BERT with Grover Augmentation

Real News and Fake News (~84k total)

Class: Label

Real: 1

Fake: 0

```
import tensorflow as tf

# Get the GPU device name.
device_name = tf.test.gpu_device_name()

# The device name should look like the following:
if device_name == '/device:GPU:0':
    print('Found GPU at: {}'.format(device_name))
else:
    raise SystemError('GPU device not found')
```

```
Found GPU at: /device:GPU:0
```

```
import torch

# If there's a GPU available...
if torch.cuda.is_available():

    # Tell PyTorch to use the GPU.
    device = torch.device("cuda")

    print('There are %d GPU(s) available.' % torch.cuda.device_count())

    print('We will use the GPU:', torch.cuda.get_device_name(0))

# If not
```

```
# if not...
else:
    print('No GPU available, using the CPU instead.')
    device = torch.device("cpu")
```

```
There are 1 GPU(s) available.
We will use the GPU: Tesla P100-PCIE-16GB
```

```
!pip install transformers
```

```
Requirement already satisfied: transformers in /usr/local/lib/python3.6/dist-packages (2.8.0)
Requirement already satisfied: sacremoses in /usr/local/lib/python3.6/dist-packages (from transformers) (0.0.
Requirement already satisfied: boto3 in /usr/local/lib/python3.6/dist-packages (from transformers) (1.12.40)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.6/dist-packages (from transformers
Requirement already satisfied: tokenizers==0.5.2 in /usr/local/lib/python3.6/dist-packages (from transformers
Requirement already satisfied: sentencepiece in /usr/local/lib/python3.6/dist-packages (from transformers) (0
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from transformers) (1.18.2)
Requirement already satisfied: filelock in /usr/local/lib/python3.6/dist-packages (from transformers) (3.0.12
Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from transformers) (2.21.0
Requirement already satisfied: dataclasses; python_version < "3.7" in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.6/dist-packages (from transformers) (4.38
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from sacremoses->transformers)
Requirement already satisfied: joblib in /usr/local/lib/python3.6/dist-packages (from sacremoses->transformer
Requirement already satisfied: click in /usr/local/lib/python3.6/dist-packages (from sacremoses->transformers
Requirement already satisfied: botocore<1.16.0,>=1.15.40 in /usr/local/lib/python3.6/dist-packages (from boto
Requirement already satisfied: s3transfer<0.4.0,>=0.3.0 in /usr/local/lib/python3.6/dist-packages (from boto3
Requirement already satisfied: jmespath<1.0.0,>=0.7.1 in /usr/local/lib/python3.6/dist-packages (from boto3->
Requirement already satisfied: urllib3<1.25,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests
Requirement already satisfied: idna<2.9,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests->trans
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from requests
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (from requests->t
Requirement already satisfied: docutils<0.16,>=0.10 in /usr/local/lib/python3.6/dist-packages (from botocore<
Requirement already satisfied: python-dateutil<3.0.0,>=2.1 in /usr/local/lib/python3.6/dist-packages (from bo
```

No Augmentation

```
# import pandas as pd
# import numpy as np
```

```
# import sklearn
# from sklearn.model_selection import train_test_split

# file = "combined_{}.csv"
# dfs = []
# for i in range(3):
#     fp = file.format(i+1)
#     read = pd.read_csv(fp)
#     read = read[['label', 'clean_text']]
#     dfs.append(read)

# dfs[2] = dfs[2][:-13000]

# data = pd.concat(dfs)
# data.tail()
# data.reset_index(inplace=True, drop=True)
# print('All Data:', data.shape)

# data.dropna(inplace=True)
# train_data, test_data = train_test_split(data, test_size=0.2)

# print('\nTrain Data:', train_data.shape)
# print(train_data[train_data.label == 1].shape[0], "Real")
# print(train_data[train_data.label == 0].shape[0], "Fake")

# print('\nTest Data:', test_data.shape)
# print(test_data[test_data.label == 1].shape[0], "Real")
# print(test_data[test_data.label == 0].shape[0], "Fake")

# sentences = train_data.clean_text.values
# labels = train_data.label.values

# train_data.head(10)
```

Grover Augmentation

```
# Grover Augmentation

import pandas as pd
import numpy as np

import sklearn
from sklearn.model_selection import train_test_split

file = "combined_{}.csv"
dfs = []
for i in range(3):
    fp = file.format(i+1)
    read = pd.read_csv(fp)
    read = read[['label', 'clean_text']]
    dfs.append(read)


real_news = dfs[2].copy()
dfs[2] = real_news[:-13000]
data = pd.concat(dfs)
data.tail()
data.reset_index(inplace=True, drop=True)


data.dropna(inplace=True)
train_data, test_data = train_test_split(data, test_size=0.3)

print('Train Data:', train_data.shape)
print(train_data[train_data.label == 1].shape[0], "Real")
print(train_data[train_data.label == 0].shape[0], "Fake")

print('\nTest Data:', test_data.shape)
print(test_data[test_data.label == 1].shape[0], "Real")
print(test_data[test_data.label == 0].shape[0], "Fake")


grover_augmentation = pd.read_csv('Grover_clean.csv')[['label', 'clean_text']]
real_news_offset = real_news[-13000:]
train_data = pd.concat([train_data, grover_augmentation, real_news_offset])
```

```
train_data.dropna(inplace=True)

print('\n-------------------------------After Augmentation -------------------------------\n')
print('Train Data:', train_data.shape)
print(train_data[train_data.label == 1].shape[0], "Real")
print(train_data[train_data.label == 0].shape[0], "Fake")

print('\nTest Data:', test_data.shape)
print(test_data[test_data.label == 1].shape[0], "Real")
print(test_data[test_data.label == 0].shape[0], "Fake")

sentences = train_data.clean_text.values
labels = train_data.label.values

train_data.head(10)
```

```
Train Data: (41621, 2)
22037 Real
19584 Fake

Test Data: (17838, 2)
9412 Real
8426 Fake

------------------------------After Augmentation ------------------------------

Train Data: (67411, 2)
35037 Real
32374 Fake

Test Data: (17838, 2)
9412 Real
8426 Fake
```

	label	clean_text
29804	0	posted pm patriotrising comments clinton im...
28779	0	female veterans release antitrump ad problem b...
54560	1	nearly three weeks us presidential election la...
38830	0	says track record raising taxes
27662	0	cancer agency fire withholding carcinogenic gl...
14753	0	moscow culture department offer lecture series...
11651	0	iswhy every single american needs vote trump f...
56649	1	miquilena wrong cubs win world series weeks de...
51973	1	music dance far idle pastimes universal forms ...
17956	0	news new year coming new administration sworn ...

```
from transformers import BertTokenizer

# Load the BERT tokenizer.
```

```
print('Loading BERT tokenizer...')
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased', do_lower_case=True)

# Print the original sentence.
print(' Original: ', sentences[0])

# Print the sentence split into tokens.
print('Tokenized: ', tokenizer.tokenize(sentences[0]))

# Print the sentence mapped to token ids.
print('Token IDs: ', tokenizer.convert_tokens_to_ids(tokenizer.tokenize(sentences[0])))
```

```
Loading BERT tokenizer...
 Original:  posted   pm patriotrising  comments clinton image added pathological lying wikipedia page happene
Tokenized:  ['posted', 'pm', 'patriot', '##ris', '##ing', 'comments', 'clinton', 'image', 'added', 'path', '#
Token IDs:  [6866, 7610, 16419, 6935, 2075, 7928, 7207, 3746, 2794, 4130, 10091, 4688, 16948, 3931, 3047, 822
```

```
# Tokenize all of the sentences and map the tokens to thier word IDs.
input_ids = []

# For every sentence...
for sent in sentences:
    # `encode` will:
    #   (1) Tokenize the sentence.
    #   (2) Prepend the `[CLS]` token to the start.
    #   (3) Append the `[SEP]` token to the end.
    #   (4) Map tokens to their IDs.
    encoded_sent = tokenizer.encode(
                        sent,                      # Sentence to encode.
                        add_special_tokens = True, # Add '[CLS]' and '[SEP]'
                        max_length = 512  # Truncate all sentences.
                        #return_tensors = 'pt',     # Return pytorch tensors.
                   )

    # Add the encoded sentence to the list.
    input_ids.append(encoded_sent)

# Print sentence 0, now as a list of IDs.
```

```
print('Original: ', sentences[0])
print('Token IDs:', input_ids[0])
```

```
Original:  posted   pm patriotrising  comments clinton image added pathological lying wikipedia page happened
Token IDs: [101, 6866, 7610, 16419, 6935, 2075, 7928, 7207, 3746, 2794, 4130, 10091, 4688, 16948, 3931, 3047,
```

```
import statistics

print('Avg sentence length: ', statistics.mean([len(sen) for sen in input_ids]))
```

```
Avg sentence length:  297.8258741155004
```

```
print('Max sentence length: ', max([len(sen) for sen in input_ids]))
```

```
Max sentence length:  512
```

```
import keras
# We'll borrow the `pad_sequences` utility function to do this.
from keras.preprocessing.sequence import pad_sequences

# Set the maximum sequence length.
# I've chosen 64 somewhat arbitrarily. It's slightly larger than the
# maximum training sentence length of 47...
MAX_LEN = 256

print('\nPadding/truncating all sentences to %d values...' % MAX_LEN)

print('\nPadding token: "{:}", ID: {:}'.format(tokenizer.pad_token, tokenizer.pad_token_id))

# Pad our input tokens with value 0.
# "post" indicates that we want to pad and truncate at the end of the sequence,
# as opposed to the beginning.
input_ids = pad_sequences(input_ids, maxlen=MAX_LEN, dtype="long",
                          value=0, truncating="post", padding="post")

print('\nDone.')
```

```
Padding/truncating all sentences to 256 values...

Padding token: "[PAD]", ID: 0
Using TensorFlow backend.

Done.
```

```
# Create attention masks
attention_masks = []

# For each sentence...
for sent in input_ids:

    # Create the attention mask.
    #   - If a token ID is 0, then it's padding, set the mask to 0.
    #   - If a token ID is > 0, then it's a real token, set the mask to 1.
    att_mask = [int(token_id > 0) for token_id in sent]

    # Store the attention mask for this sentence.
    attention_masks.append(att_mask)

# Use 90% for training and 10% for validation.
train_inputs, validation_inputs, train_labels, validation_labels = train_test_split(input_ids, labels,
                                                            random_state=2018, test_size=0.1)
# Do the same for the masks.
train_masks, validation_masks, _, _ = train_test_split(attention_masks, labels,
                                             random_state=2018, test_size=0.1)

# Convert all inputs and labels into torch tensors, the required datatype
# for our model.
train_inputs = torch.tensor(train_inputs)
validation_inputs = torch.tensor(validation_inputs)

train_labels = torch.tensor(train_labels)
validation_labels = torch.tensor(validation_labels)
```

```
train_masks = torch.tensor(train_masks)
validation_masks = torch.tensor(validation_masks)


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

# The DataLoader needs to know our batch size for training, so we specify it
# here.
# For fine-tuning BERT on a specific task, the authors recommend a batch size of
# 16 or 32.

batch_size = 32

# Create the DataLoader for our training set.
train_data = TensorDataset(train_inputs, train_masks, train_labels)
train_sampler = RandomSampler(train_data)
train_dataloader = DataLoader(train_data, sampler=train_sampler, batch_size=batch_size)

# Create the DataLoader for our validation set.
validation_data = TensorDataset(validation_inputs, validation_masks, validation_labels)
validation_sampler = SequentialSampler(validation_data)
validation_dataloader = DataLoader(validation_data, sampler=validation_sampler, batch_size=batch_size)


from transformers import BertForSequenceClassification, AdamW, BertConfig

# Load BertForSequenceClassification, the pretrained BERT model with a single
# linear classification layer on top.
model = BertForSequenceClassification.from_pretrained(
    "bert-base-uncased", # Use the 12-layer BERT model, with an uncased vocab.
    num_labels = 2, # The number of output labels--2 for binary classification.
                    # You can increase this for multi-class tasks.
    output_attentions = False, # Whether the model returns attentions weights.
    output_hidden_states = False, # Whether the model returns all hidden-states.
)

# Tell pytorch to run this model on the GPU.
model.cuda()
```

```
BertForSequenceClassification(
  (bert): BertModel(
    (embeddings): BertEmbeddings(
      (word_embeddings): Embedding(30522, 768, padding_idx=0)
      (position_embeddings): Embedding(512, 768)
      (token_type_embeddings): Embedding(2, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (encoder): BertEncoder(
      (layer): ModuleList(
        (0): BertLayer(
          (attention): BertAttention(
            (self): BertSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
            (dense): Linear(in_features=768, out_features=3072, bias=True)
          )
          (output): BertOutput(
            (dense): Linear(in_features=3072, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (1): BertLayer(
          (attention): BertAttention(
            (self): BertSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): BertSelfOutput(
```

```
          (dense): Linear(in_features=768, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
      (intermediate): BertIntermediate(
        (dense): Linear(in_features=768, out_features=3072, bias=True)
      )
      (output): BertOutput(
        (dense): Linear(in_features=3072, out_features=768, bias=True)
        (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
    )
    (2): BertLayer(
      (attention): BertAttention(
        (self): BertSelfAttention(
          (query): Linear(in_features=768, out_features=768, bias=True)
          (key): Linear(in_features=768, out_features=768, bias=True)
          (value): Linear(in_features=768, out_features=768, bias=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
        (output): BertSelfOutput(
          (dense): Linear(in_features=768, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
      (intermediate): BertIntermediate(
        (dense): Linear(in_features=768, out_features=3072, bias=True)
      )
      (output): BertOutput(
        (dense): Linear(in_features=3072, out_features=768, bias=True)
        (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
        (dropout): Dropout(p=0.1, inplace=False)
      )
    )
    (3): BertLayer(
      (attention): BertAttention(
        (self): BertSelfAttention(
          (query): Linear(in_features=768, out_features=768, bias=True)
          (key): Linear(in_features=768, out_features=768, bias=True)
          (value): Linear(in_features=768, out_features=768, bias=True)
          (dropout): Dropout(p=0.1, inplace=False)
```

```
    )
    (output): BertSelfOutput(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
  )
  (intermediate): BertIntermediate(
    (dense): Linear(in_features=768, out_features=3072, bias=True)
  )
  (output): BertOutput(
    (dense): Linear(in_features=3072, out_features=768, bias=True)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dropout): Dropout(p=0.1, inplace=False)
  )
)
(4): BertLayer(
  (attention): BertAttention(
    (self): BertSelfAttention(
      (query): Linear(in_features=768, out_features=768, bias=True)
      (key): Linear(in_features=768, out_features=768, bias=True)
      (value): Linear(in_features=768, out_features=768, bias=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (output): BertSelfOutput(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
  )
  (intermediate): BertIntermediate(
    (dense): Linear(in_features=768, out_features=3072, bias=True)
  )
  (output): BertOutput(
    (dense): Linear(in_features=3072, out_features=768, bias=True)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dropout): Dropout(p=0.1, inplace=False)
  )
)
(5): BertLayer(
  (attention): BertAttention(
    (self): BertSelfAttention(
      (query): Linear(in_features=768, out_features=768, bias=True)
      (key): Linear(in_features=768, out_features=768, bias=True)
```

```
            (key): Linear(in_features=768, out_features=768, bias=True)
            (value): Linear(in_features=768, out_features=768, bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072, bias=True)
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
      (6): BertLayer(
        (attention): BertAttention(
          (self): BertSelfAttention(
            (query): Linear(in_features=768, out_features=768, bias=True)
            (key): Linear(in_features=768, out_features=768, bias=True)
            (value): Linear(in_features=768, out_features=768, bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072, bias=True)
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
      (7): BertLayer(
        (attention): BertAttention(
```

```
          (self): BertSelfAttention(
            (query): Linear(in_features=768, out_features=768, bias=True)
            (key): Linear(in_features=768, out_features=768, bias=True)
            (value): Linear(in_features=768, out_features=768, bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072, bias=True)
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
      (8): BertLayer(
        (attention): BertAttention(
          (self): BertSelfAttention(
            (query): Linear(in_features=768, out_features=768, bias=True)
            (key): Linear(in_features=768, out_features=768, bias=True)
            (value): Linear(in_features=768, out_features=768, bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072, bias=True)
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
```

```
      )
      (9): BertLayer(
        (attention): BertAttention(
          (self): BertSelfAttention(
            (query): Linear(in_features=768, out_features=768, bias=True)
            (key): Linear(in_features=768, out_features=768, bias=True)
            (value): Linear(in_features=768, out_features=768, bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072, bias=True)
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
      (10): BertLayer(
        (attention): BertAttention(
          (self): BertSelfAttention(
            (query): Linear(in_features=768, out_features=768, bias=True)
            (key): Linear(in_features=768, out_features=768, bias=True)
            (value): Linear(in_features=768, out_features=768, bias=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (output): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072, bias=True)
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
```

```
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (11): BertLayer(
            (attention): BertAttention(
              (self): BertSelfAttention(
                (query): Linear(in_features=768, out_features=768, bias=True)
                (key): Linear(in_features=768, out_features=768, bias=True)
                (value): Linear(in_features=768, out_features=768, bias=True)
                (dropout): Dropout(p=0.1, inplace=False)
              )
              (output): BertSelfOutput(
                (dense): Linear(in_features=768, out_features=768, bias=True)
                (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
                (dropout): Dropout(p=0.1, inplace=False)
              )
            )
            (intermediate): BertIntermediate(
              (dense): Linear(in_features=768, out_features=3072, bias=True)
            )
            (output): BertOutput(
              (dense): Linear(in_features=3072, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
        )
      )
      (pooler): BertPooler(
        (dense): Linear(in_features=768, out_features=768, bias=True)
        (activation): Tanh()
      )
    )
    (dropout): Dropout(p=0.1, inplace=False)
    (classifier): Linear(in_features=768, out_features=2, bias=True)
  )
```

```
# Note: AdamW is a class from the huggingface library (as opposed to pytorch)
# I believe the 'W' stands for 'Weight Decay fix"
optimizer = AdamW(model.parameters(),
                  lr = 2e-5, # args.learning_rate - default is 5e-5, our notebook had 2e-5
                  eps = 1e-8 # args.adam_epsilon  - default is 1e-8.
                )
```

```
from transformers import get_linear_schedule_with_warmup

# Number of training epochs (authors recommend between 2 and 4)
epochs = 5

# Total number of training steps is number of batches * number of epochs.
total_steps = len(train_dataloader) * epochs

# Create the learning rate scheduler.
scheduler = get_linear_schedule_with_warmup(optimizer,
                                            num_warmup_steps = 0, # Default value in run_glue.py
                                            num_training_steps = total_steps)
```

```
# Function to calculate the accuracy of our predictions vs labels
def flat_accuracy(preds, labels):
    pred_flat = np.argmax(preds, axis=1).flatten()
    labels_flat = labels.flatten()
    return np.sum(pred_flat == labels_flat) / len(labels_flat)
```

```
import time
import datetime

def format_time(elapsed):
    '''
    Takes a time in seconds and returns a string hh:mm:ss
    '''
    # Round to the nearest second.
    elapsed_rounded = int(round((elapsed)))

    # Format as hh:mm:ss
    return str(datetime.timedelta(seconds=elapsed_rounded))
```

```
torch.cuda.empty_cache()
```

```
import random
```

```
import random

# This training code is based on the `run_glue.py` script here:
# https://github.com/huggingface/transformers/blob/5bfcd0485ece086ebcbed2d008813037968a9e58/examples/run_glue.py#L


# Set the seed value all over the place to make this reproducible.
seed_val = 42

random.seed(seed_val)
np.random.seed(seed_val)
torch.manual_seed(seed_val)
torch.cuda.manual_seed_all(seed_val)

# Store the average loss after each epoch so we can plot them.
loss_values = []

# For each epoch...
for epoch_i in range(0, epochs):

    # ========================================
    #               Training
    # ========================================

    # Perform one full pass over the training set.

    print("")
    print('======== Epoch {:} / {:} ========'.format(epoch_i + 1, epochs))
    print('Training...')

    # Measure how long the training epoch takes.
    t0 = time.time()

    # Reset the total loss for this epoch.
    total_loss = 0

    # Put the model into training mode. Don't be mislead--the call to
    # `train` just changes the *mode*, it doesn't *perform* the training.
    # `dropout` and `batchnorm` layers behave differently during training
    # vs. test (source: https://stackoverflow.com/questions/51433378/what-does-model-train-do-in-pytorch)
```

```
    # vs. test (source: https://stackoverflow.com/questions/51433378/what-does-model-train-do-in-pytorch)
    model.train()

    # For each batch of training data...
    for step, batch in enumerate(train_dataloader):

        # Progress update every 40 batches.
        if step % 40 == 0 and not step == 0:
            # Calculate elapsed time in minutes.
            elapsed = format_time(time.time() - t0)

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

        # Unpack this training batch from our dataloader.
        #
        # As we unpack the batch, we'll also copy each tensor to the GPU using the
        # `to` method.
        #
        # `batch` contains three pytorch tensors:
        #   [0]: input ids
        #   [1]: attention masks
        #   [2]: labels
        b_input_ids = batch[0].to(device)
        b_input_mask = batch[1].to(device)
        b_labels = batch[2].to(device)

        # Always clear any previously calculated gradients before performing a
        # backward pass. PyTorch doesn't do this automatically because
        # accumulating the gradients is "convenient while training RNNs".
        # (source: https://stackoverflow.com/questions/48001598/why-do-we-need-to-call-zero-grad-in-pytorch)
        model.zero_grad()

        # Perform a forward pass (evaluate the model on this training batch).
        # This will return the loss (rather than the model output) because we
        # have provided the `labels`.
        # The documentation for this `model` function is here:
        # https://huggingface.co/transformers/v2.2.0/model_doc/bert.html#transformers.BertForSequenceClassificatio
        outputs = model(b_input_ids,
                    token_type_ids=None,
```

```
                    token_type_ids=None,
                    attention_mask=b_input_mask,
                    labels=b_labels)

        # The call to `model` always returns a tuple, so we need to pull the
        # loss value out of the tuple.
        loss = outputs[0]

        # Accumulate the training loss over all of the batches so that we can
        # calculate the average loss at the end. `loss` is a Tensor containing a
        # single value; the `.item()` function just returns the Python value
        # from the tensor.
        total_loss += loss.item()

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

        # Clip the norm of the gradients to 1.0.
        # This is to help prevent the "exploding gradients" problem.
        torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)

        # Update parameters and take a step using the computed gradient.
        # The optimizer dictates the "update rule"--how the parameters are
        # modified based on their gradients, the learning rate, etc.
        optimizer.step()

        # Update the learning rate.
        scheduler.step()

    # Calculate the average loss over the training data.
    avg_train_loss = total_loss / len(train_dataloader)

    # Store the loss value for plotting the learning curve.
    loss_values.append(avg_train_loss)

    print("")
    print("  Average training loss: {0:.2f}".format(avg_train_loss))
    print("  Training epcoh took: {:}".format(format_time(time.time() - t0)))

    # ========================================
```

```
    "
    #               Validation
    # ========================================
    # After the completion of each training epoch, measure our performance on
    # our validation set.

    print("")
    print("Running Validation...")

    t0 = time.time()

    # Put the model in evaluation mode--the dropout layers behave differently
    # during evaluation.
    model.eval()

    # Tracking variables
    eval_loss, eval_accuracy = 0, 0
    nb_eval_steps, nb_eval_examples = 0, 0

    # Evaluate data for one epoch
    for batch in validation_dataloader:

        # Add batch to GPU
        batch = tuple(t.to(device) for t in batch)

        # Unpack the inputs from our dataloader
        b_input_ids, b_input_mask, b_labels = batch

        # Telling the model not to compute or store gradients, saving memory and
        # speeding up validation
        with torch.no_grad():

            # Forward pass, calculate logit predictions.
            # This will return the logits rather than the loss because we have
            # not provided labels.
            # token_type_ids is the same as the "segment ids", which
            # differentiates sentence 1 and 2 in 2-sentence tasks.
            # The documentation for this `model` function is here:
            # https://huggingface.co/transformers/v2.2.0/model_doc/bert.html#transformers.BertForSequenceClassific
            outputs = model(b_input_ids,
```

```
            outputs = model(b_input_ids,
                            token_type_ids=None,
                            attention_mask=b_input_mask)

        # Get the "logits" output by the model. The "logits" are the output
        # values prior to applying an activation function like the softmax.
        logits = outputs[0]

        # Move logits and labels to CPU
        logits = logits.detach().cpu().numpy()
        label_ids = b_labels.to('cpu').numpy()

        # Calculate the accuracy for this batch of test sentences.
        tmp_eval_accuracy = flat_accuracy(logits, label_ids)

        # Accumulate the total accuracy.
        eval_accuracy += tmp_eval_accuracy

        # Track the number of batches
        nb_eval_steps += 1

    # Report the final accuracy for this validation run.
    print("  Accuracy: {0:.3f}".format(eval_accuracy/nb_eval_steps))
    print("  Validation took: {:}".format(format_time(time.time() - t0)))

print("")
print("Training complete!")
```

```
======== Epoch 1 / 5 ========
Training...
  Batch    40  of  1,896.    Elapsed: 0:00:30.
  Batch    80  of  1,896.    Elapsed: 0:01:01.
  Batch   120  of  1,896.    Elapsed: 0:01:31.
  Batch   160  of  1,896.    Elapsed: 0:02:02.
  Batch   200  of  1,896.    Elapsed: 0:02:32.
  Batch   240  of  1,896.    Elapsed: 0:03:02.
  Batch   280  of  1,896.    Elapsed: 0:03:33.
  Batch   320  of  1,896.    Elapsed: 0:04:03.
  Batch   360  of  1,896.    Elapsed: 0:04:34.
  Batch   400  of  1,896.    Elapsed: 0:05:04.
  Batch   440  of  1,896.    Elapsed: 0:05:34.
  Batch   480  of  1,896.    Elapsed: 0:06:05.
  Batch   520  of  1,896.    Elapsed: 0:06:35.
  Batch   560  of  1,896.    Elapsed: 0:07:06.
  Batch   600  of  1,896.    Elapsed: 0:07:36.
  Batch   640  of  1,896.    Elapsed: 0:08:07.
  Batch   680  of  1,896.    Elapsed: 0:08:37.
  Batch   720  of  1,896.    Elapsed: 0:09:08.
  Batch   760  of  1,896.    Elapsed: 0:09:38.
  Batch   800  of  1,896.    Elapsed: 0:10:09.
  Batch   840  of  1,896.    Elapsed: 0:10:39.
  Batch   880  of  1,896.    Elapsed: 0:11:10.
  Batch   920  of  1,896.    Elapsed: 0:11:40.
  Batch   960  of  1,896.    Elapsed: 0:12:11.
  Batch 1,000  of  1,896.    Elapsed: 0:12:41.
  Batch 1,040  of  1,896.    Elapsed: 0:13:12.
  Batch 1,080  of  1,896.    Elapsed: 0:13:42.
  Batch 1,120  of  1,896.    Elapsed: 0:14:13.
  Batch 1,160  of  1,896.    Elapsed: 0:14:43.
  Batch 1,200  of  1,896.    Elapsed: 0:15:14.
  Batch 1,240  of  1,896.    Elapsed: 0:15:44.
  Batch 1,280  of  1,896.    Elapsed: 0:16:15.
  Batch 1,320  of  1,896.    Elapsed: 0:16:45.
  Batch 1,360  of  1,896.    Elapsed: 0:17:15.
  Batch 1,400  of  1,896.    Elapsed: 0:17:46.
  Batch 1,440  of  1,896.    Elapsed: 0:18:16.
  Batch 1,480  of  1,896.    Elapsed: 0:18:47.
  Batch 1,520  of  1,896.    Elapsed: 0:19:17.
  Batch 1,560  of  1,896.    Elapsed: 0:19:48.
  Batch 1,600  of  1,896.    Elapsed: 0:20:18.
```

```
  Batch 1,640  of  1,896.    Elapsed: 0:20:49.
  Batch 1,680  of  1,896.    Elapsed: 0:21:19.
  Batch 1,720  of  1,896.    Elapsed: 0:21:50.
  Batch 1,760  of  1,896.    Elapsed: 0:22:20.
  Batch 1,800  of  1,896.    Elapsed: 0:22:51.
  Batch 1,840  of  1,896.    Elapsed: 0:23:21.
  Batch 1,880  of  1,896.    Elapsed: 0:23:52.

  Average training loss: 0.28
  Training epcoh took: 0:24:04

Running Validation...
  Accuracy: 0.900
  Validation took: 0:00:51

======== Epoch 2 / 5 ========
Training...
  Batch    40  of  1,896.    Elapsed: 0:00:30.
  Batch    80  of  1,896.    Elapsed: 0:01:01.
  Batch   120  of  1,896.    Elapsed: 0:01:31.
  Batch   160  of  1,896.    Elapsed: 0:02:02.
  Batch   200  of  1,896.    Elapsed: 0:02:32.
  Batch   240  of  1,896.    Elapsed: 0:03:03.
  Batch   280  of  1,896.    Elapsed: 0:03:33.
  Batch   320  of  1,896.    Elapsed: 0:04:04.
  Batch   360  of  1,896.    Elapsed: 0:04:34.
  Batch   400  of  1,896.    Elapsed: 0:05:05.
  Batch   440  of  1,896.    Elapsed: 0:05:35.
  Batch   480  of  1,896.    Elapsed: 0:06:06.
  Batch   520  of  1,896.    Elapsed: 0:06:36.
  Batch   560  of  1,896.    Elapsed: 0:07:07.
  Batch   600  of  1,896.    Elapsed: 0:07:37.
  Batch   640  of  1,896.    Elapsed: 0:08:07.
  Batch   680  of  1,896.    Elapsed: 0:08:38.
  Batch   720  of  1,896.    Elapsed: 0:09:08.
  Batch   760  of  1,896.    Elapsed: 0:09:39.
  Batch   800  of  1,896.    Elapsed: 0:10:09.
  Batch   840  of  1,896.    Elapsed: 0:10:40.
  Batch   880  of  1,896.    Elapsed: 0:11:10.
  Batch   920  of  1,896.    Elapsed: 0:11:41.
  Batch   960  of  1,896.    Elapsed: 0:12:11.
  Batch 1,000  of  1,896.    Elapsed: 0:12:42.
  Batch 1,040  of  1,896.    Elapsed: 0:13:12.
  Batch 1,080  of  1,896.    Elapsed: 0:13:43.
```

```
  Batch 1,120  of  1,896.    Elapsed: 0:14:13.
  Batch 1,160  of  1,896.    Elapsed: 0:14:44.
  Batch 1,200  of  1,896.    Elapsed: 0:15:14.
  Batch 1,240  of  1,896.    Elapsed: 0:15:44.
  Batch 1,280  of  1,896.    Elapsed: 0:16:15.
  Batch 1,320  of  1,896.    Elapsed: 0:16:45.
  Batch 1,360  of  1,896.    Elapsed: 0:17:16.
  Batch 1,400  of  1,896.    Elapsed: 0:17:46.
  Batch 1,440  of  1,896.    Elapsed: 0:18:17.
  Batch 1,480  of  1,896.    Elapsed: 0:18:47.
  Batch 1,520  of  1,896.    Elapsed: 0:19:18.
  Batch 1,560  of  1,896.    Elapsed: 0:19:48.
  Batch 1,600  of  1,896.    Elapsed: 0:20:19.
  Batch 1,640  of  1,896.    Elapsed: 0:20:49.
  Batch 1,680  of  1,896.    Elapsed: 0:21:20.
  Batch 1,720  of  1,896.    Elapsed: 0:21:50.
  Batch 1,760  of  1,896.    Elapsed: 0:22:21.
  Batch 1,800  of  1,896.    Elapsed: 0:22:51.
  Batch 1,840  of  1,896.    Elapsed: 0:23:22.
  Batch 1,880  of  1,896.    Elapsed: 0:23:52.

  Average training loss: 0.15
  Training epcoh took: 0:24:04

Running Validation...
  Accuracy: 0.913
  Validation took: 0:00:51

======== Epoch 3 / 5 ========
Training...
  Batch    40  of  1,896.    Elapsed: 0:00:30.
  Batch    80  of  1,896.    Elapsed: 0:01:01.
  Batch   120  of  1,896.    Elapsed: 0:01:31.
  Batch   160  of  1,896.    Elapsed: 0:02:02.
  Batch   200  of  1,896.    Elapsed: 0:02:32.
  Batch   240  of  1,896.    Elapsed: 0:03:03.
  Batch   280  of  1,896.    Elapsed: 0:03:33.
  Batch   320  of  1,896.    Elapsed: 0:04:04.
  Batch   360  of  1,896.    Elapsed: 0:04:34.
  Batch   400  of  1,896.    Elapsed: 0:05:05.
  Batch   440  of  1,896.    Elapsed: 0:05:35.
  Batch   480  of  1,896.    Elapsed: 0:06:06.
  Batch   520  of  1,896.    Elapsed: 0:06:36.
  Batch   560  of  1,896.    Elapsed: 0:07:07.
```

```
  Batch   560  of  1,896.    Elapsed: 0:07:07.
  Batch   600  of  1,896.    Elapsed: 0:07:37.
  Batch   640  of  1,896.    Elapsed: 0:08:08.
  Batch   680  of  1,896.    Elapsed: 0:08:38.
  Batch   720  of  1,896.    Elapsed: 0:09:09.
  Batch   760  of  1,896.    Elapsed: 0:09:39.
  Batch   800  of  1,896.    Elapsed: 0:10:10.
  Batch   840  of  1,896.    Elapsed: 0:10:40.
  Batch   880  of  1,896.    Elapsed: 0:11:11.
  Batch   920  of  1,896.    Elapsed: 0:11:41.
  Batch   960  of  1,896.    Elapsed: 0:12:12.
  Batch 1,000  of  1,896.    Elapsed: 0:12:42.
  Batch 1,040  of  1,896.    Elapsed: 0:13:13.
  Batch 1,080  of  1,896.    Elapsed: 0:13:43.
  Batch 1,120  of  1,896.    Elapsed: 0:14:13.
  Batch 1,160  of  1,896.    Elapsed: 0:14:44.
  Batch 1,200  of  1,896.    Elapsed: 0:15:14.
  Batch 1,240  of  1,896.    Elapsed: 0:15:45.
  Batch 1,280  of  1,896.    Elapsed: 0:16:15.
  Batch 1,320  of  1,896.    Elapsed: 0:16:46.
  Batch 1,360  of  1,896.    Elapsed: 0:17:16.
  Batch 1,400  of  1,896.    Elapsed: 0:17:47.
  Batch 1,440  of  1,896.    Elapsed: 0:18:17.
  Batch 1,480  of  1,896.    Elapsed: 0:18:48.
  Batch 1,520  of  1,896.    Elapsed: 0:19:18.
  Batch 1,560  of  1,896.    Elapsed: 0:19:49.
  Batch 1,600  of  1,896.    Elapsed: 0:20:19.
  Batch 1,640  of  1,896.    Elapsed: 0:20:50.
  Batch 1,680  of  1,896.    Elapsed: 0:21:20.
  Batch 1,720  of  1,896.    Elapsed: 0:21:51.
  Batch 1,760  of  1,896.    Elapsed: 0:22:21.
  Batch 1,800  of  1,896.    Elapsed: 0:22:52.
  Batch 1,840  of  1,896.    Elapsed: 0:23:22.
  Batch 1,880  of  1,896.    Elapsed: 0:23:53.

  Average training loss: 0.10
  Training epcoh took: 0:24:05

Running Validation...
  Accuracy: 0.919
  Validation took: 0:00:51

======== Epoch 4 / 5 ========
Training...
```