1.PAY ATTENTION

a) auto-regressive self-attention.
As we can know, to achieve self-attention, we have these formulas:

$y_i = \sum_{j=1}^{n} W_{ij} x_j$, $w_{ij} = x_i^T x_j$, $W_{ij} = softmax(w_{ij})$

Since every token only attends to its own position and all previous positions in auto-regressive self-attention. Assume that i is the index of the input elements, $i = 1, \dots, n$. For the token i, it needs to consider i values.

Thus, the number of dot products $N = 1 + 2 + \cdots + n = \frac{n(1+n)}{2}$

Here is the n grid and shade/mark the squares that depict the calculated attention scores. The cell with 'X' means that this cells needs to be calculated.

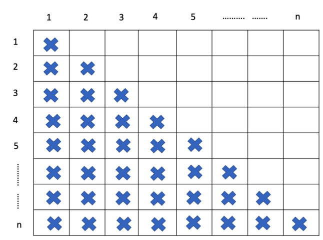


Figure 1. grid of auto-regressive self-attention

b) strided self-attention.
As we can know, to achieve self-attention, we have these formulas:

$y_i = \sum_{j=1}^{n} W_{ij} x_j$, $w_{ij} = x_i^T x_j$, $W_{ij} = softmax(w_{ij})$

Since every token attends to at most t positions prior to it, plus itself in strided self-attention. Assume that i is the index of the input elements, $i = 1, \dots, n$.

For the token i where $i \leq t+1$, it needs to consider i values.
For the token i where $i > t+1$, it needs to consider $t+1$ values.

Thus, the number of dot products $N = \sum_{i=1}^{t+1} i + \sum_{i=t+2}^{n} t + 1 = \frac{(1+t+1)(t+1)}{2} + (n-t-1)(t+1) = \frac{t^2+3t+2}{2} + nt + n - t^2 - 2t - 1 = -\frac{1}{2}t^2 - \frac{1}{2}t + nt + n$

Here is the n grid and shade/mark the squares that depict the calculated attention scores. The cell with 'X' means that this cells needs to be calculated. In this grid, we assume t is 3.

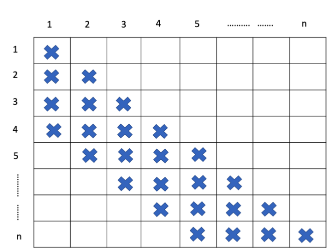


Figure 2. grid of strided self-attention

c) windowed self-attention.
As we can know, to achieve self-attention, we have these formulas:

$y_i = \sum_{j=1}^{n} W_{ij}x_j$, $w_{ij} = x_i^T x_j$, $W_{ij} = softmax(w_{ij})$

Since the n tokens are partitioned into windows of size w (assume w divides n), and every token attends to all positions within its window and prior to it, plus itself in windowed self-attention. Assume that i is the index of the input elements, $i = 1, \ldots, n$.

As we can image, in each window, the n grid is the same as the n grid that we draw in question (a).

Thus, the number of dot products in each window $N = 1 + 2 + \cdots + w = \frac{w(1+w)}{2}$. And the total number of dot products $N = \frac{n}{w} \times \frac{w(1+w)}{2} = \frac{n(1+w)}{2}$

Here is the n grid and shade/mark the squares that depict the calculated attention scores. The cell with 'X' means that this cells needs to be calculated.

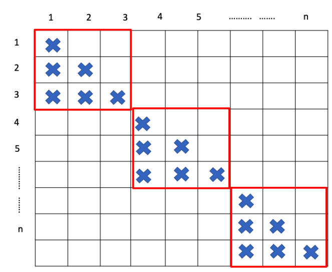


Figure 3. grid of windowed self-attention

2.RNNS FOR IMAGES.

a) the number of trainable parameters.
As we known, the equation for the hidden unit is given as follows:

$$h^{i,j} = \sigma(W_{in}x^{i,j} + W_{left}h^{i-1,j} + W_{top}h^{i,j-1})$$

Assume that the input grid is $n \times n$, each input $x^{i,j}$ is a c-channel vector, and the hidden state $h^{i,j-1}$ has dimension h.

Thus, the size of each input $x^{i,j}$ is $1 \times c$.
For input $x^{0,0}$, $h^{0,0} = \sigma(W_{in}x^{i,j})$ and $h^{0,0}$ has dimension h, which means the size of $h^{0,0}$ is $1 \times h$, we can know that the size of W_{in} is $h \times c$
And since the size of $h^{0,0}$ is $1 \times h$ and the size of $W_{left}h^{i-1,j}$ should also be $1 \times h$, we can know that the size of W_{left} is $h \times h$. So does the W_{top}.

As we known, the parameters here would be shared in the RNN. Therefore, the number of trainable parameters $N = hc + 2h^2$

b) the number of arithmetic operations.

First, lets calculate the arithmetic operations in $W_{in}x^{i,j}$:
For each hidden unit, it needs to do c times multiple operations and $c-1$ times add operations. There are h hidden units. Thus, the number of multiple operations is hc and the number of add operations is $h(c-1)$

Then. lets calculate the arithmetic operations in $W_{left}h^{i-1,j}$.
For each hidden unit, it needs to do h times multiple operations and $h-1$ times add operations. There are h hidden units. Thus, the number of multiple operations is h^2 and the number of add operations is $h(h-1)$.
And the case in $W_{top}h^{i-1,j}$ is the same.

Therefore, for each time we calculate $h^{i,j}$, we need to do $hc+2h^2 = o(h^2)$ multiple operations. For add operations, besides those we counted above, we still need to sum three matrix up and each of them has h values. Thus, we need to do $h(c-1)+2h(h-1)+2h = O(h^2)$ add operations. Totally $hc+2h^2+h(c-1)+2h(h-1)+2h = O(h^2)$ arithmetic operations for calculating each $h^{i,j}$.

Also there are cases that the number operations is different.
For example, for $h^{i,j}$ when $i \geq 1 and j = 0$ or $j \geq 1 and i = 0$, we need to do $hc+h^2 = o(h^2)$ multiple operations and $h(c-1)+h(h-1)+h = O(h^2)$ add operations. However, the big-Oh notation are the same, thus in the following calculation we don't need to consider and measure these cases separately.
For $h^{0,0}$, we need to do $hc = o(h)$ multiple operations and $h(c-1) = O(h)$ add operations. However, we only have one case of this, so when we have $n > 1$ we can ignore this.

Considering input grid is $n \times n$, the total number of arithmetic operations is $O(h^2) \times n^2 = O(n^2h^2)$, where the numbers of add operations and multiple operations are the same as $O(n^2h^2)$.

c) regular convnet verse RNN.

CNNs employ filters within convolutional layers to transform data. Whereas, RNNs reuse activation functions from other data points in the sequence to generate the next output in a series.

Advantage: This RNN architecture can interpret temporal information such as videos (which are essentially a sequence of individual images) while CNN cannot. As this RNN architecture can analyze the current image with the images that it has already analyzed. Thus, it can explore the sequence relationship/pattern better. RNN is more used for cases where the data contains temporal properties, such as a time series. Similarly, where the data is context sensitive, the function of memory provided by the feedback loops is critical for adequate performance. while CNN cannot do this.
Moreover, this RNN architecture can take the inputs that have variable length.

Disadvantage: This RNN architecture is not as general as CNN on computer vision. CNN can be used on most of the images tasks such as image classification, segmentation or object detection.
CNNs can better learn the position and scale of features in a variety of images, making them especially good at the classification of hierarchical or spatial data and the extraction of unlabelled features, while this RNN architecture cannot do this.
And This RNN architecture might require more hyperparameters and supervision compring to CNN, which using small size of filters to do convolution on images.

In this problem we will use the BERT model for sentiment analysis. We will start with a pre-trained BERT model and fine-tune it on a dataset of Google Play store reviews.

Setup

Install [the Transformers library (https://huggingface.co/transformers/)](https://huggingface.co/transformers/) by Hugging Face:

In [1]:
```
!pip install -q -U watermark
```

In [2]:
```
!pip install -qq transformers
```

In [3]:
```
%reload_ext watermark
%watermark -v -p numpy,pandas,torch,transformers
```

```
CPython 3.6.9
IPython 5.5.0

numpy 1.18.5
pandas 1.1.3
torch 1.6.0+cu101
transformers 3.4.0
```

Data Exploration

Download the Google Play app reviews dataset using the following commands:

In [4]:
```
!gdown --id 1S6qMioqPJjyBLpLVz4gmRTnJHnjitnuV
!gdown --id 1zdmewp7ayS4js4VtrJEHzAheSW-5NBZv
```

```
Downloading...
From: https://drive.google.com/uc?id=1S6qMioqPJjyBLpLVz4gmRTnJHnjitnuV
To: /content/apps.csv
100% 134k/134k [00:00<00:00, 42.9MB/s]
Downloading...
From: https://drive.google.com/uc?id=1zdmewp7ayS4js4VtrJEHzAheSW-5NBZv
To: /content/reviews.csv
7.17MB [00:00, 33.4MB/s]
```

Here is how it looks like:

In [5]:
```
import pandas as pd
df = pd.read_csv("reviews.csv")
df.head()
```

Out[5]:

	userName	userImage	content	score	thumbsUpCount	reviewCreatedVersion	at	replyC
0	Andrew Thomas	https://lh3.googleusercontent.com/a-/AOh14GiHd...	Update: After getting a response from the deve...	1	21	4.17.0.3	2020-04-05 22:25:57	Accor our TC the te ha
1	Craig Haines	https://lh3.googleusercontent.com/-hoe0kwSJgPQ...	Used it for a fair amount of time without any ...	1	11	4.17.0.3	2020-04-04 13:40:01	It sour you lo diffe
2	steven adkins	https://lh3.googleusercontent.com/a-/AOh14GiXw...	Your app sucks now!!!!! Used to be good but no...	1	17	4.17.0.3	2020-04-01 16:18:13	This odd! not a any
3	Lars Panzerbjørn	https://lh3.googleusercontent.com/a-/AOh14Gg-h...	It seems OK, but very basic. Recurring tasks n...	1	192	4.17.0.2	2020-03-12 08:17:34	We this op par Adv
4	Scott Prewitt	https://lh3.googleusercontent.com/-K-X1-YsVd6U...	Absolutely worthless. This app runs a prohibit...	1	42	4.17.0.2	2020-03-14 17:41:01	We'r you f way! the

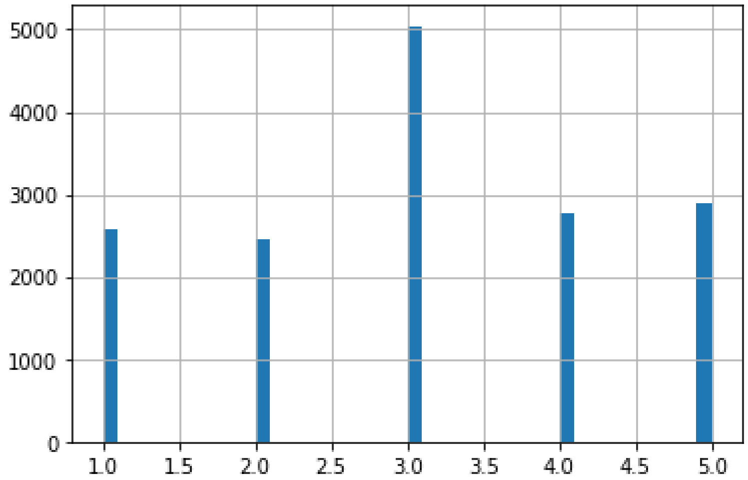
Let's first check the size of the dataset.

In [6]:
```
# TODO: Q1. How many samples are there in this dataset?
print("The size of the dataset:",len(df))
```

```
The size of the dataset: 15746
```

In [7]:
```
# TODO: Q2. Plot a histogram of review scores. These can be accessed in the df.score field in the abo
ve dataframe. Which score is the most common?
df["score"].hist(bins=40)
print("3 is the the most common value of the column score.")
```

```
3 is the the most common value of the column score.
```



If correctly plotted, you should be able to see that this is a somewhat imbalanced dataset. Let's first convert the dataset into three classes: negative, neutral, and positive sentiment:

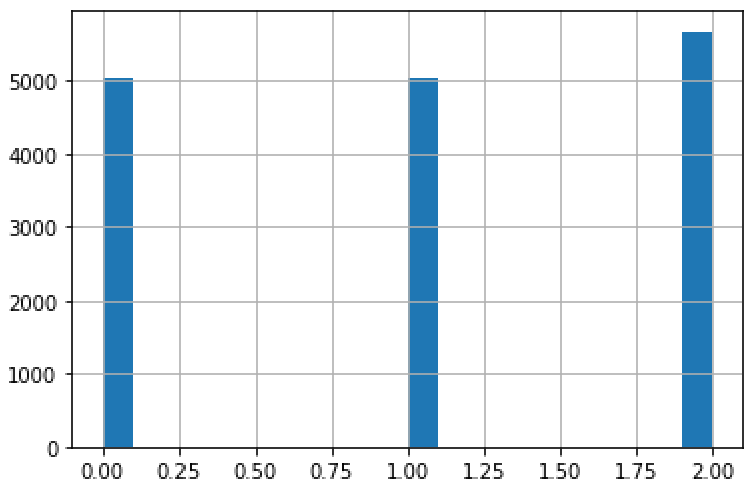
In [8]:
```
def to_sentiment(rating):
  rating = int(rating)
  if rating <= 2:
    return 0
  elif rating == 3:
    return 1
  else:
    return 2

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

In [9]:
```
class_names = ['negative', 'neutral', 'positive']
```

In [10]:
```
# TODO: Q3. Plot the histogram of review sentiments, and show that it is now approximately balanced.
df["sentiment"].hist(bins=20)
```

Out[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6934edcc18>
```



Data Preprocessing

Let's now load a pre-trained BERT model and the corresponding tokenizer, which converts text data into tokens.

In [11]:
```
PRE_TRAINED_MODEL_NAME = 'bert-base-cased'
```

In [12]:
```
from transformers import BertTokenizer

tokenizer = BertTokenizer.from_pretrained(PRE_TRAINED_MODEL_NAME)
```

Let's see how tokenization works. Here is the test sentence. Convert into tokens using the `tokenizer.tokenize` and `tokenizer.convert_tokens_to_ids` methods.

In [13]:
```
sample_txt = 'Every day feels like the same during the lock down.'
```

In [14]:
```
# TODO: Q4. Print the tokens and token ids of the sample text above.
print(tokenizer.tokenize(sample_txt))
print(tokenizer.convert_tokens_to_ids(tokenizer.tokenize(sample_txt)))
```

```
['Every', 'day', 'feels', 'like', 'the', 'same', 'during', 'the', 'lock', 'down', '.']
[4081, 1285, 5115, 1176, 1103, 1269, 1219, 1103, 5842, 1205, 119]
```

BERT has special tokens for sentence separators [SEP] and unknown words [UNK]. This can be done using the `encode_plus()` (https://huggingface.co/transformers/main_classes/tokenizer.html#transformers.PreTrainedTokenizer.encode_plus) method, which takes the test sentence and encodes it into `input_ids` .

In [15]:
```
encoding = tokenizer.encode_plus(
  sample_txt,
  max_length=32,
  add_special_tokens=True, # Add '[CLS]' and '[SEP]'
  return_token_type_ids=False,
  pad_to_max_length=True,
  return_attention_mask=True,
  return_tensors='pt',  # Return PyTorch tensors
)

encoding.keys()
```

```
Truncation was not explicitely activated but `max_length` is provided a specific value, please use `
truncation=True` to explicitely truncate examples to max length. Defaulting to 'longest_first' trunc
ation strategy. If you encode pairs of sequences (GLUE-style) with the tokenizer you can select this
strategy more precisely by providing a specific strategy to `truncation`.
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,
```

Out[15]:
```
dict_keys(['input_ids', 'attention_mask'])
```

The token ids are now stored in a Tensor and padded to a length of 32:

In [16]:
```
print(len(encoding['input_ids'][0]))
encoding['input_ids'][0]
```

```
32
```

Out[16]:
```
tensor([ 101, 4081, 1285, 5115, 1176, 1103, 1269, 1219, 1103, 5842, 1205,  119,
         102,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
           0,    0,    0,    0,    0,    0,    0,    0])
```

The attention mask has the same length:

In [17]:
```
print(len(encoding['attention_mask'][0]))
encoding['attention_mask']
```

```
32
```

Out[17]:
```
tensor([[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, 0, 0, 0, 0, 0]])
```

Use the `tokenizer.convert_ids_to_tokens` method to invert the encoded token ids (the above tensor of length 32) and visualize the sentence.

In [18]:
```
# TODO: Q5. Invert the encoded token ids.
print(tokenizer.convert_ids_to_tokens(encoding['input_ids'][0]))
```

```
['[CLS]', 'Every', 'day', 'feels', 'like', 'the', 'same', 'during', 'the', 'lock', 'down', '.', '[SE
P]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PA
D]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]', '[PAD]']
```

Most reviews in the dataset contain less than around 120 tokens, but let us choose a maximum length of 160.

In [19]:
```
MAX_LEN = 160
```

Building the dataset

Let's now create a dataset using the tokenizer. Here is some code that does this:

In [20]:
```
# class GPReviewDataset(Dataset):
class GPReviewDataset():

  def __init__(self, reviews, targets, tokenizer, max_len):
    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 = str(self.reviews[item])
    target = self.targets[item]

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

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

The tokenizer is doing most of the heavy lifting for us. We also return the review texts, so it'll be easier to evaluate the predictions from our model. Let's split the data into 90-5-5 train-validation-test.

In [25]:
```
# TODO: Q6. Create three data frames: df_train, df_val, df_test as above and print their shapes.
shuffle_df = df.sample(frac=1.0)

rows, cols = shuffle_df.shape
split_index_1 = int(rows * 0.05)
split_index_2 = int(rows * 0.1)

df_test = shuffle_df.iloc[0: split_index_1, :]
df_val= shuffle_df.iloc[split_index_1:split_index_2, :]
df_train = shuffle_df.iloc[split_index_2: rows, :]

train_samples_size = len(df_train)
val_samples_size = len(df_val)
test_samples_size = len(df_test)

print("The shape of the traning set: ",df_train.shape)
print("The shape of the validation set: ",df_val.shape)
print("The shape of the testing set: ",df_test.shape)

print("The number of samples in training set: ",train_samples_size)
print("The number of samples in validation set: ",val_samples_size)
print("The number of samples in testing set: ",test_samples_size)
```

```
The shape of the traning set:  (14172, 12)
The shape of the validation set:  (787, 12)
The shape of the testing set:  (787, 12)
The number of samples in training set:  14172
The number of samples in validation set:  787
The number of samples in testing set:  787
```

We also need to create a couple of data loaders:

In [26]:
```
from torch.utils.data import DataLoader
def create_data_loader(df, tokenizer, max_len, batch_size):
  ds = GPReviewDataset(
    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 [27]:
```
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)

# print(len(train_data_loader))
# print(len(val_data_loader))
# print(len(test_data_loader))
```

Let's have a look at an example batch from our training data loader:

In [28]:
```
import torch
data = next(iter(train_data_loader))
data.keys()
print(data['input_ids'].shape)
print(data['attention_mask'].shape)
print(data['targets'].shape)
print(data['targets'])
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

torch.Size([16, 160])
torch.Size([16, 160])
torch.Size([16])
tensor([0, 2, 1, 1, 2, 0, 2, 1, 1, 0, 2, 1, 0, 0, 2, 1])
```

Let's now load the basic BertModel (https://huggingface.co/transformers/model_doc/bert.html#bertmodel) and build our sentiment classifier on top of it. Load the model using:

In [29]:
```
from transformers import BertModel
bert_model = BertModel.from_pretrained(PRE_TRAINED_MODEL_NAME)
```

And encode our sample text:

In [30]:
```
last_hidden_state, pooled_output = bert_model(
  input_ids=encoding['input_ids'],
  attention_mask=encoding['attention_mask']
)
```

The `last_hidden_state` is the sequence of hidden states of the last layer of the model. The `pooled_output` can be thought of as a summary of the content in the test sentence. Try printing out the sizes of `last_hidden_state` and `pooled_output` :

In [31]:
```
# TODO: Q7. Print the sizes of the hidden states and the pooled output.
print("The sizes of the hidden states: ", last_hidden_state.shape)
print("The sizes of the pooled output: ", pooled_output.shape)
```

```
The sizes of the hidden states:  torch.Size([1, 32, 768])
The sizes of the pooled output:  torch.Size([1, 768])
```

We can use all of this knowledge to create a classifier that uses the BERT model:

In [32]:
```
import torch.nn as nn
class SentimentClassifier(nn.Module):

  def __init__(self, n_classes):
    super(SentimentClassifier, self).__init__()
    self.bert = BertModel.from_pretrained(PRE_TRAINED_MODEL_NAME)
    self.drop = nn.Dropout(p=0.3)
    self.out = nn.Linear(self.bert.config.hidden_size, n_classes)

  def forward(self, input_ids, attention_mask):
    _, pooled_output = self.bert(
      input_ids=input_ids,
      attention_mask=attention_mask
    )
    output = self.drop(pooled_output)
    return self.out(output)
```

Note that our sentiment classifier takes the BERT backbone and adds a dropout layer (for regularization) and a linear dense layer, which we train using cross-entropy. Let's create an instance and move it to the GPU:

In [33]:
```
device = torch.device('cuda')
model = SentimentClassifier(len(class_names))
model = model.to(device)
```

We'll move the example batch of our training data to the GPU:

In [34]:
```
input_ids = data['input_ids'].to(device)
attention_mask = data['attention_mask'].to(device)
```

To get the predicted probabilities from our trained model, we'll apply the softmax function to the outputs:

In [35]:
```python
from torch.nn import functional as F

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

Out[35]:
```
tensor([[0.3880, 0.2686, 0.3434],
        [0.5506, 0.2484, 0.2010],
        [0.3667, 0.3850, 0.2483],
        [0.3008, 0.3867, 0.3125],
        [0.3844, 0.2969, 0.3187],
        [0.4768, 0.2033, 0.3198],
        [0.4767, 0.1381, 0.3852],
        [0.3656, 0.3089, 0.3256],
        [0.4025, 0.2819, 0.3155],
        [0.2053, 0.2775, 0.5172],
        [0.4521, 0.1833, 0.3646],
        [0.3584, 0.2365, 0.4051],
        [0.4720, 0.2088, 0.3192],
        [0.3665, 0.2788, 0.3547],
        [0.3459, 0.1729, 0.4812],
        [0.4657, 0.2086, 0.3257]], device='cuda:0', grad_fn=<SoftmaxBackward>)
```

Check the prediction and the target format so as to produce the correct predictions

In [36]:
```
import numpy as np
targets = data["targets"].to(device)
outputs = model(
  input_ids=input_ids,
  attention_mask=attention_mask
)

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

print(preds)
print(targets)

correct_predictions = 0
correct_predictions += (preds == targets).sum()

print(correct_predictions)
n_examples = len(preds)

print("data size:", len(preds))
train_acc = correct_predictions.double() / n_examples
print(train_acc)
print(f'Train accuracy {train_acc}')
```

```
tensor([2, 2, 2, 0, 1, 0, 0, 0, 1, 0, 2, 0, 0, 1, 2, 2], device='cuda:0')
tensor([0, 2, 1, 1, 2, 0, 2, 1, 1, 0, 2, 1, 0, 0, 2, 1], device='cuda:0')
tensor(7, device='cuda:0')
data size: 16
tensor(0.4375, device='cuda:0', dtype=torch.float64)
Train accuracy 0.4375
```

Training

To train the model, we will use the AdamW optimizer and a linear learning-rate scheduler with no warmup steps, along with the cross-entropy loss. Five epochs (full passes through the training data should be enough) should be enough, but you can experiment with more epochs.

In [37]:
```
from transformers import AdamW
import transformers

EPOCHS = 5

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

# scheduler = get_linear_schedule_with_warmup(
scheduler = transformers.get_linear_schedule_with_warmup(
  optimizer,
  num_warmup_steps=0,
  num_training_steps=total_steps
)

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

Let's continue with writing a helper function for training our model for one epoch:

In [38]:
```
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:
    # TODO Q8. Complete the incomplete code snippets below to finish training.

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

    outputs = model(
      input_ids=input_ids,
      attention_mask=attention_mask
    )

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

    correct_predictions += (preds == targets).sum()
    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)
```

Let's write another function that helps us evaluate the model on a given data loader.

In [39]:
```
def eval_model(model, data_loader, loss_fn, device, n_examples):
  model = model.eval()

  # TODO: Q9. Reproduce the above code but only evaluate the model (without any weight updates).input
_ids = d["input_ids"].to(device)
  losses = []
  correct_predictions = 0

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

    outputs = model(
      input_ids=input_ids,
      attention_mask=attention_mask
    )

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

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

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

Using those two, we can write our training loop.

In [40]:

```
%%time
from collections import defaultdict

history = defaultdict(list)
best_accuracy = 0

for epoch in range(EPOCHS):

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

  # TODO: Q10. Complete the code below to track train and test accuracy.losses

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

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

  val_acc, val_loss = eval_model(model, val_data_loader, loss_fn, device, val_samples_size)

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

  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.bin')
    best_accuracy = val_acc
```

```
Epoch 1/5
----------

/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
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/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
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or Bert).
  FutureWarning,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Train loss 0.7797234255828922 accuracy 0.640770533446232
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
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or Bert).
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or Bert).
  FutureWarning,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
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th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Val   loss 0.6337454545497895 accuracy 0.7280813214739518

Epoch 2/5
----------
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
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/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Train loss 0.49418334006153164 accuracy 0.8052497883149873
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Val   loss 0.5775604197382926 accuracy 0.7928843710292249

Epoch 3/5
----------
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Train loss 0.2925225176814834 accuracy 0.9066469093988145
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Val   loss 0.6026012329757213 accuracy 0.8259212198221093

Epoch 4/5
----------
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Train loss 0.20565006219252155 accuracy 0.9424216765453006
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
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/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
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th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Val   loss 0.7144597454741597 accuracy 0.841168996188056

Epoch 5/5
----------
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
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=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
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/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
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or Bert).
  FutureWarning,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Train loss 0.15515340510918707 accuracy 0.9588625458650861
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,

Val   loss 0.705768810622394 accuracy 0.8475222363405337

CPU times: user 21min 29s, sys: 14min 55s, total: 36min 25s
Wall time: 36min 40s
```

Note that we're storing the best model, indicated by the highest validation accuracy.

Plot train and validation accuracy as a function of epoch count.

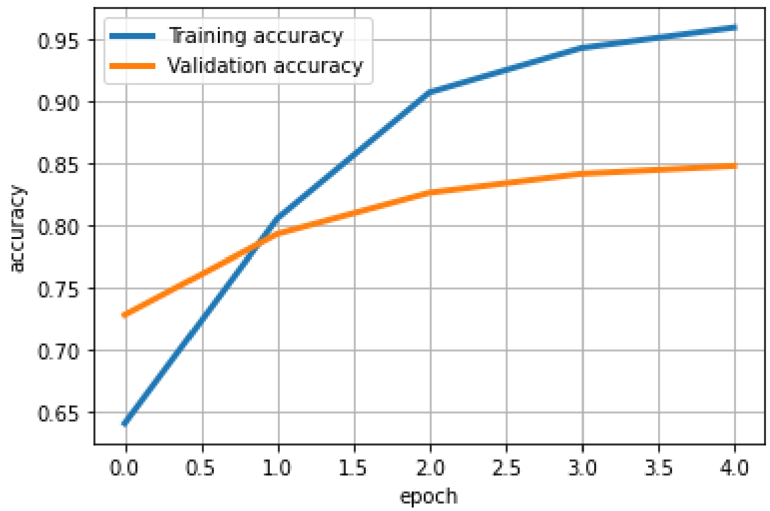
In [41]:
```
# TODO: Q11. Plot train/validation accuracies.
import matplotlib.pyplot as plt

train_acc_plot = history['train_acc'];

val_acc_plot = history['val_acc'];

plt.plot(range(EPOCHS),train_acc_plot,'-',linewidth=3,label='Training accuracy')
plt.plot(range(EPOCHS),val_acc_plot,'-',linewidth=3,label='Validation accuracy')
plt.xlabel('epoch')
plt.ylabel('accuracy')
plt.grid(True)
plt.legend()
```

Out[41]: <matplotlib.legend.Legend at 0x7f6934ef72b0>



You might try to fine-tune the parameters (learning rate, batch size) a bit more if accuracy is not good enough.

Evaluation

So how good is our model on predicting sentiment?

We'll define a helper function to get the predictions from our model:

In [42]:
```
def get_predictions(model, data_loader):
  model = model.eval()

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

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

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

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

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

      review_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 review_texts, predictions, prediction_probs, real_values
```

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

In [43]:
```
y_review_texts, y_pred, y_pred_probs, y_test = get_predictions(
  model,
  test_data_loader
)
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
=True` or `padding='longest'` to pad to the longest sequence in the batch, or use `padding='max_leng
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
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  FutureWarning,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
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th'` to pad to a max length. In this case, you can give a specific length with `max_length` (e.g. `m
ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,
```
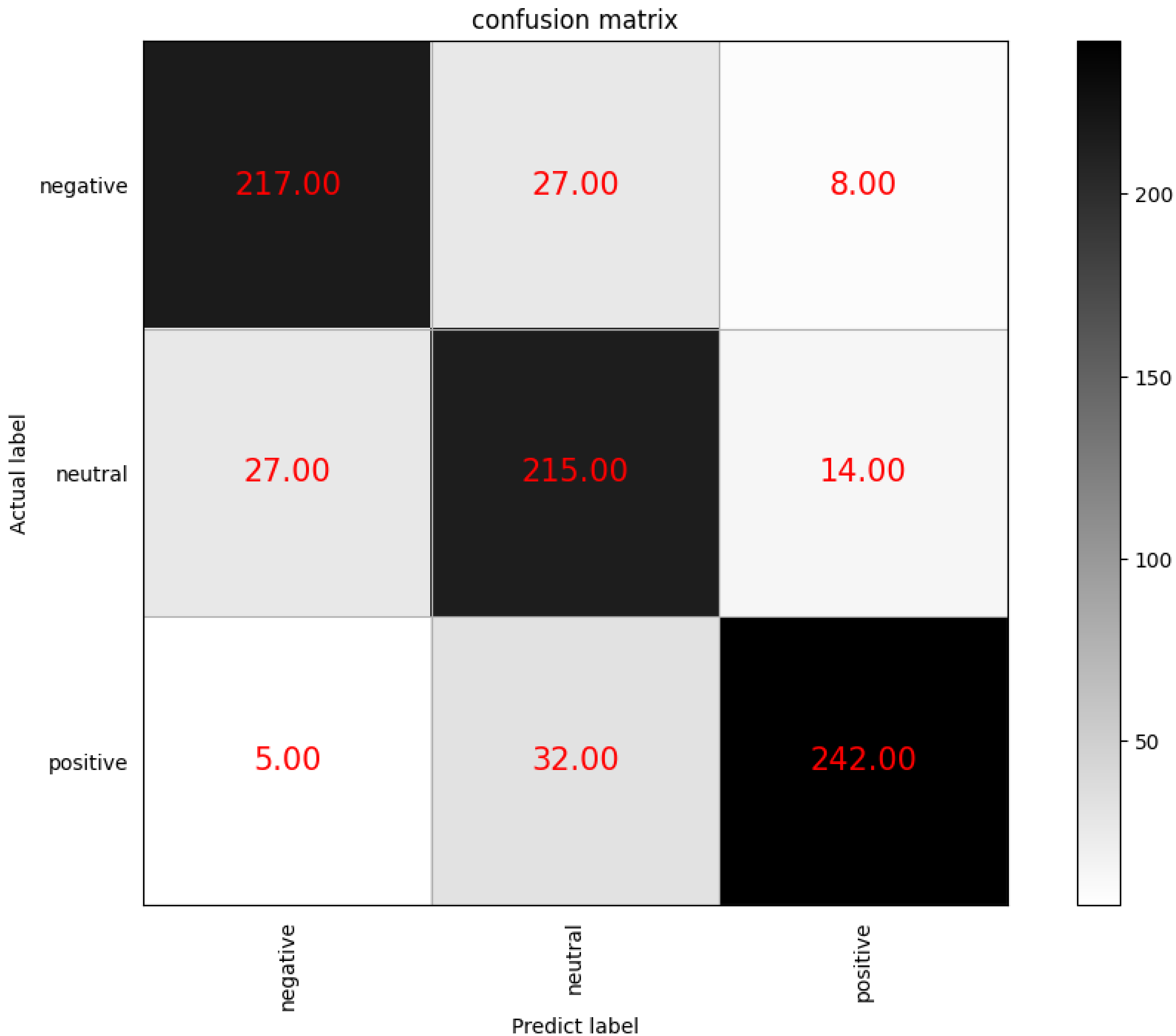

Let us compare true sentiment vs predicted sentiment by plotting a confusion matrix of `y_test` vs `y_pred` .

In [44]:
```
# TODO. Q12. Plot the 3x3 confusion matrix and show that the model finds it a bit difficult to classi
fy neutral reviews.
%matplotlib inline
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import numpy as np

def plot_confusion_matrix(cm, savename, title='Confusion Matrix'):

    plt.figure(figsize=(12, 8), dpi=100)
    np.set_printoptions(precision=2)

    # calculate the possibility value of each cell
    ind_array = np.arange(len(class_names))
    x, y = np.meshgrid(ind_array, ind_array)
    for x_val, y_val in zip(x.flatten(), y.flatten()):
        c = cm[y_val][x_val]
        if c > 0.001:
            plt.text(x_val, y_val, "%0.2f" % (c,), color='red', fontsize=15, va='center', ha='center'
)

    plt.imshow(cm, interpolation='nearest', cmap=plt.cm.binary)
    plt.title(title)
    plt.colorbar()
    xlocations = np.array(range(len(class_names)))
    plt.xticks(xlocations, class_names, rotation=90)
    plt.yticks(xlocations, class_names)
    plt.ylabel('Actual label')
    plt.xlabel('Predict label')

    # offset the tick
    tick_marks = np.array(range(len(class_names))) + 0.5
    plt.gca().set_xticks(tick_marks, minor=True)
    plt.gca().set_yticks(tick_marks, minor=True)
    plt.gca().xaxis.set_ticks_position('none')
    plt.gca().yaxis.set_ticks_position('none')
    plt.grid(True, which='minor', linestyle='-')
    plt.gcf().subplots_adjust(bottom=0.15)

    # show confusion matrix
    plt.savefig(savename, format='png')
    plt.show()
```

```
matrix = confusion_matrix(y_test, y_pred)
plot_confusion_matrix(matrix, 'confusion_matrix.png', title='confusion matrix')
```


confusion matrix
negative
neutral
positive
Actual label
217.00
27.00
8.00
27.00
215.00
14.00
5.00
32.00
242.00
negative
neutral
positive
Predict label
200
150
100
50

Predicting on Raw Text

Let's use our model to predict the sentiment of some raw text:

In [45]:
```
review_text = "I love Deep Learning! Best course evah!!!1!!"
```

Use your trained model to predict the sentiment expressed in `review_text` .

In [46]:
```
# TODO: Q13. Print the predicted sentiment in `review_text`.
encoding = tokenizer.encode_plus(
  review_text,
  max_length=32,
  add_special_tokens=True, # Add '[CLS]' and '[SEP]'
  return_token_type_ids=False,
  pad_to_max_length=True,
  return_attention_mask=True,
  return_tensors='pt',  # Return PyTorch tensors
)


outputs = model(
    input_ids=encoding['input_ids'].to(device),
    attention_mask=encoding['attention_mask'].to(device)
  )

_, preds = torch.max(outputs, dim=1)
print("The prediction of the reiew_text is:", class_names[int(preds)])
```

```
The prediction of the reiew_text is: positive

/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:1944: FutureWarning:
The `pad_to_max_length` argument is deprecated and will be removed in a future version, use `padding
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ax_length=45`) or leave max_length to None to pad to the maximal input size of the model (e.g. 512 f
or Bert).
  FutureWarning,
```

References

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- L11 Language Models - Alec Radford (OpenAI) (https://www.youtube.com/watch?v=BnpB3GrpsfM)
- The Illustrated BERT, ELMo, and co. (https://jalammar.github.io/illustrated-bert/)
- BERT Fine-Tuning Tutorial with PyTorch (https://mccormickml.com/2019/07/22/BERT-fine-tuning/)
- How to Fine-Tune BERT for Text Classification? (https://arxiv.org/pdf/1905.05583.pdf)
- Huggingface Transformers (https://huggingface.co/transformers/)
- BERT Explained: State of the art language model for NLP (https://towardsdatascience.com/bert-explained-state-of-the-art-language-model-for-nlp-f8b21a9b6270)