublas-
cu12-12.4.5.8 nvidia-cuda-cupti-cu12-12.4.127 nvidia-cuda-nvrtc-cu12-
12.4.127 nvidia-cuda-runtime-cu12-12.4.127 nvidia-cudnn-cu12-9.1.0.70
nvidia-cufft-cu12-11.2.1.3 nvidia-curand-cu12-10.3.5.147 nvidia-
cusolver-cu12-11.6.1.9 nvidia-cusparse-cu12-12.3.1.170 nvidia-
nvjitlink-cu12-12.4.127 trl-0.16.1 xxhash-3.5.0
Collecting nvidia-ml-py3
  Downloading nvidia-ml-py3-7.352.0.tar.gz (19 kB)
  Preparing metadata (setup.py) ... l-py3
  Building wheel for nvidia-ml-py3 (setup.py) ... l-py3:
filename=nvidia ml py3-7.352.0-py3-none-any.whl size=19172
sha256=caeb12e4756a8a16be4bed56d931ce8e48f81c4ebf0185c828dff2e6a1edae9
  Stored in directory:
/root/.cache/pip/wheels/47/50/9e/29dc79037d74c3c1bb4a8661fb608e8674b7e
4260d6a3f8f51
Successfully built nvidia-ml-py3
Installing collected packages: nvidia-ml-py3
Successfully installed nvidia-ml-py3-7.352.0
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.11/dist-packages (1.6.1)
Requirement already satisfied: numpy>=1.19.5 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (2.0.2)
Requirement already satisfied: scipy>=1.6.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
import os
import pandas as pd
import torch
from transformers import RobertaModel, RobertaTokenizer,
TrainingArguments, Trainer, DataCollatorWithPadding,
RobertaForSequenceClassification
from peft import LoraConfig, get_peft_model, PeftModel
from datasets import load dataset, Dataset, ClassLabel
import pickle
```

# Load Tokenizer and Preprocess Data

```
base_model = 'roberta-base'

dataset = load_dataset('ag_news', split='train')
tokenizer = RobertaTokenizer.from_pretrained(base_model)

def preprocess(examples):
```

```
tokenized = tokenizer(examples['text'], truncation=True,
padding=True)
    return tokenized
tokenized dataset = dataset.map(preprocess, batched=True,
remove columns=["text"])
tokenized dataset = tokenized dataset.rename column("label", "labels")
/usr/local/lib/python3.11/dist-packages/huggingface hub/utils/
auth.py:94: UserWarning:
The secret `HF TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your
settings tab (https://huggingface.co/settings/tokens), set it as
secret in your Google Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to
access public models or datasets.
 warnings.warn(
{"model id": "ac3ef2a4cbd54af49b4956e9419fd122", "version major": 2, "vers
ion minor":0}
{"model id":"76360a417ad949ffbbc5483b1d6cba46","version major":2,"vers
ion minor":0}
{"model id":"2191cef2956b468ebec4d04195710d95","version major":2,"vers
ion minor":0}
{"model id": "5123ee2abf964f61ac25564ba2b28df3", "version major": 2, "vers
ion minor":0}
{"model id": "9adac11d09e647fe95f734ed26694685", "version major": 2, "vers
ion minor":0}
{"model id": "90d2dd39019f4f85ae62981cd91ffe8c", "version major": 2, "vers
ion minor":0}
{"model id": "3894f9e0c0804a7fb77c1c62a2ba1b2e", "version major": 2, "vers
ion minor":0}
{"model id":"69cc5130c71f4aa19f37a887497d49dd","version major":2,"vers
ion minor":0}
{"model id": "aldc69fc59634d19ace6ec2f3adcdaf3", "version major": 2, "vers
ion minor":0}
{"model id": "9b6d85322b3e48e0ae9168676a559f3a", "version major": 2, "vers
ion minor":0}
{"model_id": "6640646067ac41d19dce32b4fba89aa3", "version_major": 2, "vers
ion minor":0}
```

```
# Extract the number of classess and their names
num_labels = dataset.features['label'].num_classes
class_names = dataset.features["label"].names
print(f"number of labels: {num_labels}")
print(f"the labels: {class_names}")

# Create an id2label mapping
# We will need this for our classifier.
id2label = {i: label for i, label in enumerate(class_names)}

data_collator = DataCollatorWithPadding(tokenizer=tokenizer,
return_tensors="pt")

number of labels: 4
the labels: ['World', 'Sports', 'Business', 'Sci/Tech']
```

#### Load Pre-trained Model

Set up config for pretrained model and download it from hugging face

```
model = RobertaForSequenceClassification.from pretrained(
    base model,
    id2label=id2label)
model
Xet Storage is enabled for this repo, but the 'hf xet' package is not
installed. Falling back to regular HTTP download. For better
performance, install the package with: `pip install
huggingface_hub[hf_xet]` or `pip install hf_xet`
WARNING: hugging face hub.file download: Xet Storage is enabled for this
repo, but the 'hf_xet' package is not installed. Falling back to
regular HTTP download. For better performance, install the package
with: `pip install huggingface hub[hf xet]` or `pip install hf xet`
{"model id": "74a68b127b80494ca460c219c4cd59b8", "version major": 2, "vers
ion minor":0}
Some weights of RobertaForSequenceClassification were not initialized
from the model checkpoint at roberta-base and are newly initialized:
['classifier.dense.bias', 'classifier.dense.weight',
'classifier.out_proj.bias', 'classifier.out_proj.weight']
You should probably TRAIN this model on a down-stream task to be able
to use it for predictions and inference.
RobertaForSequenceClassification(
  (roberta): RobertaModel(
    (embeddings): RobertaEmbeddings(
      (word embeddings): Embedding(50265, 768, padding idx=1)
      (position embeddings): Embedding(514, 768, padding idx=1)
      (token type embeddings): Embedding(1, 768)
```

```
(LayerNorm): LayerNorm((768,), eps=1e-05,
elementwise affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    (encoder): RobertaEncoder(
      (layer): ModuleList(
        (0-11): 12 x RobertaLayer(
          (attention): RobertaAttention(
            (self): RobertaSdpaSelfAttention(
              (query): Linear(in features=768, out features=768,
bias=True)
              (key): Linear(in features=768, out features=768,
bias=True)
              (value): Linear(in features=768, out features=768,
bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            (output): RobertaSelfOutput(
              (dense): Linear(in features=768, out features=768,
bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-05,
elementwise affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
          (intermediate): RobertaIntermediate(
            (dense): Linear(in features=768, out features=3072,
bias=True)
            (intermediate act fn): GELUActivation()
          (output): RobertaOutput(
            (dense): Linear(in features=3072, out features=768,
bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-05,
elementwise affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
        )
    )
  (classifier): RobertaClassificationHead(
    (dense): Linear(in features=768, out features=768, bias=True)
    (dropout): Dropout(p=0.1, inplace=False)
    (out proj): Linear(in features=768, out features=4, bias=True)
  )
)
```

### Anything from here on can be modified

```
# Split the original training set
split_datasets = tokenized_dataset.train_test_split(test_size=640,
seed=42)
train_dataset = split_datasets['train']
eval_dataset = split_datasets['test']
```

# Setup LoRA Config

Setup PEFT config and get peft model for finetuning

```
# # PEFT Config
# peft config = LoraConfig(
      r=2,
#
      lora alpha=4,
#
      lora dropout=0.05,
      bias = 'none',
#
      target modules = ['query'],
      task_type="SEQ CLS",
#
# )
# Configure LoRA
peft config = LoraConfig(
    r=7, # LoRA rank
    lora alpha=16, # Alpha parameter for scaling
    lora dropout=0.05, # Dropout probability for LoRA layers
    target modules=["query", "key", "value"], # Apply LoRA to these
layers
    bias="none", # Don't train bias parameters
    task type="SEQ CLS", # Specify the task type
)
peft model = get peft model(model, peft config)
peft model
PeftModelForSequenceClassification(
  (base model): LoraModel(
    (model): RobertaForSequenceClassification(
      (roberta): RobertaModel(
        (embeddings): RobertaEmbeddings(
          (word embeddings): Embedding(50265, 768, padding idx=1)
          (position_embeddings): Embedding(514, 768, padding_idx=1)
          (token type embeddings): Embedding(1, 768)
          (LayerNorm): LayerNorm((768,), eps=1e-05,
elementwise affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        (encoder): RobertaEncoder(
```

```
(layer): ModuleList(
            (0-11): 12 x RobertaLayer(
              (attention): RobertaAttention(
                (self): RobertaSdpaSelfAttention(
                  (query): lora.Linear(
                     (base_layer): Linear(in features=768,
out features=768, bias=True)
                     (lora dropout): ModuleDict(
                       (default): Dropout(p=0.05, inplace=False)
                     (lora A): ModuleDict(
                       (default): Linear(in_features=768,
out features=7, bias=False)
                     (lora B): ModuleDict(
                       (default): Linear(in features=7,
out features=768, bias=False)
                     (lora embedding A): ParameterDict()
                     (lora embedding B): ParameterDict()
                     (lora magnitude vector): ModuleDict()
                  (key): lora.Linear(
                    (base layer): Linear(in features=768,
out features=768, bias=True)
                     (lora dropout): ModuleDict(
                       (default): Dropout(p=0.05, inplace=False)
                     (lora A): ModuleDict(
                       (default): Linear(in features=768,
out features=7, bias=False)
                     (lora B): ModuleDict(
                       (default): Linear(in features=7,
out features=768, bias=False)
                     (lora embedding A): ParameterDict()
                     (lora embedding B): ParameterDict()
                     (lora magnitude vector): ModuleDict()
                  (value): lora.Linear(
                     (base layer): Linear(in features=768,
out_features=768, bias=True)
                    (lora dropout): ModuleDict(
                       (default): Dropout(p=0.05, inplace=False)
                     (lora A): ModuleDict(
                       (default): Linear(in features=768,
out features=7, bias=False)
```

```
(lora B): ModuleDict(
                      (default): Linear(in features=7,
out features=768, bias=False)
                    (lora embedding A): ParameterDict()
                    (lora embedding B): ParameterDict()
                    (lora magnitude vector): ModuleDict()
                  (dropout): Dropout(p=0.1, inplace=False)
                (output): RobertaSelfOutput(
                  (dense): Linear(in_features=768, out features=768,
bias=True)
                  (LayerNorm): LayerNorm((768,), eps=1e-05,
elementwise_affine=True)
                  (dropout): Dropout(p=0.1, inplace=False)
              (intermediate): RobertaIntermediate(
                (dense): Linear(in features=768, out features=3072,
bias=True)
                (intermediate act fn): GELUActivation()
              )
              (output): RobertaOutput(
                (dense): Linear(in features=3072, out features=768,
bias=True)
                (LayerNorm): LayerNorm((768,), eps=1e-05,
elementwise affine=True)
                (dropout): Dropout(p=0.1, inplace=False)
          )
        )
      (classifier): ModulesToSaveWrapper(
        (original module): RobertaClassificationHead(
          (dense): Linear(in features=768, out features=768,
bias=True)
          (dropout): Dropout(p=0.1, inplace=False)
          (out proj): Linear(in features=768, out features=4,
bias=True)
        (modules to save): ModuleDict(
          (default): RobertaClassificationHead(
            (dense): Linear(in_features=768, out_features=768,
bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
            (out proj): Linear(in features=768, out features=4,
```

### Training Setup

```
# To track evaluation accuracy during training
from sklearn.metrics import accuracy score, precision score,
recall score, f1 score
def compute metrics(pred):
    labels = pred.label ids
    preds = pred.predictions.argmax(-1)
    # Calculate accuracy
    accuracy = accuracy score(labels, preds)
    return {
        'accuracy': accuracy
    }
# Setup Training args
output dir = "results"
training_args = TrainingArguments(
    output dir=output dir,
    report to=None,
    eval strategy='steps',
    logging steps=100,
    learning rate=1e-5,
    num train epochs=1,
    \max \text{ steps}=1200,
    use cpu=False,
    dataloader num workers=4,
    per device train batch size=16,
    per device eval batch size=64,
    optim="adamw_torch",
```

```
gradient_checkpointing=False,
   gradient_checkpointing_kwargs={'use_reentrant':True}
)

def get_trainer(model):
   return Trainer(
        model=model,
        args=training_args,
        compute_metrics=compute_metrics,
        train_dataset=train_dataset,
        eval_dataset=eval_dataset,
        data_collator=data_collator,
)
```

#### Start Training

```
peft lora finetuning trainer = get trainer(peft model)
result = peft lora finetuning trainer.train()
No label names provided for model class
`PeftModelForSequenceClassification`. Since `PeftModel` hides base
models input arguments, if label names is not given, label names can't
be set automatically within `Trainer`. Note that empty label names
list will be used instead.
/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py
:624: UserWarning: This DataLoader will create 4 worker processes in
total. Our suggested max number of worker in current system is 2,
which is smaller than what this DataLoader is going to create. Please
be aware that excessive worker creation might get DataLoader running
slow or even freeze, lower the worker number to avoid potential
slowness/freeze if necessary.
 warnings.warn(
wandb: WARNING The `run_name` is currently set to the same value as
`TrainingArguments.output dir`. If this was not intended, please
specify a different run name by setting the
TrainingArguments.run name` parameter.
wandb: Using wandb-core as the SDK backend. Please refer to
https://wandb.me/wandb-core for more information.
<IPython.core.display.Javascript object>
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:
https://wandb.ai/authorize
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 not shared publicly.

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: dataencapsulate (dataencapsulate-new-york-university) to https://api.wandb.ai. Use `wandb login --relogin` to force relogin

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

<IPvthon.core.display.HTML object>

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please

be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py :624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running

```
slow or even freeze, lower the worker number to avoid potential
slowness/freeze if necessary.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py
:624: UserWarning: This DataLoader will create 4 worker processes in
total. Our suggested max number of worker in current system is 2,
which is smaller than what this DataLoader is going to create. Please
be aware that excessive worker creation might get DataLoader running
slow or even freeze, lower the worker number to avoid potential
slowness/freeze if necessary.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py
:624: UserWarning: This DataLoader will create 4 worker processes in
total. Our suggested max number of worker in current system is 2,
which is smaller than what this DataLoader is going to create. Please
be aware that excessive worker creation might get DataLoader running
slow or even freeze, lower the worker number to avoid potential
slowness/freeze if necessary.
 warnings.warn(
```

#### **Evaluate Finetuned Model**

### Performing Inference on Custom Input

Uncomment following functions for running inference on custom inputs

```
def classify(model, tokenizer, text):
    device = torch.device("cuda" if torch.cuda.is available() else
"cpu")
    inputs = tokenizer(text, truncation=True, padding=True,
return tensors="pt").to(device)
    output = model(**inputs)
    prediction = output.logits.argmax(dim=-1).item()
    print(f'\n Class: {prediction}, Label: {id2label[prediction]},
Text: {text}')
    return id2label[prediction]
classify( peft model, tokenizer, "Kederis proclaims innocence Olympic
champion Kostas Kederis today left hospital ahead of his date with IOC
inquisitors claiming his ...")
classify( peft model, tokenizer, "Wall St. Bears Claw Back Into the
Black (Reuters) Reuters - Short-sellers, Wall Street's dwindling\band
of ultra-cynics, are seeing green again.")
 Class: 1, Label: Sports, Text: Kederis proclaims innocence Olympic
champion Kostas Kederis today left hospital ahead of his date with IOC
```

```
inquisitors claiming his ...
Class: 2, Label: Business, Text: Wall St. Bears Claw Back Into the
Black (Reuters) Reuters - Short-sellers, Wall Street's dwindlingand of
ultra-cynics, are seeing green again.
{"type":"string"}
```

#### Run Inference on eval dataset

```
from torch.utils.data import DataLoader
import evaluate
from tqdm import tqdm
def evaluate model(inference model, dataset, labelled=True,
batch size=8, data collator=None):
    Evaluate a PEFT model on a dataset.
   Args:
        inference model: The model to evaluate.
        dataset: The dataset (Hugging Face Dataset) to run inference
on.
        labelled (bool): If True, the dataset includes labels and
metrics will be computed.
                         If False, only predictions will be returned.
        batch size (int): Batch size for inference.
        data collator: Function to collate batches. If None, the
default collate fn is used.
    Returns:
        If labelled is True, returns a tuple (metrics, predictions)
        If labelled is False, returns the predictions.
    # Create the DataLoader
    eval dataloader = DataLoader(dataset, batch size=batch size,
collate fn=data collator)
    device = torch.device("cuda" if torch.cuda.is available() else
"cpu")
    inference model.to(device)
    inference model.eval()
    all predictions = []
    if labelled:
        metric = evaluate.load('accuracy')
    # Loop over the DataLoader
    for batch in tqdm(eval dataloader):
        # Move each tensor in the batch to the device
```

```
batch = {k: v.to(device) for k, v in batch.items()}
        with torch.no grad():
            outputs = inference model(**batch)
        predictions = outputs.logits.argmax(dim=-1)
        all predictions.append(predictions.cpu())
        if labelled:
            # Expecting that labels are provided under the "labels"
key.
            references = batch["labels"]
            metric.add batch(
                predictions=predictions.cpu().numpy(),
                references=references.cpu().numpy()
            )
    # Concatenate predictions from all batches
    all predictions = torch.cat(all predictions, dim=0)
    if labelled:
        eval metric = metric.compute()
        print("Evaluation Metric:", eval metric)
        return eval metric, all predictions
    else:
        return all predictions
# Check evaluation accuracy
, = evaluate model(peft model, eval dataset, True, 8,
data collator)
{"model id": "76ffaf23694c4125bd2130e44e3270f1", "version major": 2, "vers
ion minor":0}
100% | 80/80 [00:11<00:00, 6.91it/s]
Evaluation Metric: {'accuracy': 0.8890625}
```

#### Run Inference on unlabelled dataset

```
#Load your unlabelled data
unlabelled_dataset = pd.read_pickle("test_unlabelled.pkl")
test_dataset = unlabelled_dataset.map(preprocess, batched=True,
remove_columns=["text"])
unlabelled_dataset

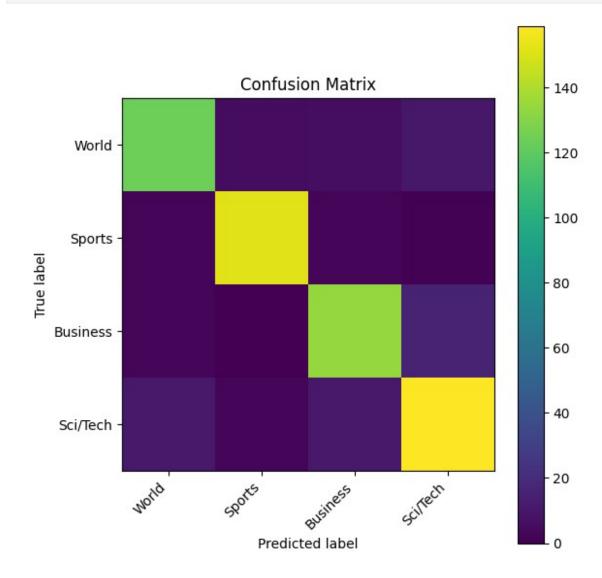
{"model_id":"90af531e8f364d358a6db8a15088bb09","version_major":2,"vers
ion_minor":0}

Dataset({
    features: ['text'],
```

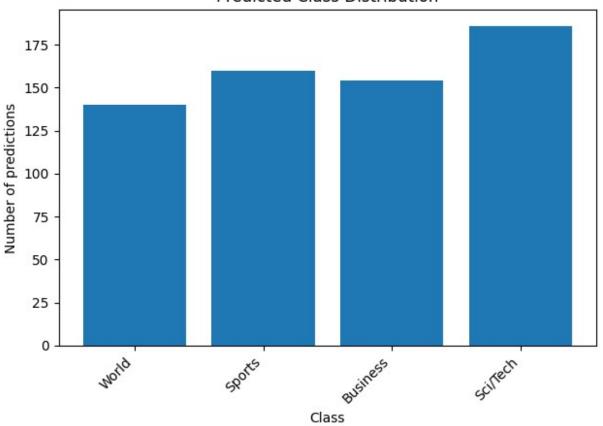
```
num rows: 8000
})
# Run inference and save predictions
preds = evaluate_model(peft_model, test dataset, False, 8,
data collator)
df output = pd.DataFrame({
    'ID': range(len(preds)),
    'Label': preds.numpy() # or preds.tolist()
})
df output.to csv(os.path.join(output dir,"inference output.csv"),
index=False)
print("Inference complete. Predictions saved to inference output.csv")
         | 1000/1000 [01:51<00:00, 8.96it/s]
100%|
Inference complete. Predictions saved to inference output.csv
# % Cell 1: Compute predictions, overall & per-class metrics, and
class distribution
from sklearn.metrics import classification report, confusion matrix
import numpy as np
import pandas as pd
# 1. Run predictions on validation set
pred output = peft lora finetuning trainer.predict(eval dataset)
preds = np.argmax(pred output.predictions, axis=1)
labels = pred output.label ids
# 2. Overall performance + per-category metrics
report = classification report(labels, preds,
                               target names=list(id2label.values()),
                               output dict=True)
report df = pd.DataFrame(report).transpose()
print("\n=== Classification Report ===")
print(report df)
# 3. Predicted class distribution
class dist =
pd.Series(preds).value counts().sort index().rename axis('class id').r
eset index(name='count')
class dist['class name'] = class dist['class id'].map(id2label)
print("\n=== Predicted Class Distribution ===")
print(class dist)
/usr/local/lib/python3.11/dist-packages/torch/utils/data/
dataloader.py:624: UserWarning: This DataLoader will create 4 worker
processes in total. Our suggested max number of worker in current
system is 2, which is smaller than what this DataLoader is going to
```

```
create. Please be aware that excessive worker creation might get
DataLoader running slow or even freeze, lower the worker number to
avoid potential slowness/freeze if necessary.
 warnings.warn(
<IPython.core.display.HTML object>
=== Classification Report ===
              precision
                           recall f1-score
                                                support
               0.885714 0.855172
World
                                   0.870175
                                             145.000000
Sports
               0.950000 0.962025
                                   0.955975
                                             158.000000
               0.870130 0.875817
Business
                                   0.872964
                                             153.000000
Sci/Tech
               0.854839 0.864130
                                   0.859459
                                             184.000000
accuracy
              0.889062 0.889062
                                   0.889062
                                               0.889062
                         0.889286
               0.890171
                                   0.889643
                                             640.000000
macro avq
weighted avg 0.888982
                         0.889062
                                   0.888943
                                             640.000000
=== Predicted Class Distribution ===
   class id count class name
0
               140
                        World
          0
1
          1
               160
                       Sports
2
          2
               154
                     Business
3
          3
               186
                     Sci/Tech
# % Cell 2: Confusion matrix & class-distribution bar chart
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import confusion matrix
# Confusion matrix
conf mat = confusion matrix(labels, preds)
fig, ax = plt.subplots(figsize=(6,6))
im = ax.imshow(conf mat, interpolation='nearest')
ax.set xticks(np.arange(len(id2label)))
ax.set yticks(np.arange(len(id2label)))
ax.set xticklabels(list(id2label.values()), rotation=45, ha='right')
ax.set vticklabels(list(id2label.values()))
ax.set xlabel("Predicted label")
ax.set ylabel("True label")
ax.set title("Confusion Matrix")
fig.colorbar(im, ax=ax)
plt.tight layout()
plt.show()
# Class distribution bar plot
fig, ax = plt.subplots()
ax.bar(class dist['class name'], class dist['count'])
ax.set xlabel("Class")
ax.set_ylabel("Number of predictions")
```

```
ax.set_title("Predicted Class Distribution")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

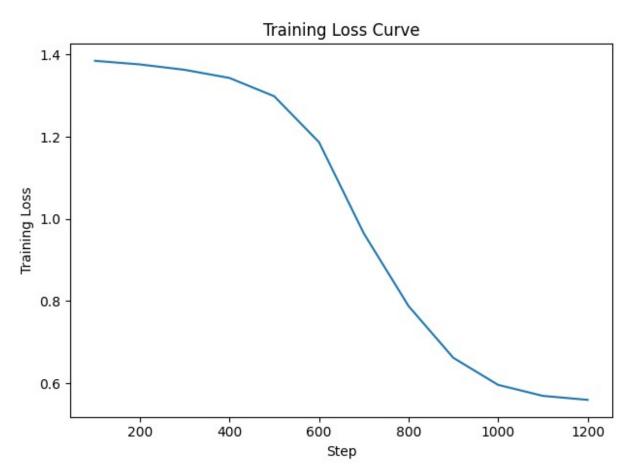


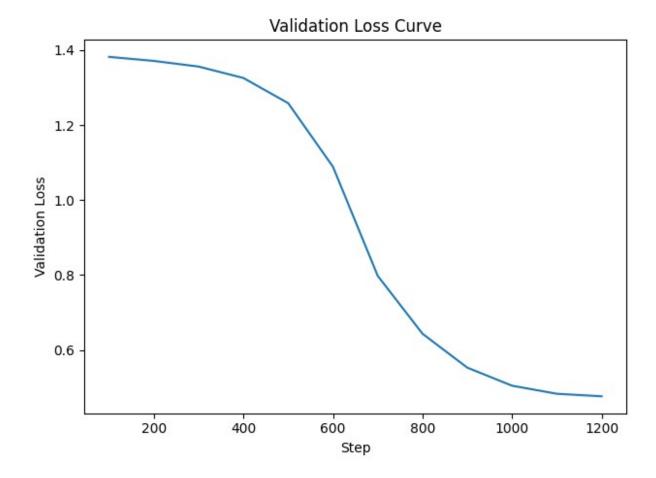


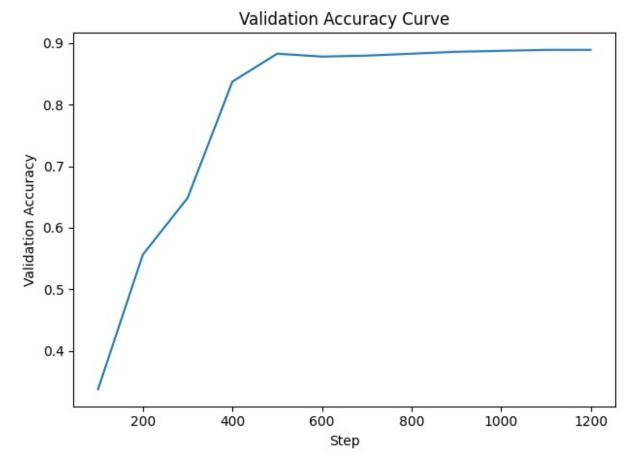


```
# % Cell 3: Training & validation loss/accuracy curves
import matplotlib.pyplot as plt
# Extract from trainer state
history = peft lora finetuning trainer.state.log history
# Training loss entries (ones with 'loss' but no 'eval loss')
train steps = [e['step'] for e in history if 'loss' in e and
'eval loss' not in e]
train losses = [e['loss'] for e in history if 'loss' in e and
'eval loss' not in e]
# Validation metrics (those with 'eval loss' and 'eval accuracy')
eval_steps = [e['step'] for e in history if 'eval_loss' in e]
eval_losses = [e['eval_loss'] for e in history if 'eval_loss' in e]
eval accs = [e['eval accuracy'] for e in history if 'eval accuracy'
in el
# Plot training loss
plt.figure()
plt.plot(train steps, train losses)
plt.xlabel("Step")
```

```
plt.ylabel("Training Loss")
plt.title("Training Loss Curve")
plt.tight_layout()
plt.show()
# Plot validation loss
plt.figure()
plt.plot(eval_steps, eval_losses)
plt.xlabel("Step")
plt.ylabel("Validation Loss")
plt.title("Validation Loss Curve")
plt.tight layout()
plt.show()
# Plot validation accuracy
plt.figure()
plt.plot(eval steps, eval accs)
plt.xlabel("Step")
plt.ylabel("Validation Accuracy")
plt.title("Validation Accuracy Curve")
plt.tight_layout()
plt.show()
```







```
# %% Cell: Combined Loss Curve (Figure 1)
import matplotlib.pyplot as plt
# extract from your trainer state, as before
history = peft lora finetuning trainer.state.log history
train steps = [e['step'] for e in history if 'loss' in e and
'eval loss' not in e]
train losses = [e['loss'] for e in history if 'loss' in e and
'eval loss' not in el
eval_steps = [e['step'] for e in history if 'eval_loss' in e]
eval losses = [e['eval loss'] for e in history if 'eval loss' in e]
plt.figure()
plt.plot(train steps, train losses, label='Train Loss')
plt.plot(eval steps, eval losses, label='Val Loss')
plt.xlabel('Step')
plt.ylabel('Loss')
plt.title('Figure 1: Training vs Validation Loss')
plt.legend()
plt.tight_layout()
plt.show()
```

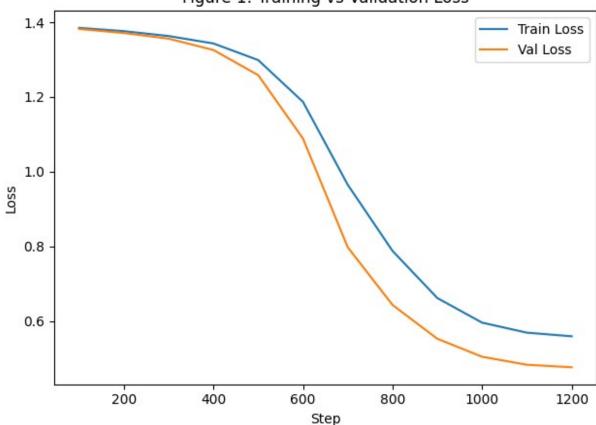


Figure 1: Training vs Validation Loss

```
# % Cell: Figure 2 — Training vs Validation Accuracy
# 1) Get train & val accuracy in one pass each
train_pred = peft_lora_finetuning_trainer.predict(train_dataset)
         = peft_lora_finetuning_trainer.predict(eval_dataset)
# Depending on your HF version the metric key may be 'test accuracy'
or 'eval accuracy'
train acc = train pred.metrics.get('test accuracy',
train pred.metrics.get('eval accuracy'))
val acc = val pred.metrics.get('test accuracy',
val pred.metrics.get('eval accuracy'))
# 2) Plot bar chart
import matplotlib.pyplot as plt
plt.figure()
plt.bar(['Train','Validation'], [train acc, val acc])
plt.ylim(0, 1.0)
plt.ylabel('Accuracy')
plt.title('Figure 2: Training vs Validation Accuracy')
plt.tight layout()
plt.show()
```

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

<IPython.core.display.HTML object>

/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.

warnings.warn(

<IPython.core.display.HTML object>

