Department of Computer Science and Engineering (Data Science)

Advanced Computational Linguistics

Experiment No. 7

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Batch: D11

Aim: To study perform various Natural Language Processing task like Text summarization, Sentiment Analysis using available libraries like Hugging Face's Transformers, TensorFlow or PyTorch

Introduction:

Text Summarization using BERT

Extractive Summarization: BERT can be utilized for extractive summarization, where key sentences or phrases are selected from the original text to form a summary.

Sentence Embedding's: Use BERT to generate embedding's for each sentence in the text.

Similarity Measures: Calculate similarity scores between sentences (e.g., using cosine similarity).

Select Top Sentences: Choose sentences with the highest similarity scores to form the summary.

Abstractive Summarization: This involves generating a summary that might not directly include sentences from the original text. BERT can aid in this by fine-tuning a model specifically for abstractive summarization.

Fine-tuning: Fine-tune the pre-trained BERT model on a summarization dataset (e.g., CNN/Daily Mail dataset).

Sequence-to-sequence Model: Employ techniques like seq2seq models or transformers to generate summaries.

Sentiment Analysis using BERT

Fine-tuning BERT: The pre-trained BERT model can be fine-tuned on a sentiment analysis dataset. The model's classification layers can be adjusted for sentiment analysis.

Dataset Preparation: Obtain a labeled dataset for sentiment analysis (e.g., IMDB movie reviews, Twitter sentiment dataset).

Tokenization and Fine-tuning: Tokenize the text, prepare input sequences, and fine-tune BERT on the sentiment classification task.

Prediction: After fine-tuning, use the trained model to predict sentiment labels (positive, negative, neutral) for new text inputs.

Tools and Libraries:

Hugging Face's Transformers: This library provides easy access to pre-trained models like BERT and various other NLP-related functionalities for tasks like tokenization, model loading, and fine-tuning.

TensorFlow or PyTorch: Use these deep learning frameworks to implement BERT-based models and fine-tuning for specific tasks.

Lab Experiment to be performed in this session:

1. Perform Text Summarization using BERT (BERT summarizer library can be directly installed in python using the following commands python pip install bert-extractive-summarizer for the eases of the implementation.)
2. Perform Sentiment Analysis using BERT.

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In [1]:
```
!pip install -qq transformers
```

In [2]:
```
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
import matplotlib.pyplot as plt
from matplotlib import rc
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_r
eport
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
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

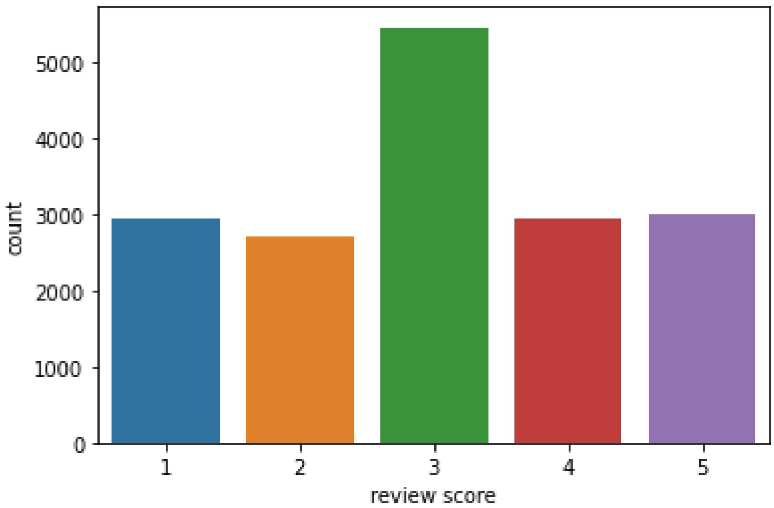
In [3]:
```
device = torch.device("cuda:0" if torch.cuda.is_available() 
se "cpu")
```

In [4]:
```
df = pd.read_csv("../input/google-play-storeappreviews/revie
s.csv")
df.head()
```

Out[4]:

	reviewId	userName	
0	gp:AOqpTOG-nGuDe0w6if400pTvNJnK3MlfnEcJLIB84aR...	Ben Maybe	lh.googleuse
1	gp:AOqpTOH85sc18Ajgcgj6-IGmA7Gp34fVsrbyBJ274IZ...	Anthony Duarte	lh.googleuse
2	gp:AOqpTOGxyMqOStnhbQ_mLfnLUfd1DHAt5uRXqDNArML...	Through Genesis	lh.googleuse
3	gp:AOqpTOE3fQQpkWOMbSHW-DwukAnILBbMwBHEcbReiit...	Sydney Stoll	lh.googleuse
4	gp:AOqpTOG2AXuKqrR8FIN43a5BGZY4Iha5SFQZZ6o9vOR...	ChuCannon	lh.googleuse

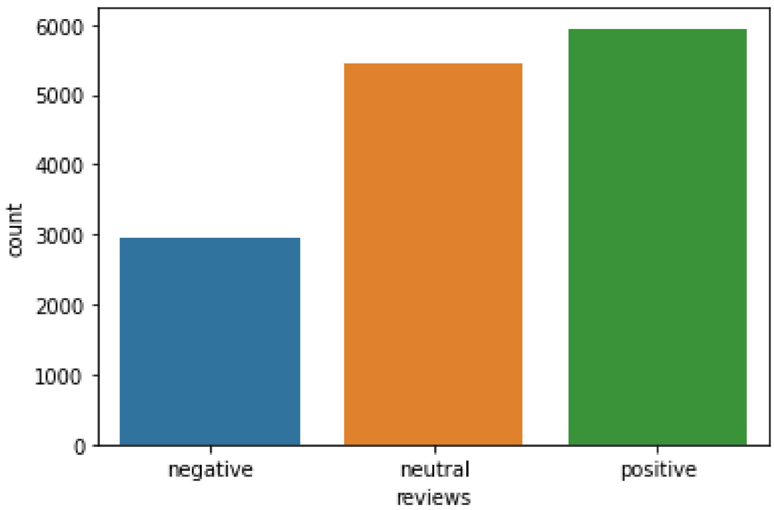
In [5]:
```
sns.countplot(df.score)
plt.xlabel('review score');
```



In [6]:
```
def sentiment(rating):
    if rating < 2:
        return 0

    if rating==3:
        return 1

    if rating > 3:
        return 2

df['sentiment'] = df.score.apply(sentiment)
```

In [7]:
```
ax = sns.countplot(df.sentiment)
plt.xlabel('reviews')
ax.set_xticklabels(['negative', 'neutral', 'positive'])
```

Out[7]:
```
[Text(0, 0, 'negative'), Text(1, 0, 'neutral'), Text(2, 0, 'p
sitive')]
```



Tokenizing and Data Preprocessing

In [8]:
```
PRE_TRAINED_MODEL_NAME = 'bert-base-cased'
```

In [9]:
```
tokenizer = BertTokenizer.from_pretrained(PRE_TRAINED_MODEL_
ME)
```

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Downloading: 100% 426k/426k [00:00<00:00, 717kB/s]

Downloading: 100% 570/570 [00:00<00:00, 20.8kB/s]

one way

In [10]:
```
# sample_txt = 'When was I last outside? I am stuck at home :
r 2 weeks.'
# tokens = tokenizer.tokenize(sample_txt)
# token_ids = tokenizer.convert_tokens_to_ids
# print(f'Sentence: {sample_txt}\n')
# print(f'Tokens: {tokens}\n')
# print(f'Token IDs: {token_ids}')
```

[SEP] token has to be inserted at the end of a single input. When a task requires more than one input such as NLI and Q-A tasks, [SEP] token helps the model to understand the end of one input and the start of another input in the same sequence input.

In [11]:
```
tokenizer.sep_token, tokenizer.sep_token_id
```

Out[11]:
```
('[SEP]', 102)
```

[CLS] - we must add this token to the start of each sentence, so BERT knows we're doing classification

In [12]:
```
tokenizer.cls_token, tokenizer.cls_token_id
```

Out[12]:
```
('[CLS]', 101)
```

The BERT model receives a fixed length of sentence as input. Usually the maximum length of a sentence depends on the data we are working on. For sentences that are shorter than this maximum length, we will have to add paddings (empty tokens) to the sentences to make up the length. In the original implementation, the token [PAD] is used to represent paddings to the sentence.

In [13]:
```
tokenizer.pad_token, tokenizer.pad_token_id
```

Out[13]:
```
('[PAD]', 0)
```

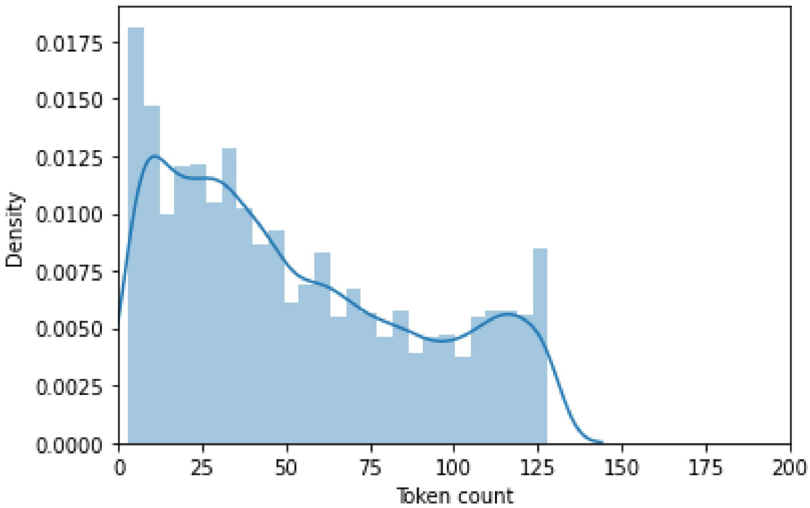
other way

In [14]:
```
token_lens = []

for text in df.content:
    tokens = tokenizer.encode(text,max_length=128)
    token_lens.append(len(tokens))
```

```
Truncation was not explicitly activated but `max_length` is p
ovided a specific value, please use `truncation=True` to expli
citly truncate examples to max length. Defaulting to 'longest_
first' truncation strategy. If you encode pairs of sequences
(GLUE-style) with the tokenizer you can select this strategy m
ore precisely by providing a specific strategy to `truncation
`.
```

In [15]:
```
sns.distplot(token_lens)
plt.xlim([0, 200]);
plt.xlabel('Token count');
```



and the other way

In [16]:
```
sample_txt = 'When was I last outside? I am stuck at home fo
2 weeks.'
```

In [17]:
```
encoding = tokenizer.encode_plus(
    sample_txt,
    max_length = 32,
    add_special_tokens = True, # [CLS] and [SEP]
    pad_to_max_length = True,
    return_token_type_ids = False,
    return_attention_mask = True,
    return_tensors = 'pt' # pt for pytorch
)
encoding.keys()
```

Out[17]:
```
dict_keys(['input_ids', 'attention_mask'])
```

In [18]:
```
# every input is now of size 32 and padded with 0
print(len(encoding['input_ids'][0]))
encoding['input_ids'][0]
```

```
32
```

Out[18]:
```
tensor([ 101, 1332, 1108,  146, 1314, 1796,  136,  146, 1821
5342, 1120, 1313,
        1111,  123, 2277,  119,  102,    0,    0,    0,    0,
0,    0,    0,
           0,    0,    0,    0,    0,    0,    0,    0])
```

In [19]:
```
encoding['attention_mask']
```

Out[19]:
```
tensor([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, (
0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0]])
```

Creating Dataset

In [20]:
```
class CustomDataset(Dataset):
    def __init__(self, reviews, targets, tokenizer, max_len):
        super().__init__()
        self.reviews = reviews
        self.targets = targets
        self.tokenizer = tokenizer
        self.max_len = max_len

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

    def __getitem__(self,item):
        review = self.reviews[item]
        target = self.targets[item]

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

        return {
            'review': review,
            'target': torch.tensor(target,dtype=torch.long),
            'input_ids': encoding['input_ids'].flatten(),
            'attention_mask': encoding['attention_mask'].flatt
en()
        }
```

In [21]:
```
df.shape
```

Out[21]:
```
(17082, 13)
```

In [22]:
```
df = df[df['sentiment'].notna()]
```

In [23]:
```
df.isnull().sum()
```

Out[23]:
```
reviewId                  0
userName                  0
userImage                 0
content                   0
score                     0
thumbsUpCount             0
reviewCreatedVersion   2179
at                        0
replyContent           7059
repliedAt              7059
sortOrder                 0
appId                     0
sentiment                 0
dtype: int64
```

In [24]:
```
MAX_LEN = 160
BATCH_SIZE = 16
RANDOM_SEED = 2002
EPOCHS = 10
```

In [25]:
```
df_train, df_test = train_test_split(df, test_size=0.2, rand
_state=RANDOM_SEED)
df_val, df_test = train_test_split(df_test, test_size=0.5, ran
dom_state=RANDOM_SEED)
```

In [26]:
```
df_train.shape, df_val.shape, df_test.shape
```

Out[26]:
```
((11491, 13), (1436, 13), (1437, 13))
```

In [27]:
```
ds = CustomDataset(
    reviews=df.content.to_numpy(),
    targets=df.sentiment.to_numpy(),
    tokenizer=tokenizer,
    max_len=MAX_LEN
    )
```

DataLoading

In [28]:
```
def Data_Loader(df, tokenizer, max_len, batch_size):
    ds = CustomDataset(
    reviews=df.content.to_numpy(),
    targets=df.sentiment.to_numpy(),
    tokenizer=tokenizer,
    max_len=max_len
    )

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

In [29]:
```
train_data_loader = Data_Loader(df_train, tokenizer, MAX_LEN
BATCH_SIZE)
val_data_loader = Data_Loader(df_val, tokenizer, MAX_LEN, BATC
H_SIZE)
test_data_loader = Data_Loader(df_test, tokenizer, MAX_LEN, BA
TCH_SIZE)
```

In [30]:
```
data = next(iter(train_data_loader))
print(data.keys())
```

```
dict_keys(['review', 'target', 'input_ids', 'attention_mask']
```

In [31]:
```
print(data['input_ids'].shape)
print(data['attention_mask'].shape)
print(data['target'].shape)
```

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

torch.Size([16, 160])

torch.Size([16])
```

Sentiment Classification with BERT and Hugging Face

Lets try it on sample text

In [32]:
```
bert_model = BertModel.from_pretrained(PRE_TRAINED_MODEL_NAM
```

Downloading: 100% 416M/416M [00:14<00:00, 31.3MB/s]

```
Some weights of the model checkpoint at bert-base-cased were
ot used when initializing BertModel: ['cls.predictions.transfo
rm.LayerNorm.bias', 'cls.predictions.decoder.weight', 'cls.pre
dictions.transform.dense.weight', 'cls.predictions.bias', 'cl
s.predictions.transform.dense.bias', 'cls.predictions.transfor
m.LayerNorm.weight', 'cls.seq_relationship.weight', 'cls.seq_r
elationship.bias']

- This IS expected if you are initializing BertModel from the
checkpoint of a model trained on another task or with another
architecture (e.g. initializing a BertForSequenceClassificatio
n model from a BertForPreTraining model).

- This IS NOT expected if you are initializing BertModel from
the checkpoint of a model that you expect to be exactly identi
cal (initializing a BertForSequenceClassification model from a
BertForSequenceClassification model).
```

The last_hidden_state is a sequence of hidden states of the last layer of the model. Obtaining the pooled_output is done by applying the BertPooler on last_hidden_state:

In [33]:
```
last_hidden_state, pooled_output = bert_model(
                                        input_ids = encoding
['input_ids'],
                                        attention_mask = encod
ing['attention_mask'],
                                        return_dict=False
                                    )
```

In [34]:
```python
last_hidden_state.shape # 1 example , 32 elements after padd
g and 768 hidden units
```

Out[34]:
```
torch.Size([1, 32, 768])
```

In [35]:
```python
pooled_output.shape # pooling procedure on 32 elements
```

Out[35]:
```
torch.Size([1, 768])
```

In [36]:
```python
bert_model.config.hidden_size
```

Out[36]:
```
768
```

Building Sentiment Classifier

In [37]:
```python
class SentimentClassifier(nn.Module):
    def __init__(self,n_classes):
        super().__init__()
        self.bert = BertModel.from_pretrained(PRE_TRAINED_MODE
L_NAME)
        self.dropout = nn.Dropout(p=0.2)
        self.linear = nn.Linear(self.bert.config.hidden_size,
n_classes)
        self.softmax = nn.Softmax(dim=1)

    def forward(self, input_ids, attention_mask):
        _, pooled_output = self.bert(
                                input_ids = input_ids,
                                attention_mask = attention_mas
k,
                                return_dict = False
                            )
        output = self.dropout(pooled_output)
        output = self.linear(output)
        return self.softmax(output)
```

In [38]:
```python
model = SentimentClassifier(n_classes = 3)
model = model.to(device)
```

```
Some weights of the model checkpoint at bert-base-cased were
ot used when initializing BertModel: ['cls.predictions.transfo
rm.LayerNorm.bias', 'cls.predictions.decoder.weight', 'cls.pre
dictions.transform.dense.weight', 'cls.predictions.bias', 'cl
s.predictions.transform.dense.bias', 'cls.predictions.transfor
m.LayerNorm.weight', 'cls.seq_relationship.weight', 'cls.seq_r
elationship.bias']

- This IS expected if you are initializing BertModel from the
checkpoint of a model trained on another task or with another
architecture (e.g. initializing a BertForSequenceClassificatio
n model from a BertForPreTraining model).

- This IS NOT expected if you are initializing BertModel from
the checkpoint of a model that you expect to be exactly identi
cal (initializing a BertForSequenceClassification model from a
BertForSequenceClassification model).
```

In [39]:

```
optimizer = AdamW(model.parameters(),lr=2e-5,correct_bias=Fal
e)

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)
```

In [40]:

```
def train_model(model, data_loader, loss_fn, optimizer, devi
e, scheduler, n_examples):
    model = model.train()
    losses = []
    correct_preds = 0

    for data in data_loader:
        input_ids = data['input_ids'].to(device)
        attention_mask = data['attention_mask'].to(device)
        targets = data['target'].to(device)

        outputs = model(input_ids,attention_mask)
        _, preds = torch.max(outputs,dim=1)
        loss = loss_fn(outputs,targets)
        correct_preds += torch.sum(preds==targets)
        losses.append(loss.item())

        loss.backward()
        nn.utils.clip_grad_norm(model.parameters(),max_norm=1.
0) #  We're avoiding exploding gradients by clipping the gradi
ents of the model using clip_gradnorm.
        optimizer.step()
        scheduler.step()
        optimizer.zero_grad()

    return correct_preds.double() / n_examples, np.mean(losse
s)
```

In [41]:
```
def eval_model(model, data_loader, loss_fn, device, n_exampl
s):
    model = model.eval()
    losses = []
    correct_preds = 0

    with torch.no_grad():
        for data in data_loader:
            input_ids = data['input_ids'].to(device)
            attention_mask = data['attention_mask'].to(device)
            targets = data['target'].to(device)

            outputs = model(input_ids,attention_mask)
            _, preds = torch.max(outputs,dim=1)
            loss = loss_fn(outputs,targets)
            correct_preds += torch.sum(preds==targets)
            losses.append(loss.item())

    return correct_preds.double() / n_examples, np.mean(losse
s)
```

In [42]:

```
%%time
history = defaultdict(list)
best_accuracy = 0

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

    train_acc, train_loss = train_model(model,train_data_loade
r, 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, los
s_fn, device, len(df_val))
    print(f'Val   loss {val_loss} accuracy {val_acc}')
    print('\n')

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

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

```
Epoch 1/10
----------
Train loss 0.8895378269472772 accuracy 0.6472891828387434
Val   loss 0.8509273495939043 accuracy 0.6908077994428969


Epoch 2/10
----------
Train loss 0.7862448751180328 accuracy 0.7575493864763728
Val   loss 0.816420171658198 accuracy 0.7325905292479109


Epoch 3/10
----------
Train loss 0.7348239190555249 accuracy 0.81341919763293
Val   loss 0.8232506129476759 accuracy 0.7249303621169917


Epoch 4/10
----------
Train loss 0.7103045571994383 accuracy 0.8397876599077538
Val   loss 0.808188118537267 accuracy 0.7437325905292479


Epoch 5/10
----------
Train loss 0.6937786942562905 accuracy 0.8571055608737272
Val   loss 0.7955854958958096 accuracy 0.7534818941504178


Epoch 6/10
```

```
----------
Train loss 0.6844588421979435 accuracy 0.8660690975546079
Val   loss 0.7986241181691488 accuracy 0.7534818941504178

Epoch 7/10
----------
Train loss 0.6769924323814137 accuracy 0.8735532155600034
Val   loss 0.7991188453303443 accuracy 0.7506963788300836

Epoch 8/10
----------
Train loss 0.670027951786349 accuracy 0.8809503089374292
Val   loss 0.788244284523858 accuracy 0.7618384401114207

Epoch 9/10
----------
Train loss 0.6658583255238593 accuracy 0.8852145157079453
Val   loss 0.7841546257336934 accuracy 0.766016713091922

Epoch 10/10
----------
Train loss 0.6618157570484782 accuracy 0.8893046732225219
Val   loss 0.784818661875195 accuracy 0.7646239554317549

CPU times: user 34min 41s, sys: 8.72 s, total: 34min 50s
```

```
Wall time: 35min 25s
```

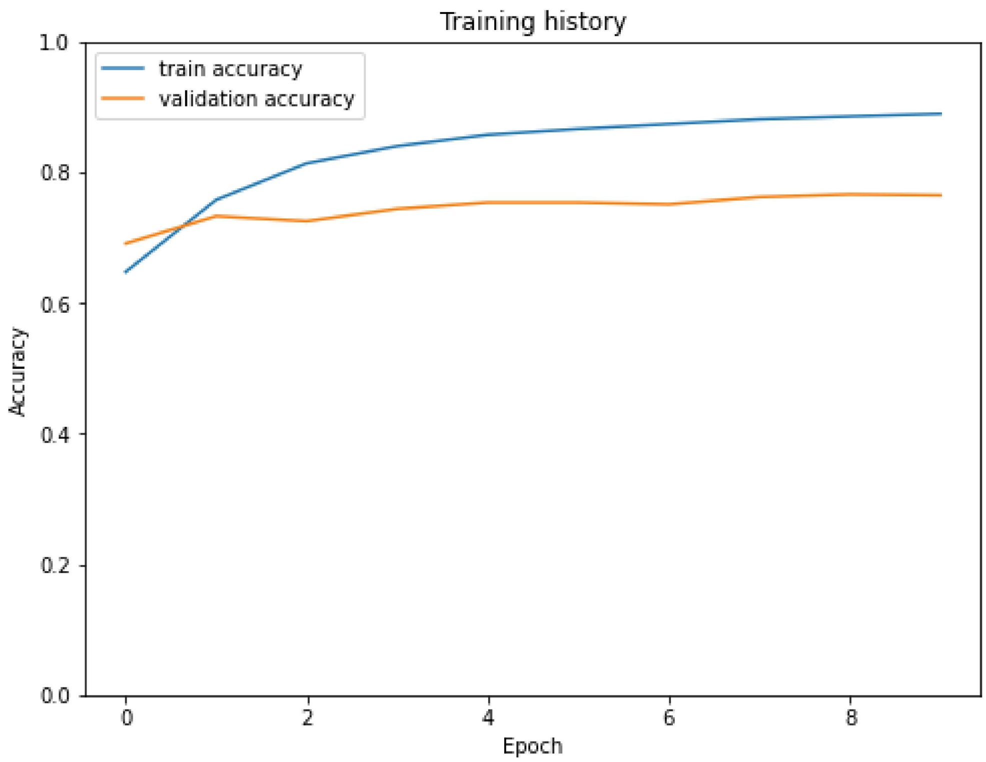
Increase number of epochs to get better results

In [43]:
```python
train_acc = [acc.cpu() for acc in history['train_acc']]
val_acc = [acc.cpu() for acc in history['val_acc']]
```

In [44]:
```python
plt.figure(figsize = (8,6))
plt.plot(train_acc, label='train accuracy')
plt.plot(val_acc, label='validation accuracy')

plt.title('Training history')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.ylim([0, 1])
```

Out[44]:
```
(0.0, 1.0)
```



In [45]:
```
def get_preds(model, data_loader):
    model = model.eval()

    review_texts = []
    predictions = []
    prediction_probs = []
    real_values = []

    with torch.no_grad():
        for data in data_loader:
            reviews = data['review']
            input_ids = data['input_ids'].to(device)
            attention_mask = data['attention_mask'].to(device)
            targets = data['target'].to(device)

            review_texts.extend(reviews)
            real_values.extend(targets)

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

            prediction_probs.extend(outputs)
            predictions.extend(preds)

        predictions = torch.stack(predictions).cpu()
        prediction_probs = torch.stack(prediction_probs).cpu()
        real_values = torch.stack(real_values).cpu()


    return review_texts, predictions, prediction_probs, real_v
alues
```

In [46]:
```
review_texts, predictions, prediction_probs, real_values = g
_preds(model,test_data_loader)
```

In [47]:
```
class_names = ['negative','neutral','positive']
```

In [48]:
```python
for i in range(3):
    print('review_texts: ',review_texts[i])
    print('predictions: ',class_names[predictions[i]])
    print('prediction_probs: ',prediction_probs[i])
    print('real_values: ',class_names[real_values[i]])
    print('\n')
```

```
review_texts:  Not bad

predictions:  neutral

prediction_probs:  tensor([2.4137e-05, 9.9993e-01, 4.2055e-0
5])

real_values:  neutral




review_texts:  Impossible for custom skills to influence multi
ple characteristics

predictions:  neutral

prediction_probs:  tensor([2.2660e-05, 9.9996e-01, 2.1047e-0
5])

real_values:  neutral




review_texts:  I just cannot be notified. Please. Fix it. So I
could give 5 stars.

predictions:  negative

prediction_probs:  tensor([9.9994e-01, 1.9388e-05, 3.9770e-0
5])

real_values:  negative
```

In [49]:
```python
print(classification_report(real_values, predictions, target_names=['negative','neutral','positive']))
```

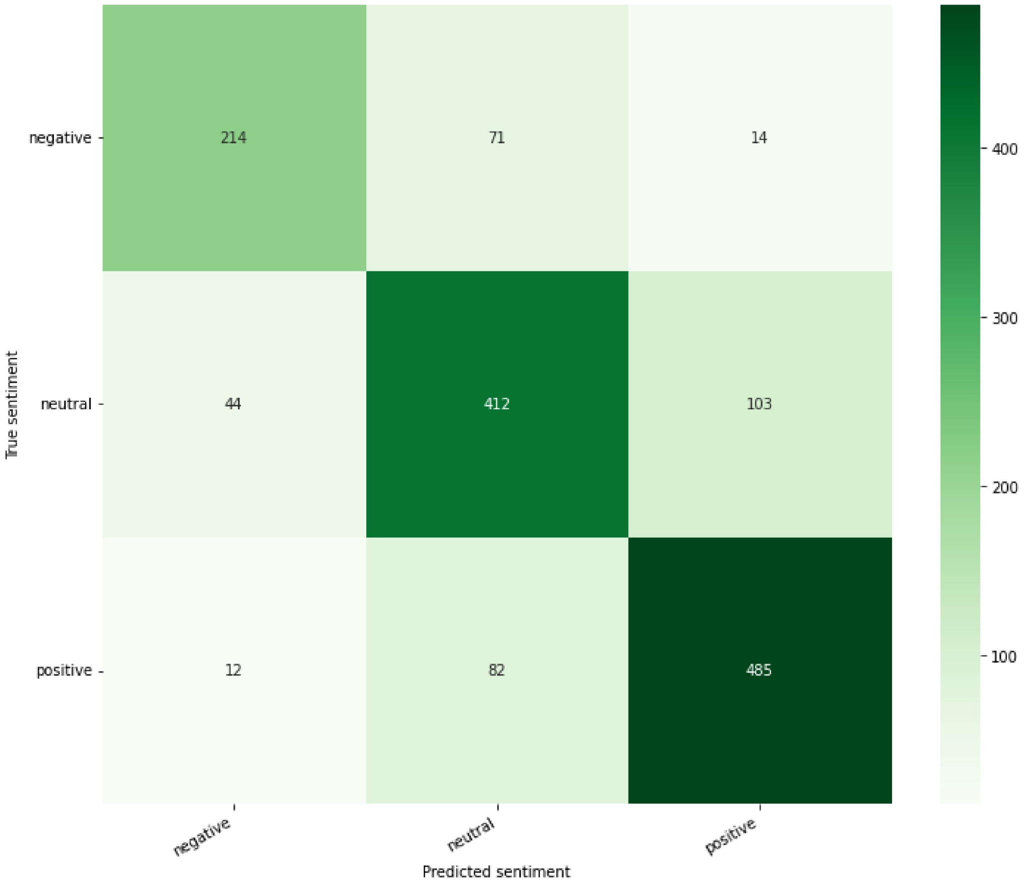
```
              precision    recall  f1-score   support

    negative       0.79      0.72      0.75       299
     neutral       0.73      0.74      0.73       559
    positive       0.81      0.84      0.82       579

    accuracy                           0.77      1437
   macro avg       0.78      0.76      0.77      1437
weighted avg       0.77      0.77      0.77      1437
```

In [50]:
```
def show_confusion_matrix(confusion_matrix):
    plt.figure(figsize = (12,10))
    hmap = sns.heatmap(confusion_matrix, annot=True, fmt="d", cmap="Greens")
    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(real_values, predictions)
df_cm = pd.DataFrame(cm, index=class_names, columns=class_names)
show_confusion_matrix(df_cm)
```



Predicting new text sample

In [51]:
```
review_text = 'This notebook is very helpful.'
```

In [52]:
```
encoded_review = tokenizer.encode_plus(
  review_text,
  max_length=MAX_LEN,
  add_special_tokens=True,
  return_token_type_ids=False,
  pad_to_max_length=True,
  return_attention_mask=True,
  return_tensors='pt',
)
```

In [53]:
```
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: This notebook is very helpful.

Sentiment  : positive
```