```
!pip install -q -U watermark
!pip install -qq transformers
```

```
%reload_ext watermark
%watermark -v -p numpy,pandas,torch,transformers
```

```
Python implementation: CPython
Python version       : 3.10.12
IPython version      : 7.34.0

numpy       : 1.23.5
pandas      : 1.5.3
torch       : 2.1.0+cu118
transformers: 4.35.0
```

```
from google.colab import drive
import pandas as pd

#drive.mount('/drive')
```

```
import os

#os.chdir("/drive/MyDrive/inflation_reports")
#os.getcwd()
```

```
print(os.listdir() )
```

```
['.config', 'data (1).csv', 'sample_data']
```

```
path = "/content/data (1).csv"
df = pd.read_csv(path, encoding='latin-1')
```

```
df.head()
```

	sentiment	sentence
0	neutral	According to Gran , the company has no plans t...
1	neutral	Technopolis plans to develop in stages an area...
2	negative	The international electronic industry company ...

```
df.shape
```

```
(4846, 2)
```

```
# check for missing values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4846 entries, 0 to 4845
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   sentiment  4846 non-null   object
 1   sentence   4846 non-null   object
dtypes: object(2)
memory usage: 75.8+ KB
```

Setup & Config

```
#@title Setup & Config
import transformers
from transformers import BertModel, BertTokenizer, AdamW, get_linear_schedule_with_warmup
import torch

import numpy as np
import pandas as pd
import seaborn as sns
from pylab import rcParams
import matplotlib.pyplot as plt
from matplotlib import rc
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from collections import defaultdict
from textwrap import wrap

from torch import nn, optim
```

```
from torch.utils.data import Dataset, DataLoader
import torch.nn.functional as F

%matplotlib inline
%config InlineBackend.figure_format='retina'

sns.set(style='whitegrid', palette='muted', font_scale=1.2)

HAPPY_COLORS_PALETTE = ["#01BEFE", "#FFDD00", "#FF7D00", "#FF006D", "#ADFF02", "#8F00FF"]

sns.set_palette(sns.color_palette(HAPPY_COLORS_PALETTE))

rcParams['figure.figsize'] = 12, 8

RANDOM_SEED = 42
np.random.seed(RANDOM_SEED)
torch.manual_seed(RANDOM_SEED)
torch.cuda.empty_cache()

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
device
```

```
device(type='cuda', index=0)
```

```
sns.countplot(df.sentiment)
plt.xlabel('Sentiment');
```

```
    --------------------------------------------------------------------------
def to_sentiment(rating):

  if rating == 'negative':
    return 0
  elif rating == 'neutral':
    return 1
  elif rating == 'positive':
    return 2

df['score'] = df.sentiment.apply(to_sentiment)
        895     # ---------------------------------------------------------------------
```

```
PRE_TRAINED_MODEL_NAME = 'ProsusAI/finbert'
#PRE_TRAINED_MODEL_NAME = 'bert-base-cased'
```

SEARCH STACK OVERFLOW

```
tokenizer = BertTokenizer.from_pretrained(PRE_TRAINED_MODEL_NAME, return_dict = False)
```

Downloading (…)okenizer_config.json: 100% 252/252 [00:00<00:00, 9.52kB/s]

Downloading (…)solve/main/vocab.txt: 100% 232k/232k [00:00<00:00, 5.05MB/s]

Downloading (…)cial_tokens_map.json: 100% 112/112 [00:00<00:00, 6.24kB/s]

Downloading (…)lve/main/config.json: 100% 758/758 [00:00<00:00, 50.8kB/s]

```
token_lens = []
print(df.sentence)

#store the token length of each sentence
# word to vec
for txt in df.sentence:
  tokens = tokenizer.encode(txt, max_length=512)
  token_lens.append(len(tokens))
```

```
Truncation was not explicitly activated but `max_length` is provided a specific value, please use `truncation=True` to explicitly truncat
0       According to Gran , the company has no plans t...
1       Technopolis plans to develop in stages an area...
2       The international electronic industry company ...
3       With the new production plant the company woul...
4       According to the company 's updated strategy f...
                              ...
4841    LONDON MarketWatch -- Share prices ended lower...
4842    Rinkuskiai 's beer sales fell by 6.5 per cent ...
```

```
4843    Operating profit fell to EUR 35.4 mn from EUR ...
4844    Net sales of the Paper segment decreased to EU...
4845    Sales in Finland decreased by 10.5 % in Januar...
Name: sentence, Length: 4846, dtype: object
```

```
sns.distplot(token_lens)
plt.xlim([0, 256]);
plt.xlabel('Token count');
```

```
<ipython-input-23-4dbe9bd8b56e>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(token_lens)
```



```
MAX_LEN = 160
```

```
class GPReviewDataset(Dataset):

  def __init__(self, sentences, labels, tokenizer, max_len):
    self.sentences = sentences
    self.labels = labels
    self.tokenizer = tokenizer
    self.max_len = max_len

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

  def __getitem__(self, item):
    sentence = str(self.sentences[item])
    label = self.labels[item]

    encoding = self.tokenizer.encode_plus(
      sentence,
      add_special_tokens=True,
      max_length=self.max_len,
      return_token_type_ids=False,
      padding = 'max_length',
      return_attention_mask=True,
      return_tensors='pt',
    )

    return {
      'financiar_text': sentence,
```

```
      'input_ids': encoding['input_ids'].flatten(),
      'attention_mask': encoding['attention_mask'].flatten(),
      'label': torch.tensor(label, dtype=torch.long)
    }


# split the data
df_train, df_test = train_test_split(df, test_size=0.2, random_state=RANDOM_SEED)
df_val, df_test = train_test_split(df_test, test_size=0.5, random_state=RANDOM_SEED)

df_train.shape, df_val.shape, df_test.shape
```

```
((3876, 3), (485, 3), (485, 3))
```

```
# create data loaders
def create_data_loader(df, tokenizer, max_len, batch_size):
  ds = GPReviewDataset(
    sentences=df.sentence.to_numpy(),
    labels=df.score.to_numpy(),
    tokenizer=tokenizer,
    max_len=max_len
  )


  return DataLoader(
    ds,
    batch_size=batch_size,
    num_workers=4
  )


BATCH_SIZE = 16

train_data_loader = create_data_loader(df_train, tokenizer, MAX_LEN, BATCH_SIZE)
val_data_loader = create_data_loader(df_val, tokenizer, MAX_LEN, BATCH_SIZE)
test_data_loader = create_data_loader(df_test, tokenizer, MAX_LEN, BATCH_SIZE)
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes
  warnings.warn(_create_warning_msg(
```

```
data = next(iter(train_data_loader))
data.keys()
```

```
dict_keys(['financiar_text', 'input_ids', 'attention_mask', 'label'])
```

```
print(data['input_ids'].shape)
print(data['attention_mask'].shape)
print(data['label'].shape)
```

```
torch.Size([16, 160])
torch.Size([16, 160])
torch.Size([16])
```

```
bert_model = BertModel.from_pretrained(PRE_TRAINED_MODEL_NAME, return_dict = False)

for param in bert_model.parameters():
    param.requires_grad = False
```

Downloading pytorch_model.bin: 100% 438M/438M [00:03<00:00, 115MB/s]

```
#create a classifier that uses the BERT model
class SentimentClassifier(nn.Module):

  def __init__(self, n_classes):
    super(SentimentClassifier, self).__init__()
    self.bert = BertModel.from_pretrained(PRE_TRAINED_MODEL_NAME, return_dict = False)
    for param in self.bert.parameters():
        param.requires_grad = False
    print(self.bert.config.hidden_size);
    self.classifier = nn.Sequential(
            nn.Linear(self.bert.config.hidden_size, 1024),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(1024, 128), # set not trainable
            nn.ReLU(),
            nn.Linear(128, 3)
        )


  def forward(self, input_ids, attention_mask):
    _, pooled_output = self.bert(
      input_ids=input_ids,
      attention_mask=attention_mask
    )
```

```
        #print(attention_mask,input_ids)
        return self.classifier(pooled_output)
```

```
class_names = ['negative', 'neutral', 'positive']
# create an instance and move it to the GPU
model = SentimentClassifier(len(class_names))
model = model.to(device)
```

```
768
```

```
input_ids = data['input_ids'].to(device)
attention_mask = data['attention_mask'].to(device)

print(input_ids.shape) # batch size x seq length
print(attention_mask.shape) # batch size x seq length
```

```
torch.Size([16, 160])
torch.Size([16, 160])
```

```
F.softmax(model(input_ids, attention_mask), dim=1)
```

```
tensor([[0.3399, 0.3086, 0.3515],
        [0.3409, 0.3017, 0.3574],
        [0.3243, 0.3183, 0.3575],
        [0.3661, 0.2990, 0.3350],
        [0.3446, 0.3173, 0.3381],
        [0.3434, 0.3145, 0.3421],
        [0.3508, 0.3001, 0.3491],
        [0.3481, 0.3050, 0.3469],
        [0.3415, 0.2935, 0.3650],
        [0.3689, 0.2898, 0.3413],
        [0.3496, 0.3016, 0.3488],
        [0.3290, 0.3067, 0.3643],
        [0.3686, 0.3119, 0.3195],
        [0.3313, 0.2907, 0.3779],
        [0.3514, 0.3124, 0.3362],
        [0.3538, 0.2934, 0.3528]], device='cuda:0', grad_fn=<SoftmaxBackward0>)
```

```
# Training

# BERT recommendations for fine-tuning:

# Batch size: 16, 32
```

```
# Learning rate (Adam): 5e-5, 3e-5, 2e-5
# Number of epochs: 2, 3, 4

# increasing the batch size reduces the training time significantly, but gives you lower accuracy

EPOCHS = 10

optimizer = AdamW(model.parameters(), lr=2e-5, correct_bias=False)
total_steps = len(train_data_loader) * EPOCHS

scheduler = get_linear_schedule_with_warmup(
  optimizer,
  num_warmup_steps=0,
  num_training_steps=total_steps
)

loss_fn = nn.CrossEntropyLoss().to(device)
```

```
/usr/local/lib/python3.10/dist-packages/transformers/optimization.py:411: FutureWarning: This implementation of AdamW is deprecated and w
  warnings.warn(
```

```
def train_epoch(
  model,
  data_loader,
  loss_fn,
  optimizer,
  device,
  scheduler,
  n_examples
):
  model = model.train()

  losses = []
  correct_predictions = 0

  for d in data_loader:
    input_ids = d["input_ids"].to(device)
    attention_mask = d["attention_mask"].to(device)
    labels = d["label"].to(device)

    outputs = model(
      input_ids=input_ids,
```

```
      attention_mask=attention_mask
    )

    _, preds = torch.max(outputs, dim=1)
    loss = loss_fn(outputs, labels)

    correct_predictions += torch.sum(preds == labels)
    losses.append(loss.item())

    loss.backward()
    nn.utils.clip_grad_norm_(model.parameters(), max_norm=1.0)
    optimizer.step()
    scheduler.step()
    optimizer.zero_grad()

  return correct_predictions.double() / n_examples, np.mean(losses)


def eval_model(model, data_loader, loss_fn, device, n_examples):
  model = model.eval()

  losses = []
  correct_predictions = 0

  with torch.no_grad():
    for d in data_loader:
      input_ids = d["input_ids"].to(device)
      attention_mask = d["attention_mask"].to(device)
      labels = d["label"].to(device)

      outputs = model(
        input_ids=input_ids,
        attention_mask=attention_mask
      )
      _, preds = torch.max(outputs, dim=1)

      loss = loss_fn(outputs, labels)

      correct_predictions += torch.sum(preds == labels)
      losses.append(loss.item())

  return correct_predictions.double() / n_examples, np.mean(losses)
```

```
!pip install torch-summary
```

```
from torchsummary import summary
```

```
Collecting torch-summary
  Downloading torch_summary-1.4.5-py3-none-any.whl (16 kB)
Installing collected packages: torch-summary
Successfully installed torch-summary-1.4.5
```

```
# print network summary
summary(model,input_size=(768,),depth=5,batch_dim=1, dtypes=['torch.IntTensor'])
```

```
│    │    │    │    └─BertAttention: 5-31                (2,363,904)
│    │    │    │    └─BertIntermediate: 5-32             (2,362,368)
│    │    │    │    └─BertOutput: 5-33                   (2,361,600)
│    │    │    └─BertLayer: 4-12                         --
│    │    │    │    └─BertAttention: 5-34                (2,363,904)
│    │    │    │    └─BertIntermediate: 5-35             (2,362,368)
│    │    │    │    └─BertOutput: 5-36                   (2,361,600)
│    └─BertPooler: 2-3                                   --
│    │    └─Linear: 3-7                                  (590,592)
│    │    └─Tanh: 3-8                                    --
├─Sequential: 1-2                                        --
│    └─Linear: 2-4                                       787,456
│    └─ReLU: 2-5                                         --
│    └─Dropout: 2-6                                      --
│    └─Linear: 2-7                                       131,200
│    └─ReLU: 2-8                                         --
│    └─Linear: 2-9                                       387
================================================================================
Total params: 110,401,283
Trainable params: 919,043
Non-trainable params: 109,482,240
================================================================================
```

```
%%time

history = defaultdict(list)
best_accuracy = 0

for epoch in range(EPOCHS):

  print(f'Epoch {epoch + 1}/{EPOCHS}')
  print('-' * 10)

  print(train_data_loader)

  train_acc, train_loss = train_epoch(
    model,
    train_data_loader,
    loss_fn,
    optimizer,
    device,
    scheduler,
    len(df_train)
  )

  print(f'Train loss {train_loss} accuracy {train_acc}')
```

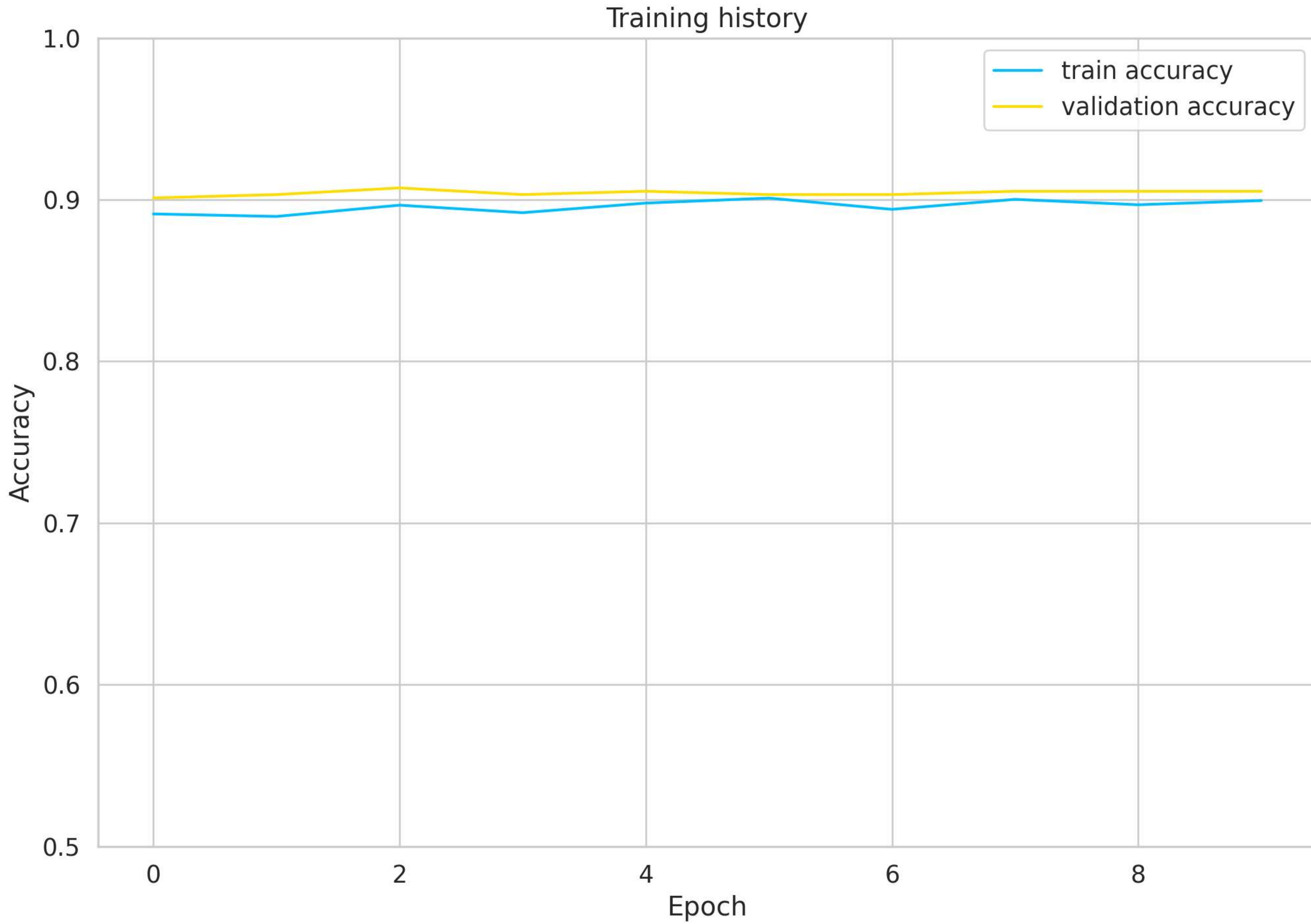
```
    val_acc, val_loss = eval_model(
      model,
      val_data_loader,
      loss_fn,
      device,
      len(df_val)
    )

    print(f'Val   loss {val_loss} accuracy {val_acc}')
    print()

    history['train_acc'].append(train_acc)
    history['train_loss'].append(train_loss.item())
    history['val_acc'].append(val_acc.item())
    history['val_loss'].append(val_loss)

    if val_acc > best_accuracy:
      torch.save(model.state_dict(), 'best_model_state.bin')
      best_accuracy = val_acc
```

```
Epoch 2/10
----------
<torch.utils.data.dataloader.DataLoader object at 0x7d3beaf1b850>
Train loss 0.2835986840964099 accuracy 0.8895768833849329
Val   loss 0.2562606853823508 accuracy 0.9030927835051547

Epoch 3/10
----------
<torch.utils.data.dataloader.DataLoader object at 0x7d3beaf1b850>
Train loss 0.2743384060545713 accuracy 0.8965428276573787
Val   loss 0.25853265773865486 accuracy 0.9072164948453608

Epoch 4/10
----------
<torch.utils.data.dataloader.DataLoader object at 0x7d3beaf1b850>
Train loss 0.275054200686545 accuracy 0.8918988648090814
Val   loss 0.25520838833143633 accuracy 0.9030927835051547
```

```
<torch.utils.data.dataloader.DataLoader object at 0x7d3beaf1b850>
Train loss 0.26442237198352814 accuracy 0.9009287925696594
Val   loss 0.2559193418391289 accuracy 0.9030927835051547

Epoch 7/10
----------
<torch.utils.data.dataloader.DataLoader object at 0x7d3beaf1b850>
Train loss 0.265232704089257 accuracy 0.8939628482972135
Val   loss 0.255051760423568 accuracy 0.9030927835051547

Epoch 8/10
----------
<torch.utils.data.dataloader.DataLoader object at 0x7d3beaf1b850>
Train loss 0.26634225627951663 accuracy 0.9001547987616099
Val   loss 0.25392321208792346 accuracy 0.9051546391752577

Epoch 9/10
----------
<torch.utils.data.dataloader.DataLoader object at 0x7d3beaf1b850>
Train loss 0.26636481910576054 accuracy 0.8968008255933951
Val   loss 0.2534826619009818 accuracy 0.9051546391752577

Epoch 10/10
----------
<torch.utils.data.dataloader.DataLoader object at 0x7d3beaf1b850>
Train loss 0.2629416573010845 accuracy 0.8993808049535603
Val   loss 0.25326885054669074 accuracy 0.9051546391752577

CPU times: user 5min 46s, sys: 5.98 s, total: 5min 52s
Wall time: 6min 38s
```

```
print(history['train_acc'])
print(history['val_acc'])

new_tensor = torch.tensor(history['train_acc'], device = 'cpu')
print(new_tensor)

plt.plot(new_tensor, label='train accuracy')
plt.plot(history['val_acc'], label='validation accuracy')
plt.title('Training history')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.ylim([0.5, 1]);
```

```
[tensor(0.8911, device='cuda:0', dtype=torch.float64), tensor(0.8896, device='cuda:0', dtype=torch.float64), tensor(0.8965, device='cuda
[0.9010309278350516, 0.9030927835051547, 0.9072164948453608, 0.9030927835051547, 0.9051546391752577, 0.9030927835051547, 0.9030927835051
tensor([0.8911, 0.8896, 0.8965, 0.8919, 0.8978, 0.9009, 0.8940, 0.9002, 0.8968,
        0.8994], dtype=torch.float64)
```



```
# calculating the accuracy on the test data
test_acc, _ = eval_model(
  model,
  test_data_loader,
  loss_fn,
  device,
  len(df_test)
)

test_acc.item()
```

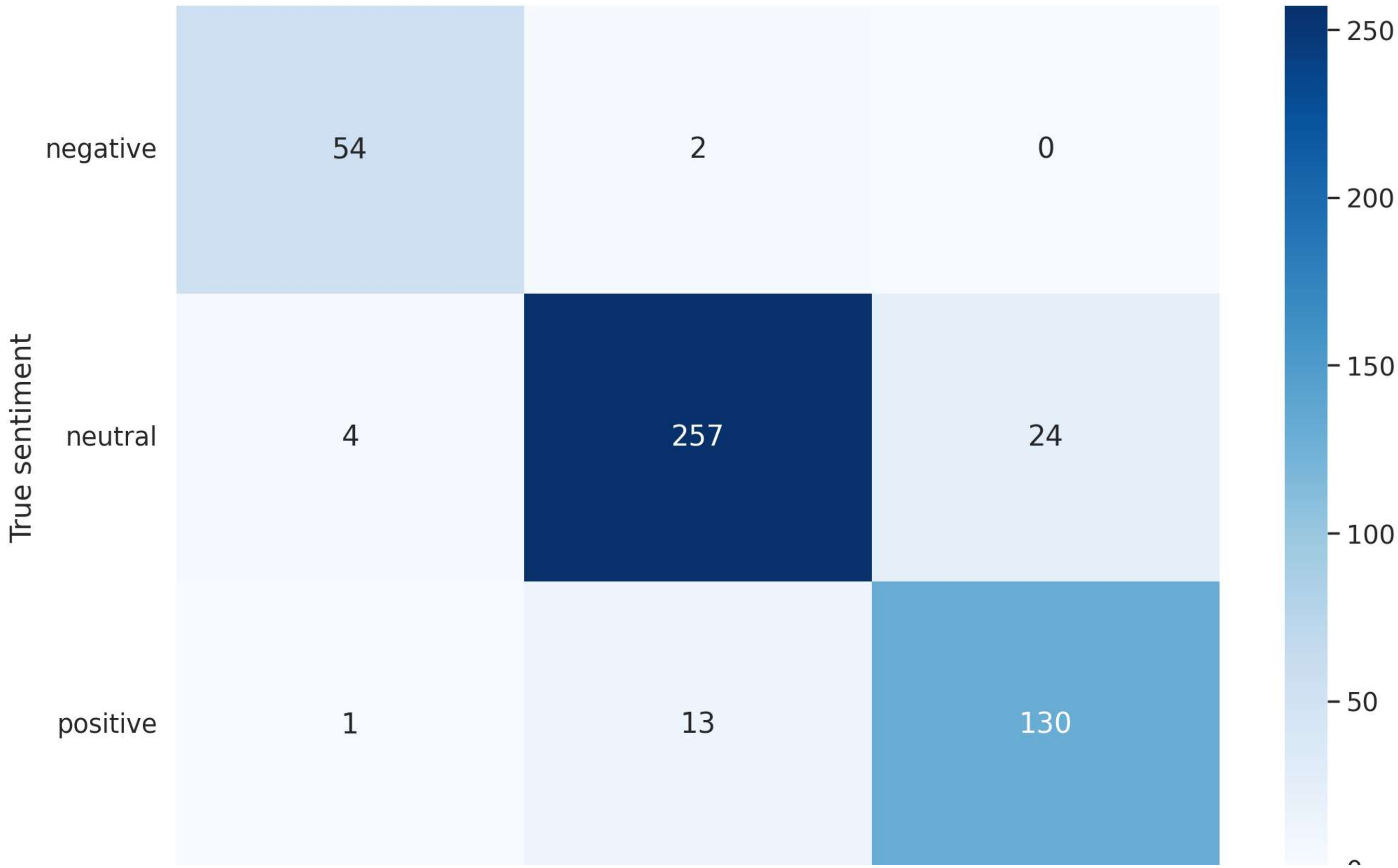
```
0.9092783505154639
```

```
# This is similar to the evaluation function,
# except that we're storing the text and the predicted probabilities
# (by applying the softmax on the model outputs)

def get_predictions(model, data_loader):
  model = model.eval()

  financiar_texts = []
  predictions = []
  prediction_probs = []
  real_values = []

  with torch.no_grad():
    for d in data_loader:

      texts = d["financiar_text"]
      input_ids = d["input_ids"].to(device)
      attention_mask = d["attention_mask"].to(device)
      targets = d["label"].to(device)

      outputs = model(
        input_ids=input_ids,
        attention_mask=attention_mask
      )
      _, preds = torch.max(outputs, dim=1)

      probs = F.softmax(outputs, dim=1)

      financiar_texts.extend(texts)
      predictions.extend(preds)
```

```
      prediction_probs.extend(probs)
      real_values.extend(targets)

  predictions = torch.stack(predictions).cpu()
  prediction_probs = torch.stack(prediction_probs).cpu()
  real_values = torch.stack(real_values).cpu()
  return financiar_texts, predictions, prediction_probs, real_values


y_review_texts, y_pred, y_pred_probs, y_test = get_predictions(
  model,
  test_data_loader
)


print(classification_report(y_test, y_pred, target_names=class_names))
```

```
                  precision    recall  f1-score   support

        negative       0.92      0.96      0.94        56
         neutral       0.94      0.90      0.92       285
        positive       0.84      0.90      0.87       144

        accuracy                           0.91       485
       macro avg       0.90      0.92      0.91       485
    weighted avg       0.91      0.91      0.91       485
```

```
def show_confusion_matrix(confusion_matrix):
  hmap = sns.heatmap(confusion_matrix, annot=True, fmt="d", cmap="Blues")
  hmap.yaxis.set_ticklabels(hmap.yaxis.get_ticklabels(), rotation=0, ha='right')
  hmap.xaxis.set_ticklabels(hmap.xaxis.get_ticklabels(), rotation=30, ha='right')
  plt.ylabel('True sentiment')
  plt.xlabel('Predicted sentiment');

cm = confusion_matrix(y_test, y_pred)
df_cm = pd.DataFrame(cm, index=class_names, columns=class_names)
show_confusion_matrix(df_cm)
```

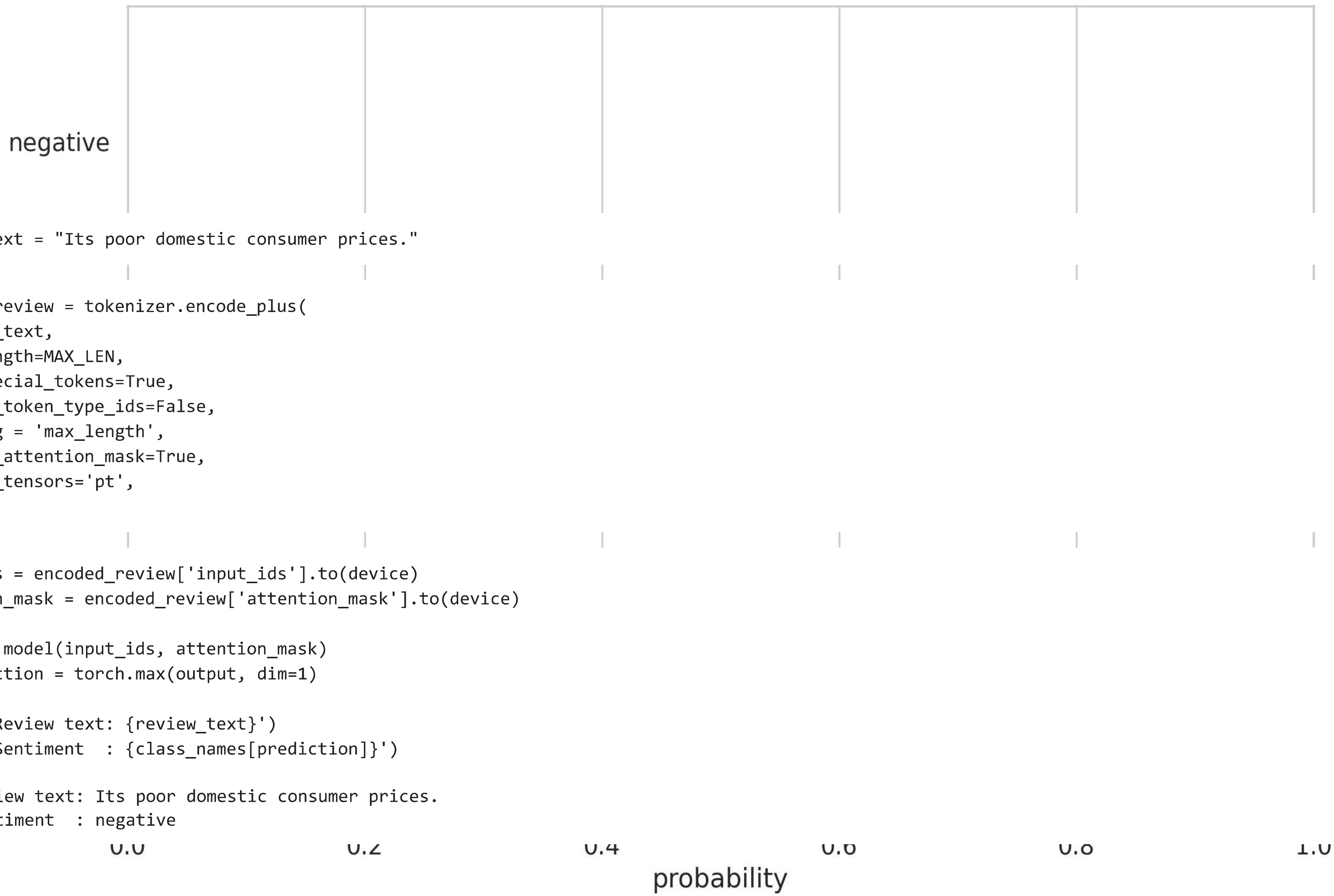



```
idx = 2

review_text = y_review_texts[idx]
true_sentiment = y_test[idx]
pred_df = pd.DataFrame({
  'class_names': class_names,
  'values': y_pred_probs[idx]
})
```

```
print("\n".join(wrap(review_text)))
print()
print(f'True sentiment: {class_names[true_sentiment]}')
```

```
As the world leaders in developing UV technology for municipal
wastewater , drinking water , and industrial water treatment systems ,
Trojan Technologies was a logical partner in providing W+Ærtsil+Æ with
UV technology for ballast water treatment .

True sentiment: neutral
```

```
sns.barplot(x='values', y='class_names', data=pred_df, orient='h')
plt.ylabel('sentiment')
plt.xlabel('probability')
plt.xlim([0, 1]);
```




```
review_text = "Its poor domestic consumer prices."

encoded_review = tokenizer.encode_plus(
  review_text,
  max_length=MAX_LEN,
  add_special_tokens=True,
  return_token_type_ids=False,
  padding = 'max_length',
  return_attention_mask=True,
  return_tensors='pt',
)

input_ids = encoded_review['input_ids'].to(device)
attention_mask = encoded_review['attention_mask'].to(device)

output = model(input_ids, attention_mask)
_, prediction = torch.max(output, dim=1)

print(f'Review text: {review_text}')
print(f'Sentiment  : {class_names[prediction]}')
```

```
Review text: Its poor domestic consumer prices.
Sentiment  : negative
```