TOXIC COMMENT CLASSIFICATION

CS 482 FINAL PROJECT
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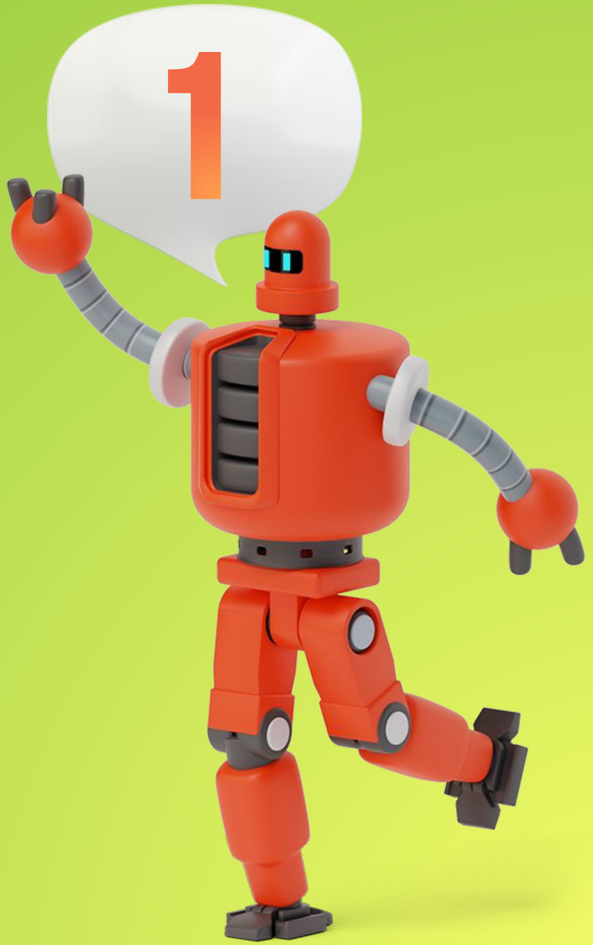
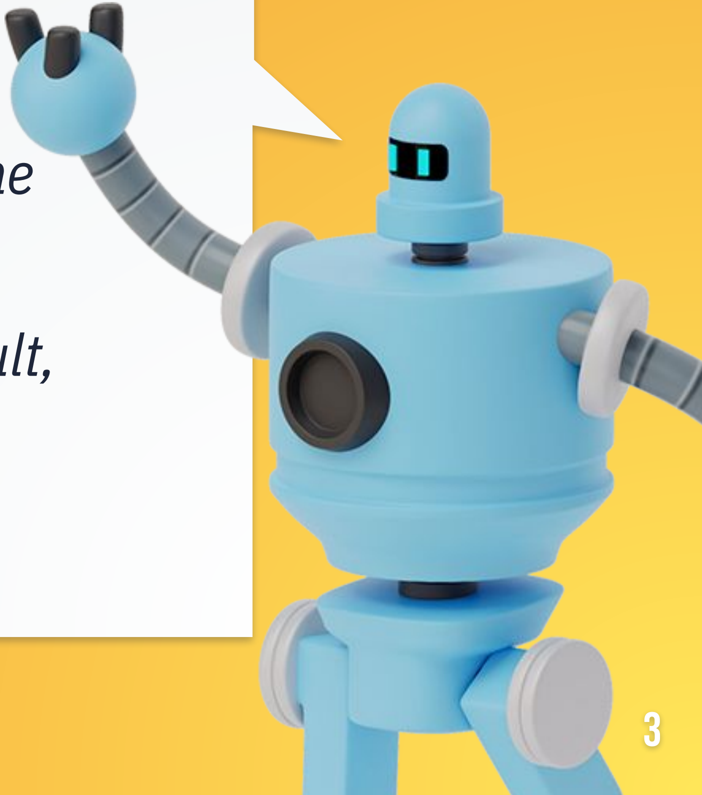
INTRODUCTION

Discussion of Challenge



The goal of the Toxic Comment Classification project is to identify and classify online comments according to the following classes of toxicity:

[toxic, severe_toxic, obscene, threat, insult, identity_hate]

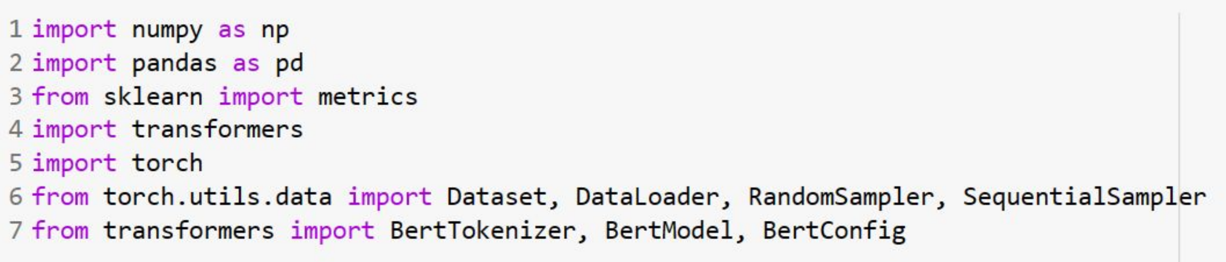


CODE WALKTHROUGH

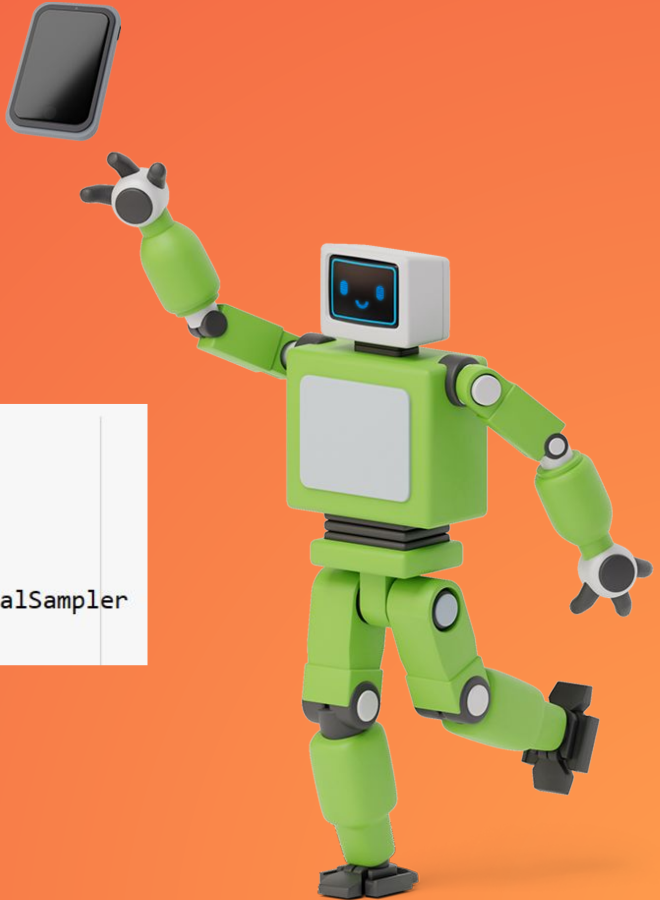
Code & App Documentation

1. PREPARING THE ENVIRONMENT

- Install necessary libraries
- Import libraries

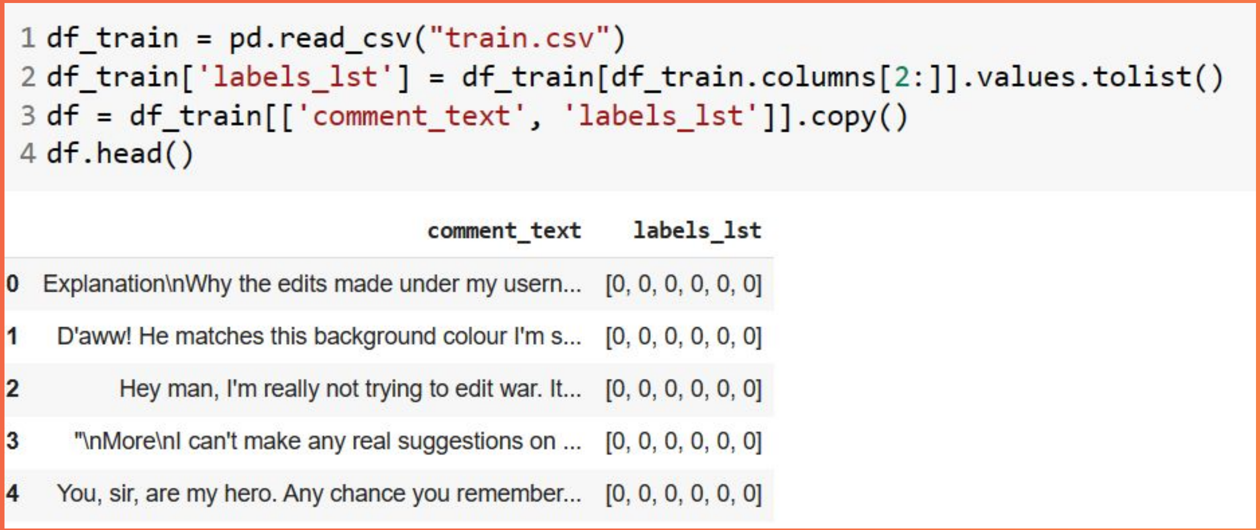


```python
import numpy as np
import pandas as pd
from sklearn import metrics
import transformers
import torch
from torch.utils.data import Dataset, DataLoader, RandomSampler, SequentialSampler
from transformers import BertTokenizer, BertModel, BertConfig
```



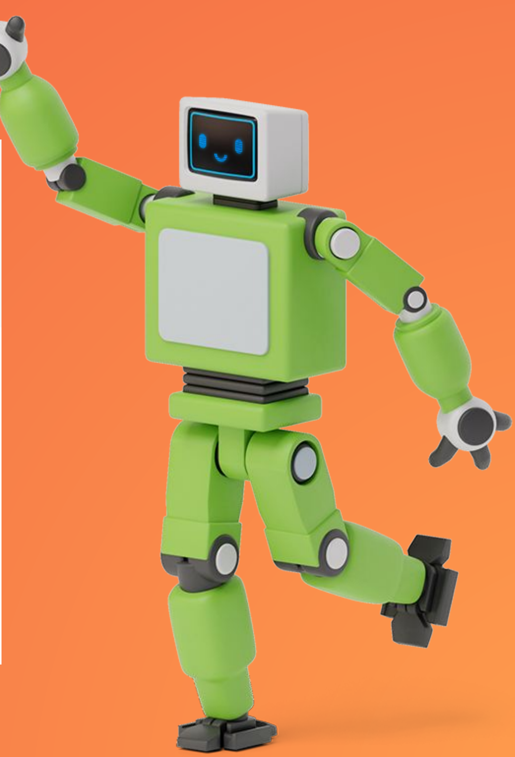
2. DATA LOADING & PREPROCESSING

- Load in csv files



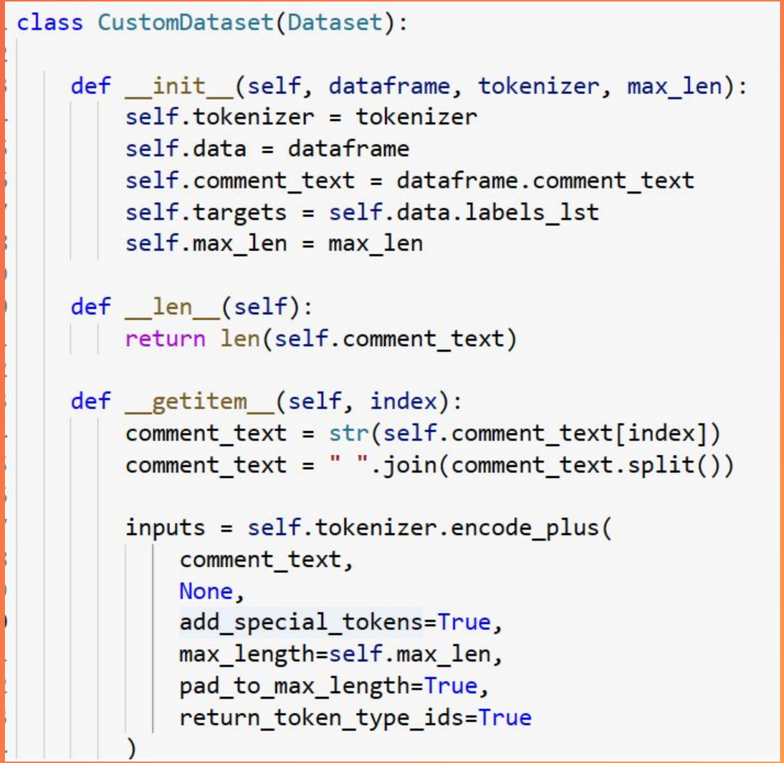
```python
df_train = pd.read_csv("train.csv")
df_train['labels_lst'] = df_train[df_train.columns[2:]].values.tolist()
df = df_train[['comment_text', 'labels_lst']].copy()
df.head()
```

	comment_text	labels_lst
0	Explanation\nWhy the edits made under my usern...	[0, 0, 0, 0, 0, 0]
1	D'aww! He matches this background colour I'm s...	[0, 0, 0, 0, 0, 0]
2	Hey man, I'm really not trying to edit war. It...	[0, 0, 0, 0, 0, 0]
3	"\nMore\nI can't make any real suggestions on ...	[0, 0, 0, 0, 0, 0]
4	You, sir, are my hero. Any chance you remember...	[0, 0, 0, 0, 0, 0]



2. DATA LOADING & PREPROCESSING

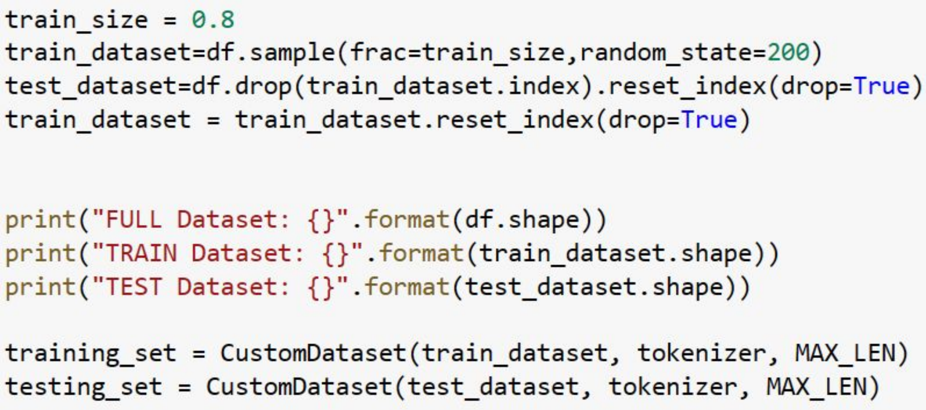
- Create custom dataset class



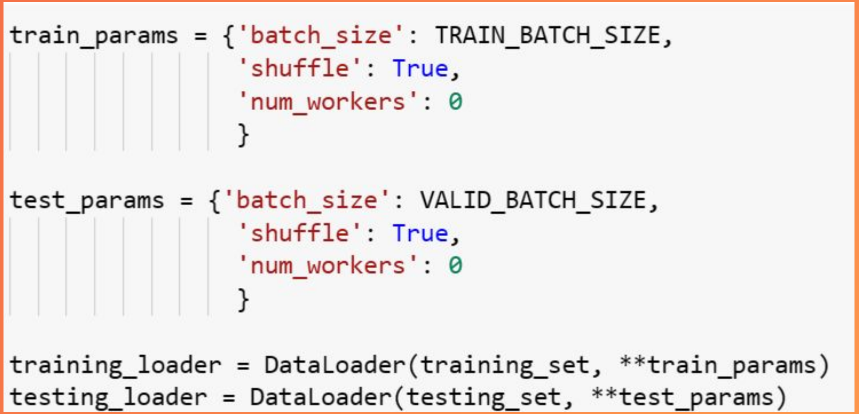
```
class CustomDataset(Dataset):

    def __init__(self, dataframe, tokenizer, max_len):
        self.tokenizer = tokenizer
        self.data = dataframe
        self.comment_text = dataframe.comment_text
        self.targets = self.data.labels_lst
        self.max_len = max_len

    def __len__(self):
        return len(self.comment_text)

    def __getitem__(self, index):
        comment_text = str(self.comment_text[index])
        comment_text = " ".join(comment_text.split())

        inputs = self.tokenizer.encode_plus(
            comment_text,
            None,
            add_special_tokens=True,
            max_length=self.max_len,
            pad_to_max_length=True,
            return_token_type_ids=True
        )
```

2. DATA LOADING & PREPROCESSING

- Create datasets for dataloaders



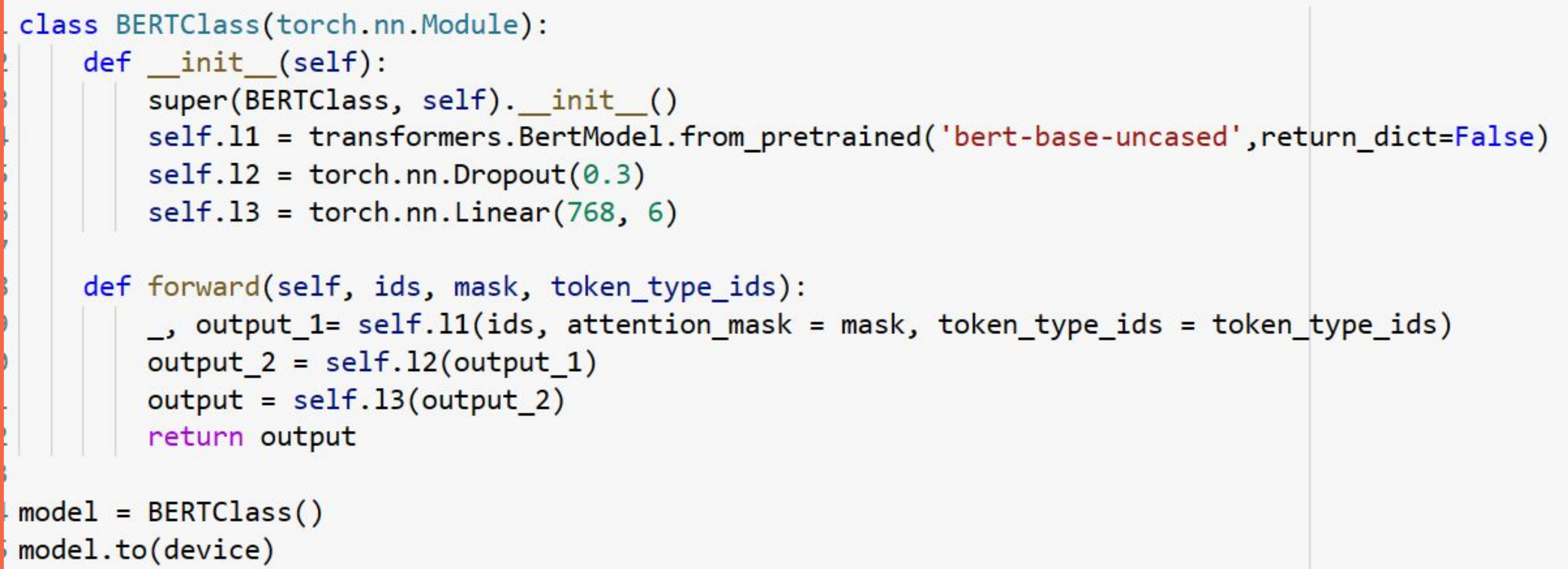
```
train_size = 0.8
train_dataset=df.sample(frac=train_size,random_state=200)
test_dataset=df.drop(train_dataset.index).reset_index(drop=True)
train_dataset = train_dataset.reset_index(drop=True)


print("FULL Dataset: {}".format(df.shape))
print("TRAIN Dataset: {}".format(train_dataset.shape))
print("TEST Dataset: {}".format(test_dataset.shape))

training_set = CustomDataset(train_dataset, tokenizer, MAX_LEN)
testing_set = CustomDataset(test_dataset, tokenizer, MAX_LEN)
```



```
train_params = {'batch_size': TRAIN_BATCH_SIZE,
                'shuffle': True,
                'num_workers': 0
                }

test_params = {'batch_size': VALID_BATCH_SIZE,
                'shuffle': True,
                'num_workers': 0
                }

training_loader = DataLoader(training_set, **train_params)
testing_loader = DataLoader(testing_set, **test_params)
```

3. CREATE MODEL

- Create custom BERT class from ‘bert-base-uncased’ pretrained model



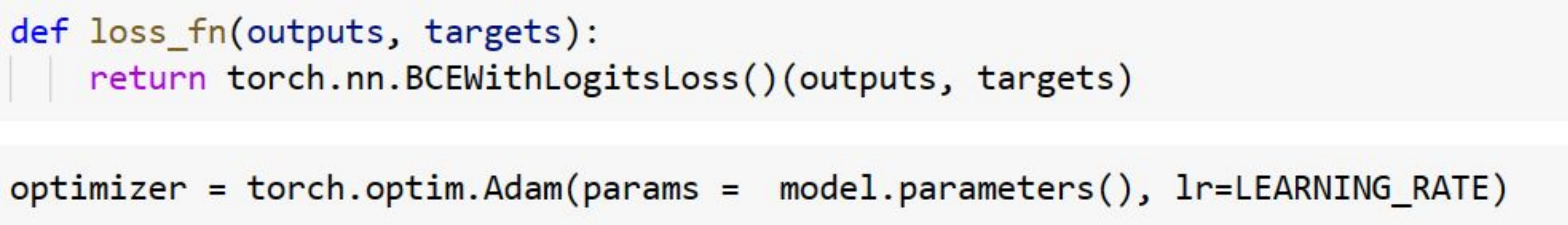
```python
class BERTClass(torch.nn.Module):
    def __init__(self):
        super(BERTClass, self).__init__()
        self.l1 = transformers.BertModel.from_pretrained('bert-base-uncased',return_dict=False)
        self.l2 = torch.nn.Dropout(0.3)
        self.l3 = torch.nn.Linear(768, 6)

    def forward(self, ids, mask, token_type_ids):
        _, output_1= self.l1(ids, attention_mask = mask, token_type_ids = token_type_ids)
        output_2 = self.l2(output_1)
        output = self.l3(output_2)
        return output

model = BERTClass()
model.to(device)
```

3. CREATE MODEL

- Model is composed of:
  - (1) pretrained ‘bert-base-uncased’ model
  - (2) dropout layer (0.3)
  - (3) output (6 neurons - class probabilities)

3. CREATE MODEL

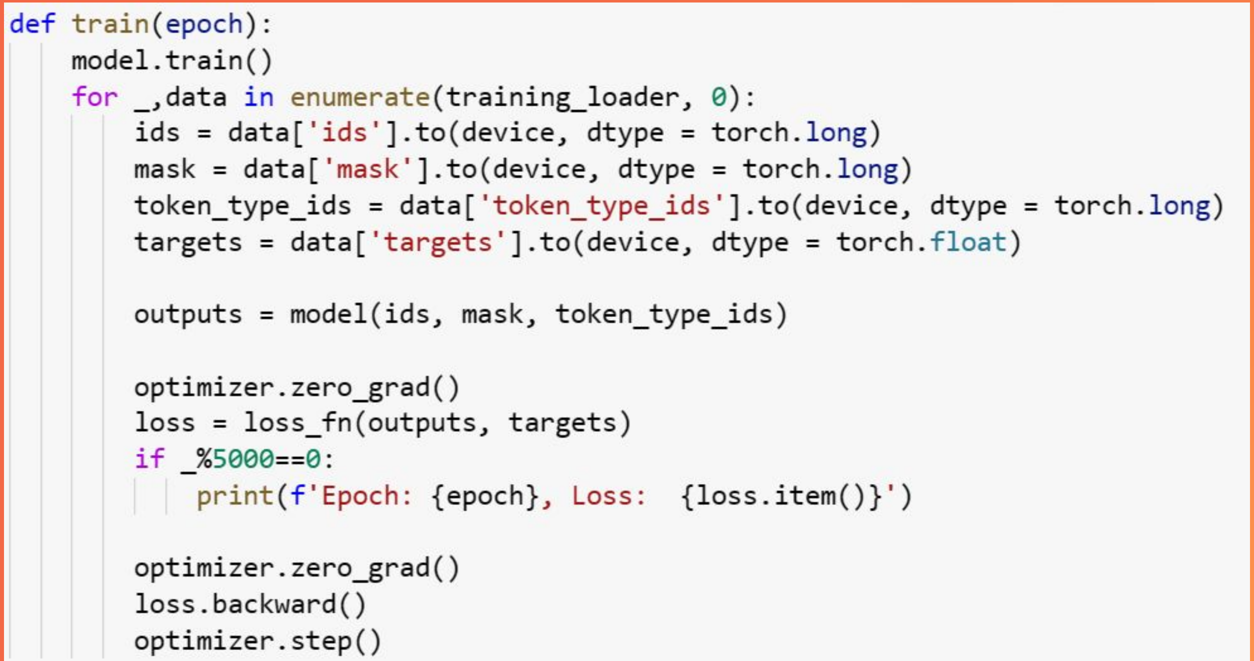
- Define loss and optimization function



```
def loss_fn(outputs, targets):
    return torch.nn.BCEWithLogitsLoss()(outputs, targets)

optimizer = torch.optim.Adam(params =  model.parameters(), lr=LEARNING_RATE)
```

4. TRAINING THE MODEL

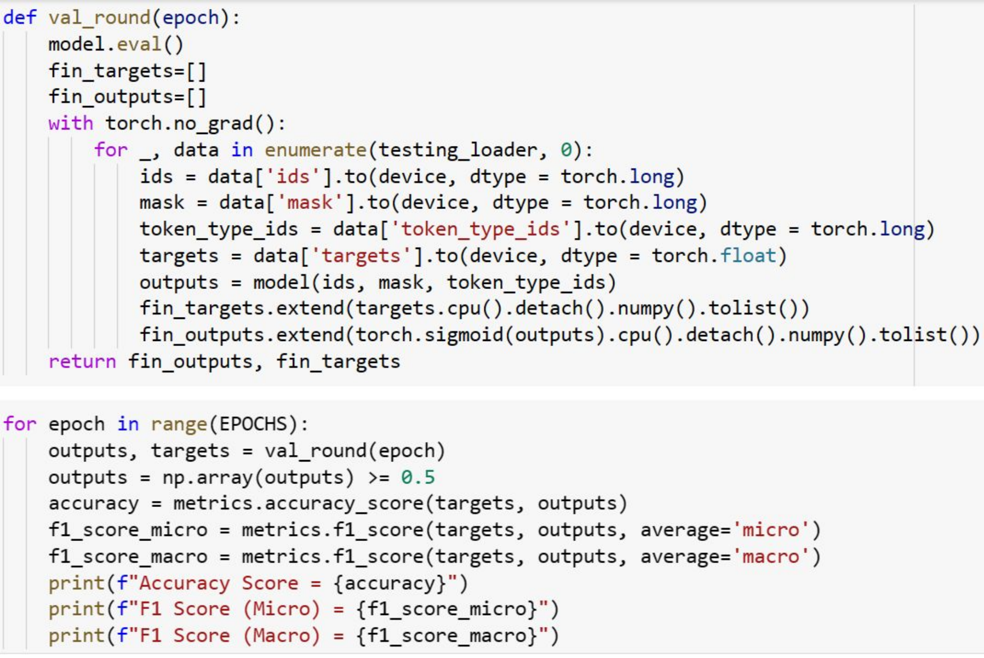
- Train the model on the training dataset



```python
def train(epoch):
    model.train()
    for _,data in enumerate(training_loader, 0):
        ids = data['ids'].to(device, dtype = torch.long)
        mask = data['mask'].to(device, dtype = torch.long)
        token_type_ids = data['token_type_ids'].to(device, dtype = torch.long)
        targets = data['targets'].to(device, dtype = torch.float)

        outputs = model(ids, mask, token_type_ids)

        optimizer.zero_grad()
        loss = loss_fn(outputs, targets)
        if _%5000==0:
            print(f'Epoch: {epoch}, Loss:  {loss.item()}')

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

5. EVALUATING THE MODEL

- Determine the accuracy of the model with a validation dataset that the model has never seen before.

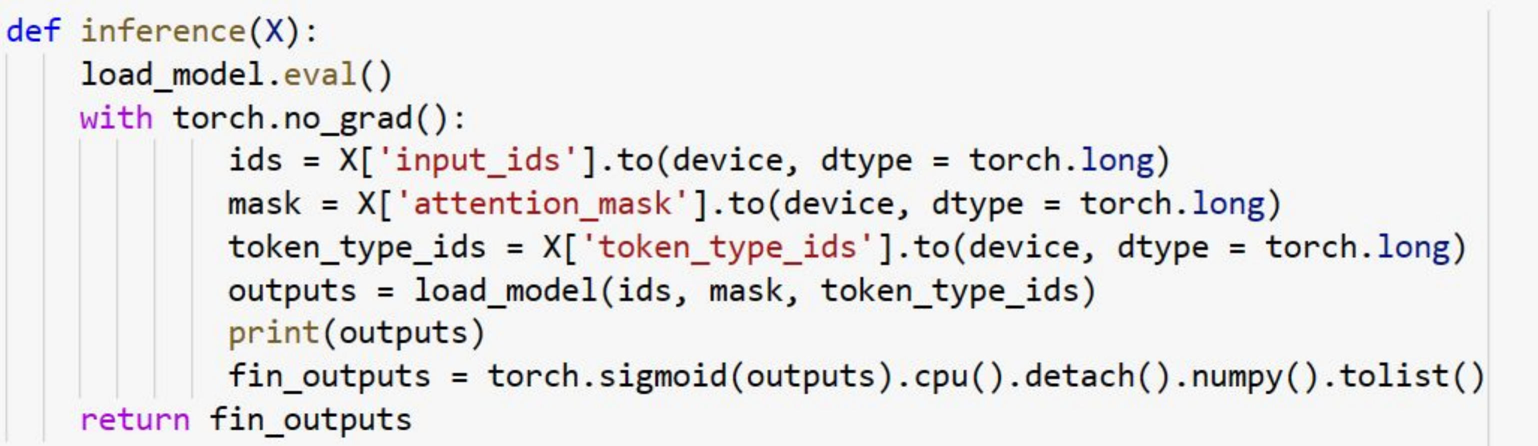


```python
def val_round(epoch):
    model.eval()
    fin_targets=[]
    fin_outputs=[]
    with torch.no_grad():
        for _, data in enumerate(testing_loader, 0):
            ids = data['ids'].to(device, dtype = torch.long)
            mask = data['mask'].to(device, dtype = torch.long)
            token_type_ids = data['token_type_ids'].to(device, dtype = torch.long)
            targets = data['targets'].to(device, dtype = torch.float)
            outputs = model(ids, mask, token_type_ids)
            fin_targets.extend(targets.cpu().detach().numpy().tolist())
            fin_outputs.extend(torch.sigmoid(outputs).cpu().detach().numpy().tolist())
    return fin_outputs, fin_targets
```

```python
for epoch in range(EPOCHS):
    outputs, targets = val_round(epoch)
    outputs = np.array(outputs) >= 0.5
    accuracy = metrics.accuracy_score(targets, outputs)
    f1_score_micro = metrics.f1_score(targets, outputs, average='micro')
    f1_score_macro = metrics.f1_score(targets, outputs, average='macro')
    print(f"Accuracy Score = {accuracy}")
    print(f"F1 Score (Micro) = {f1_score_micro}")
    print(f"F1 Score (Macro) = {f1_score_macro}")
```

6. PREDICTING VALUES WITH THE MODEL

- Create a function to use the model to predict toxicity classes based on an input text



```python
def inference(X):
    load_model.eval()
    with torch.no_grad():
            ids = X['input_ids'].to(device, dtype = torch.long)
            mask = X['attention_mask'].to(device, dtype = torch.long)
            token_type_ids = X['token_type_ids'].to(device, dtype = torch.long)
            outputs = load_model(ids, mask, token_type_ids)
            print(outputs)
            fin_outputs = torch.sigmoid(outputs).cpu().detach().numpy().tolist()
    return fin_outputs
```

EXAMPLE

```
text = "Thank you for
understanding. I think very
highly of you and would not
revert without discussion."
```

Output Class Probabilities:

```
[[0.07172095030546188,
0.0038206269964575768,
0.08545476943254471,
0.00023505152785219252
, 0.06668499857187271,
0.0045667183585464954]]
```

No toxicity detected.