DS@GT Kaggle CLEF - Fall 2024 Internal Competition

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First, let's import all the necessary libraries and packages.

```
from typing import Dict, Tuple
import contextlib

from transformers import BertForSequenceClassification, AutoTokenizer
from torch.utils.data import Dataset, DataLoader
from torch.optim import AdamW
import torch
import tqdm

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
```

```
/home/hice1/cclark339/.local/lib/python3.9/site-packages/tqdm/
auto.py:21: TqdmWarning: IProgress not found. Please update jupyter
and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

Load the Data

Now, we need to load in the training data.

```
df = pd.read_csv('data/train/train.csv')
df
```

```
            id                                                text
author
0      id26305  This process, however, afforded me no means of...
EAP
1      id17569  It never once occurred to me that the fumbling...
HPL
2      id11008  In his left hand was a gold snuff box, from wh...
EAP
3      id27763  How lovely is spring As we looked from Windsor...
MWS
```

```
4      id12958  Finding nothing else, not even gold, the Super...
HPL
...        ...                                                ...    .
..
19574  id17718  I could have fancied, while I looked at it, th...
EAP
19575  id08973  The lids clenched themselves together as if in...
EAP
19576  id05267  Mais il faut agir that is to say, a Frenchman ...
EAP
19577  id17513  For an item of news like this, it strikes us i...
EAP
19578  id00393  He laid a gnarled claw on my shoulder, and it ...
HPL

[19579 rows x 3 columns]
```

We should also split it into training and validation sets.

```
test_size = 0.1

X, y = df.drop(columns=['author']), df[['author']]

print(f'X shape: {X.shape}')
print(f'y shape: {y.shape}')

X shape: (19579, 2)
y shape: (19579, 1)

X_train, X_valid, y_train, y_valid = train_test_split(X, y,
test_size=test_size, random_state=42)

print(f'X_train shape: {X_train.shape}')
print(f'y_train shape: {y_train.shape}\n')

print(f'X_valid shape: {X_valid.shape}')
print(f'y_valid shape: {y_valid.shape}')

X_train shape: (17621, 2)
y_train shape: (17621, 1)

X_valid shape: (1958, 2)
y_valid shape: (1958, 1)
```

Tokenize the Data

Next, we'll use a pre-defined tokenizer to tokenize training and validation texts.

```
max_length = 512
```

```
tokenizer = AutoTokenizer.from_pretrained('bert-base-cased')

train_tokens = tokenizer(list(X_train['text']), padding=True,
truncation=True, max_length=max_length)
valid_tokens = tokenizer(list(X_valid['text']), padding=True,
truncation=True, max_length=max_length)
```

Encode the Labels

At this point, we should encode the labels into numerical values.

```
label2int = {
    'EAP': 0,
    'HPL': 1,
    'MWS': 2
}

y_train = y_train['author'].map(label2int).to_numpy()
y_valid = y_valid['author'].map(label2int).to_numpy()
```

Implement a Cuatom Dataset Class

Now, we need to define a class that stores the generated tokens. Our class should be applicable for both training and validation sets.

```
class TokensDataset(Dataset):
    def __init__(self, X, tokens, labels, device):
        self.X = X
        self.tokens = tokens
        self.labels = list(labels) if labels is not None else None
        self.device = device

    def __len__(self) -> int:
        return self.X.shape[0]

    def __getitem__(self, index) -> Dict:
        item = {}
        for key, value in self.tokens.items():
            item[key] = torch.tensor(value[index])

        if self.labels is not None:
            item['labels'] = torch.tensor(self.labels[index])

        return item
```

Load the Data into PyTorch DataLoaders

Next, we'll create instances of our TokensDataset class for both the training and validation sets, and then we'll wrap them in PyTorch DataLoaders.

We'll also define some of the data-specific hyperparameters, like batch size.

```
batch_size = 128
device = 'cuda' if torch.cuda.is_available() else 'cpu'

train_dataset = TokensDataset(X_train, train_tokens, y_train,
device=device)
valid_dataset = TokensDataset(X_valid, valid_tokens, y_valid,
device=device)

train_dataloader = DataLoader(train_dataset, batch_size=batch_size,
shuffle=True)
valid_dataloader = DataLoader(valid_dataset, batch_size=batch_size,
shuffle=True)
```

Initialize BERT Model, AdamW Optimizer, and Loss Function

Now, we need to initialize our model (BERT) and optimizer (AdamW). We'll also define model-specific parameters, like learning rate.

```
lr = 1e-5

model = BertForSequenceClassification.from_pretrained('bert-base-
cased', num_labels=3).to(device)
optimizer = AdamW(model.parameters(), lr=lr)
loss_fn = torch.nn.CrossEntropyLoss()
```

```
Some weights of BertForSequenceClassification were not initialized
from the model checkpoint at bert-base-cased and are newly
initialized: ['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able
to use it for predictions and inference.
```

Fine-tune the Model

Next, we'll fine-tune our pre-trained BERT model on our training dataset, performing simultaneous validation as well.

```
num_epochs = 2

def inner_loop(dataloader, model, optimizer, loss_fn, train=True) ->
Tuple[float, float, Dict]:
```

```
    loop = tqdm.tqdm(dataloader, unit='batch')

    loss = None
    acc = None

    probs_dict = {
        'id': [],
        'EAP': [],
        'HPL': [],
        'MWS': []
    }

    test_flag = False
    for j, batch in enumerate(loop):
        batch = {key: value.to(device) for key, value in
batch.items()}
        test_flag = ('labels' not in list(batch.keys()))


        # forward pass
        with contextlib.nullcontext() if train else torch.no_grad():
            outputs = model(input_ids=batch['input_ids'],
attention_mask=batch['attention_mask'])

        logits = outputs.logits
        if not test_flag:
            loss = loss_fn(logits, batch['labels']).mean()

        # backward pass
        optimizer.zero_grad()
        if train and not test_flag:
            loss.backward()
            optimizer.step()

        # prediction
        probs = torch.nn.functional.softmax(logits, dim=1)
        y_pred = probs.argmax(dim=1)

        if not test_flag:
            acc = accuracy_score(batch['labels'].cpu().detach(),
y_pred.cpu().detach())

            # set tqdm postfix
            loop.set_postfix(loss=loss.item(), acc=acc)
        else:
            for i, prob in enumerate(probs):
                probs_dict['id'] +=
[dataloader.dataset.X['id'].iloc[128 * j + i]]
                probs_dict['EAP'] += [prob[0].cpu().detach().item()]
                probs_dict['HPL'] += [prob[1].cpu().detach().item()]
```

```
                probs_dict['MWS'] += [prob[2].cpu().detach().item()]

    return loss, acc, probs_dict

train_losses = []
valid_losses = []

train_accs = []
valid_accs = []

for epoch in range(num_epochs):
    # train
    train_loss, train_acc, _ = inner_loop(train_dataloader, model,
optimizer, loss_fn, train=True)

    # validate
    valid_loss, valid_acc, _ = inner_loop(valid_dataloader, model,
optimizer, loss_fn, train=False)

    # append losses and accuracies
    train_losses.append(train_loss)
    valid_losses.append(valid_loss)

    train_accs.append(train_acc)
    valid_accs.append(valid_acc)
```

```
100%|██████████| 138/138 [02:25<00:00,  1.06s/batch, acc=0.765,
loss=0.61]
100%|██████████| 16/16 [00:02<00:00,  7.75batch/s, acc=0.842,
loss=0.497]
100%|██████████| 138/138 [02:25<00:00,  1.06s/batch, acc=0.882,
loss=0.274]
100%|██████████| 16/16 [00:02<00:00,  7.76batch/s, acc=1, loss=0.116]
```

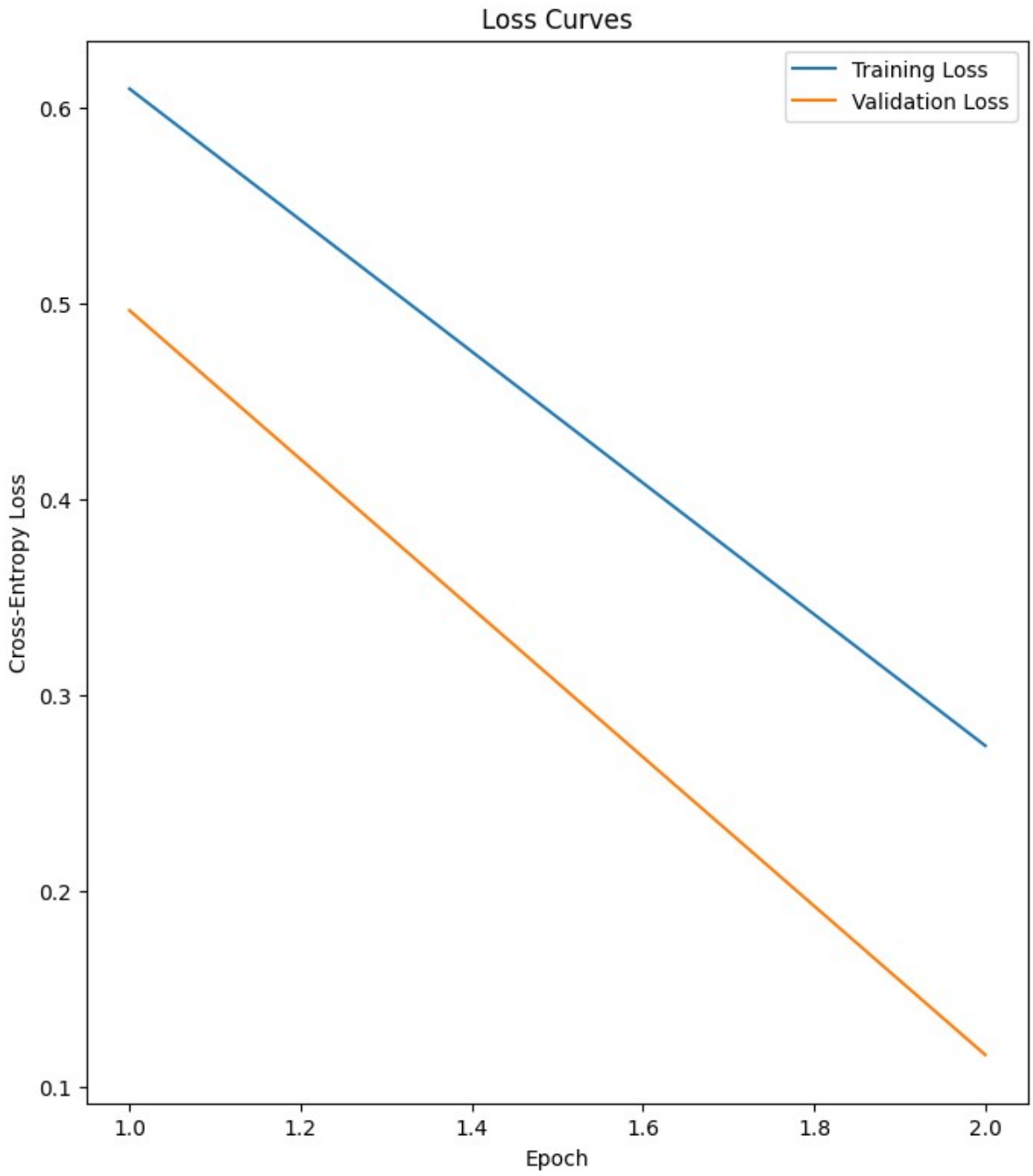
Plot Loss and Accuracy Curves

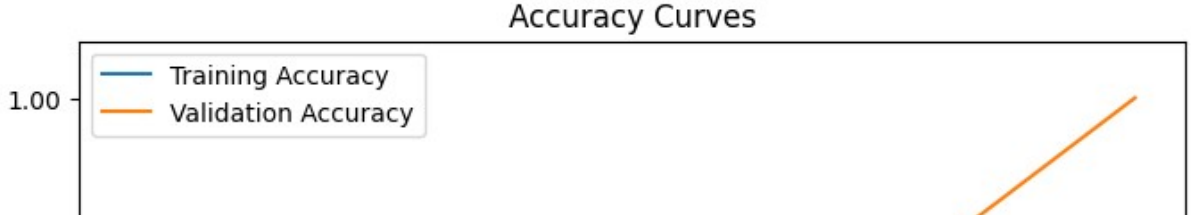
At this point, we'll plot our loss and accuracy curves.

```
train_losses = [train_loss.cpu().detach() for train_loss in
train_losses]
valid_losses = [valid_loss.cpu().detach() for valid_loss in
valid_losses]

plt.figure(figsize=(8, 20))

# plot losses
plt.subplot(2, 1, 1)
plt.plot(np.arange(1, len(train_losses) + 1), train_losses,
color='tab:blue', label='Training Loss')
plt.plot(np.arange(1, len(valid_losses) + 1), valid_losses,
```

```
color='tab:orange', label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Cross-Entropy Loss')
plt.title('Loss Curves')
plt.legend()

# plot accuracies
plt.subplot(2, 1, 2)
plt.plot(np.arange(1, len(train_accs) + 1), train_accs,
color='tab:blue', label='Training Accuracy')
plt.plot(np.arange(1, len(valid_accs) + 1), valid_accs,
color='tab:orange', label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Accuracy Curves')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x1551f81a92b0>
```


Loss Curves
Training Loss
Validation Loss
0.6
0.5
0.4
0.3
0.2
0.1
Cross-Entropy Loss
1.0
1.2
1.4
1.6
1.8
2.0
Epoch


Accuracy Curves
Training Accuracy
Validation Accuracy
1.00

Repeat Previous Steps (Except Training) on Test Set

Lastly, we need to repeat our previous steps to generate our test predictions for submission.

```
df = pd.read_csv('data/test/test.csv')
df
```

```
           id                                                text
0     id02310  Still, as I urged our leaving Ireland with suc...
1     id24541  If a fire wanted fanning, it could readily be ...
2     id00134  And when they had broken down the frail door t...
3     id27757  While I was thinking how I should possibly man...
4     id04081  I am not sure to what limit his knowledge may ...
...       ...                                                ...
8387  id11749        All this is now the fitter for my purpose.
8388  id10526               I fixed myself on a wide solitude.
8389  id13477  It is easily understood that what might improv...
8390  id13761  Be this as it may, I now began to feel the ins...
8391  id04282  Long winded, statistical, and drearily genealo...

[8392 rows x 2 columns]
```

```
X_test = df.copy()

print(f'X_test shape: {X_test.shape}')
```

```
X_test shape: (8392, 2)
```

```
test_tokens = tokenizer(list(X_test['text']), padding=True,
truncation=True, max_length=max_length)

test_dataset = TokensDataset(X_test, test_tokens, None, device=device)
test_dataloader = DataLoader(test_dataset, batch_size=batch_size,
shuffle=False)

_, _, y_probs = inner_loop(test_dataloader, model, optimizer, loss_fn,
train=False)
```

```
100%|██████████| 66/66 [00:23<00:00,  2.77batch/s]
```

```
y_probs = pd.DataFrame(y_probs)
y_probs
```

```
           id       EAP       HPL       MWS
0     id02310  0.024197  0.058086  0.917717
1     id24541  0.973773  0.021349  0.004878
2     id00134  0.016057  0.968966  0.014977
3     id27757  0.134692  0.853712  0.011596
4     id04081  0.390223  0.502815  0.106962
...       ...       ...       ...       ...
8387  id11749  0.195887  0.060416  0.743697
```

```
8388  id10526  0.336586  0.014189  0.649226
8389  id13477  0.671160  0.306234  0.022607
8390  id13761  0.062480  0.010625  0.926894
8391  id04282  0.041706  0.947501  0.010793

[8392 rows x 4 columns]
```

```
pd.to_csv('submission.csv', )
```