Install Transformers Library

```
!pip install transformers
```

```
import numpy as np
import pandas as pd
import torch
import torch.nn as nn
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
import transformers
from transformers import AutoModel, BertTokenizerFast

# specify GPU
device = torch.device("cuda")
```

Load Dataset

```
df = pd.read_csv("spamdata_v2.csv")
df.head()
```

	label	text
0	0	Go until jurong point, crazy.. Available only ...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives aro...

```
df.shape
```

```
(5572, 2)
```

```
# check class distribution
df['label'].value_counts(normalize = True)
```

```
0    0.865937
1    0.134063
Name: label, dtype: float64
```

Split train dataset into train, validation and test sets

```
train_text, temp_text, train_labels, temp_labels = train_test_split(df['text'], df['label'],
                                                                    random_state=2018,
                                                                    test_size=0.3,
                                                                    stratify=df['label'])

# we will use temp_text and temp_labels to create validation and test set
val_text, test_text, val_labels, test_labels = train_test_split(temp_text, temp_labels,
                                                                random_state=2018,
                                                                test_size=0.5,
                                                                stratify=temp_labels)
```

Import BERT Model and BERT Tokenizer

```
# import BERT-base pretrained model
bert = AutoModel.from_pretrained('bert-base-uncased')

# Load the BERT tokenizer
tokenizer = BertTokenizerFast.from_pretrained('bert-base-uncased')
```

```
Downloading: 100%    433/433 [00:00<00:00, 1.98kB/s]

Downloading: 100%    440M/440M [00:11<00:00, 37.5MB/s]

Downloading: 100%    232k/232k [00:39<00:00, 5.82kB/s]
```

```
# sample data
text = ["this is a bert model tutorial", "we will fine-tune a bert model"]

# encode text
sent_id = tokenizer.batch_encode_plus(text, padding=True, return_token_type_ids=False)
```

```
# output
print(sent_id)
```

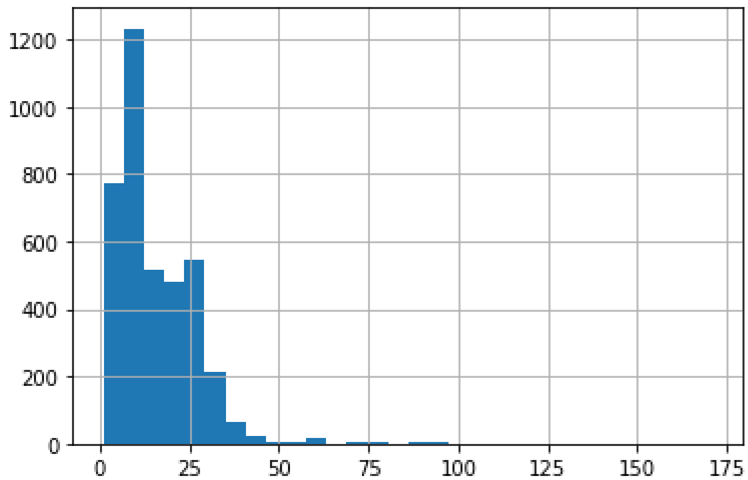
```
{'input_ids': [[101, 2023, 2003, 1037, 14324, 2944, 14924, 4818, 102, 0], [101, 2057, 2
```

Tokenization

```
# get length of all the messages in the train set
seq_len = [len(i.split()) for i in train_text]

pd.Series(seq_len).hist(bins = 30)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7efee3369828>
```




```
max_seq_len = 25
```

```
# tokenize and encode sequences in the training set
tokens_train = tokenizer.batch_encode_plus(
    train_text.tolist(),
    max_length = max_seq_len,
    pad_to_max_length=True,
    truncation=True,
    return_token_type_ids=False
)

# tokenize and encode sequences in the validation set
tokens_val = tokenizer.batch_encode_plus(
    val_text.tolist(),
    max_length = max_seq_len,
    pad_to_max_length=True,
    truncation=True,
    return_token_type_ids=False
)

# tokenize and encode sequences in the test set
tokens_test = tokenizer.batch_encode_plus(
    test_text.tolist(),
    max_length = max_seq_len,
    pad_to_max_length=True,
    truncation=True,
    return_token_type_ids=False
)
```

Convert Integer Sequences to Tensors

```
# for train set
train_seq = torch.tensor(tokens_train['input_ids'])
train_mask = torch.tensor(tokens_train['attention_mask'])
train_y = torch.tensor(train_labels.tolist())

# for validation set
val_seq = torch.tensor(tokens_val['input_ids'])
val_mask = torch.tensor(tokens_val['attention_mask'])
val_y = torch.tensor(val_labels.tolist())

# for test set
test_seq = torch.tensor(tokens_test['input_ids'])
test_mask = torch.tensor(tokens_test['attention_mask'])
test_y = torch.tensor(test_labels.tolist())
```

Create DataLoaders

```
from torch.utils.data import TensorDataset, DataLoader, RandomSampler, SequentialSampler

#define a batch size
batch_size = 32

# wrap tensors
train_data = TensorDataset(train_seq, train_mask, train_y)

# sampler for sampling the data during training
train_sampler = RandomSampler(train_data)

# dataLoader for train set
train_dataloader = DataLoader(train_data, sampler=train_sampler, batch_size=batch_size)

# wrap tensors
val_data = TensorDataset(val_seq, val_mask, val_y)

# sampler for sampling the data during training
val_sampler = SequentialSampler(val_data)

# dataLoader for validation set
val_dataloader = DataLoader(val_data, sampler = val_sampler, batch_size=batch_size)
```

Freeze BERT Parameters

```
# freeze all the parameters
for param in bert.parameters():
    param.requires_grad = False
```

Define Model Architecture

```
class BERT_Arch(nn.Module):

    def_init_(self, bert):

      super(BERT_Arch, self)._init_()

      self.bert = bert

      # dropout layer
      self.dropout = nn.Dropout(0.1)

      # relu activation function
      self.relu =  nn.ReLU()

      # dense layer 1
      self.fc1 = nn.Linear(768,512)

      # dense layer 2 (Output layer)
      self.fc2 = nn.Linear(512,2)

      #softmax activation function
      self.softmax = nn.LogSoftmax(dim=1)

    #define the forward pass
    def forward(self, sent_id, mask):

      #pass the inputs to the model
      _, cls_hs = self.bert(sent_id, attention_mask=mask)

      x = self.fc1(cls_hs)

      x = self.relu(x)

      x = self.dropout(x)

      # output layer
      x = self.fc2(x)

      # apply softmax activation
      x = self.softmax(x)
```

```
      return x
```

```
# pass the pre-trained BERT to our define architecture
model = BERT_Arch(bert)

# push the model to GPU
model = model.to(device)
```

```
# optimizer from hugging face transformers
from transformers import AdamW

# define the optimizer
optimizer = AdamW(model.parameters(), lr = 1e-3)
```

Find Class Weights

```
from sklearn.utils.class_weight import compute_class_weight

#compute the class weights
class_wts = compute_class_weight('balanced', np.unique(train_labels), train_labels)

print(class_wts)
```

```
[0.57743559 3.72848948]
```

```
# convert class weights to tensor
weights= torch.tensor(class_wts,dtype=torch.float)
weights = weights.to(device)

# loss function
cross_entropy  = nn.NLLLoss(weight=weights)

# number of training epochs
epochs = 10
```

Fine-Tune BERT

```
# function to train the model
def train():

  model.train()

  total_loss, total_accuracy = 0, 0
```

```
  # empty list to save model predictions
  total_preds=[]

  # iterate over batches
  for step,batch in enumerate(train_dataloader):

    # progress update after every 50 batches.
    if step % 50 == 0 and not step == 0:
      print('  Batch {:>5,}  of  {:>5,}.'.format(step, len(train_dataloader)))

    # push the batch to gpu
    batch = [r.to(device) for r in batch]

    sent_id, mask, labels = batch

    # clear previously calculated gradients
    model.zero_grad()

    # get model predictions for the current batch
    preds = model(sent_id, mask)

    # compute the loss between actual and predicted values
    loss = cross_entropy(preds, labels)

    # add on to the total loss
    total_loss = total_loss + loss.item()

    # backward pass to calculate the gradients
    loss.backward()

    # clip the the gradients to 1.0. It helps in preventing the exploding gradient problem
    torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)

    # update parameters
    optimizer.step()

    # model predictions are stored on GPU. So, push it to CPU
    preds=preds.detach().cpu().numpy()

    # append the model predictions
    total_preds.append(preds)

  # compute the training loss of the epoch
  avg_loss = total_loss / len(train_dataloader)

  # predictions are in the form of (no. of batches, size of batch, no. of classes).
  # reshape the predictions in form of (number of samples, no. of classes)
  total_preds  = np.concatenate(total_preds, axis=0)

  #returns the loss and predictions
```

```
  return avg_loss, total_preds


# function for evaluating the model
def evaluate():

  print("\nEvaluating...")

  # deactivate dropout layers
  model.eval()

  total_loss, total_accuracy = 0, 0

  # empty list to save the model predictions
  total_preds = []

  # iterate over batches
  for step,batch in enumerate(val_dataloader):

    # Progress update every 50 batches.
    if step % 50 == 0 and not step == 0:

      # Calculate elapsed time in minutes.
      elapsed = format_time(time.time() - t0)

      # Report progress.
      print('  Batch {:>5,}  of  {:>5,}.'.format(step, len(val_dataloader)))

    # push the batch to gpu
    batch = [t.to(device) for t in batch]

    sent_id, mask, labels = batch

    # deactivate autograd
    with torch.no_grad():

      # model predictions
      preds = model(sent_id, mask)

      # compute the validation loss between actual and predicted values
      loss = cross_entropy(preds,labels)

      total_loss = total_loss + loss.item()

      preds = preds.detach().cpu().numpy()

      total_preds.append(preds)

  # compute the validation loss of the epoch
  avg_loss = total_loss / len(val_dataloader)

  # reshape the predictions in form of (number of samples, no. of classes)
```

```
    total_preds  = np.concatenate(total_preds, axis=0)

    return avg_loss, total_preds
```

Start Model Training

```
# set initial loss to infinite
best_valid_loss = float('inf')

# empty lists to store training and validation loss of each epoch
train_losses=[]
valid_losses=[]

#for each epoch
for epoch in range(epochs):

    print('\n Epoch {:} / {:}'.format(epoch + 1, epochs))

    #train model
    train_loss, _ = train()

    #evaluate model
    valid_loss, _ = evaluate()

    #save the best model
    if valid_loss < best_valid_loss:
        best_valid_loss = valid_loss
        torch.save(model.state_dict(), 'saved_weights.pt')

    # append training and validation loss
    train_losses.append(train_loss)
    valid_losses.append(valid_loss)

    print(f'\nTraining Loss: {train_loss:.3f}')
    print(f'Validation Loss: {valid_loss:.3f}')
```

```
 Epoch 1 / 10
  Batch    50  of    122.
  Batch   100  of    122.

Evaluating...

Training Loss: 0.526
Validation Loss: 0.656

 Epoch 2 / 10
  Batch    50  of    122.
  Batch   100  of    122.

Evaluating...

Training Loss: 0.345
Validation Loss: 0.231

 Epoch 3 / 10
  Batch    50  of    122.
  Batch   100  of    122.

Evaluating...

Training Loss: 0.344
Validation Loss: 0.194

 Epoch 4 / 10
  Batch    50  of    122.
  Batch   100  of    122.

Evaluating...

Training Loss: 0.223
Validation Loss: 0.171

 Epoch 5 / 10
  Batch    50  of    122.
  Batch   100  of    122.

Evaluating...

Training Loss: 0.219
Validation Loss: 0.178

 Epoch 6 / 10
  Batch    50  of    122.
  Batch   100  of    122.

Evaluating...

Training Loss: 0.215
Validation Loss: 0.180

 Epoch 7 / 10
  Batch    50  of    122.
```

```
  Batch   100  of    122.

Evaluating...

Training Loss: 0.247
Validation Loss: 0.262

 Epoch 8 / 10
  Batch    50  of    122.
  Batch   100  of    122.

Evaluating...

Training Loss: 0.224
Validation Loss: 0.217

 Epoch 9 / 10
  Batch    50  of    122.
  Batch   100  of    122.
```

Load Saved Model

```
#load weights of best model
path = 'saved_weights.pt'
model.load_state_dict(torch.load(path))
```

```
<All keys matched successfully>
Training Loss: 0.231
```

Get Predictions for Test Data

```
# get predictions for test data
with torch.no_grad():
  preds = model(test_seq.to(device), test_mask.to(device))
  preds = preds.detach().cpu().numpy()
```

```
# model's performance
preds = np.argmax(preds, axis = 1)
print(classification_report(test_y, preds))
```

```
              precision    recall  f1-score   support

           0       0.99      0.98      0.98       724
           1       0.88      0.92      0.90       112

    accuracy                           0.97       836
   macro avg       0.93      0.95      0.94       836
weighted avg       0.97      0.97      0.97       836
```

```
# confusion matrix
pd.crosstab(test_y, preds)
```

col_0	0	1
row_0		
0	710	14
1	9	103