Exercises Hand-In 3 e2

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```
In [1]:
# Import required libraries
import pandas as pd
import numpy as np
import sklearn
from sklearn.model selection import train test split
from sklearn.metrics import roc curve, roc auc score
import torch
from torch import cuda
import matplotlib.pyplot as plt
import re
# Print the versions of the libraries to check if they are installed correctly
print(f"Pandas version: {pd.__version__}")
print(f"Numpy version: {np.__version__}}")
print(f"Sklearn version: {sklearn.__version__}")
print(f"Re version: {re.__version__}}")
print(f"Torch version: {torch.__version__}}")
print(f"Matplotlib version: {plt.matplotlib. version }")
Pandas version: 2.2.2
Numpy version: 1.26.4
Sklearn version: 1.2.2
Re version: 2.2.1
Torch version: 2.1.2
Matplotlib version: 3.7.5
In [2]:
# Test if GPU is available
torch.cuda.get device name(0) if cuda.is available() else "No GPU available"
Out[2]:
'Tesla P100-PCIE-16GB'
In [3]:
# Install AugmentedSocialScientist to use Bert
!pip install AugmentedSocialScientist
# Clear output after install AugmentedSocialScientist
from IPython.display import clear output
clear output()
# Import and use Bert from AugmentedSocialScientist
from AugmentedSocialScientist.models import Bert
# Create an instance of Bert
bert = Bert()
There are 1 GPU(s) available.
We will use GPU 0: Tesla P100-PCIE-16GB
In [4]:
# Import csv file to a pandas dataframe
df tweets = pd.read csv('/kaggle/input/tweet-global-warming/1377884570 tweet global warmi
ng.csv', encoding='ISO-8859-1', engine='python')
df tweets.dropna(inplace=True) # Drop rows with missing values
```

```
# Replace Yes/Y with 1 and No/N with 0
df_tweets['existence'] = df_tweets['existence'].map({'Y': 1, 'Yes': 1, 'N': 0, 'No': 0})
.astype(int)

# Remove "[link]" from the tweets
df_tweets['tweet'] = df_tweets['tweet'].replace('\\[link\\]', '', regex=True)

# Display the first 5 rows of the dataframe to check if the data is loaded correctly
df_tweets.head()
```

Out[4]:

	tweet	existence	existence.confidence
0	Global warming report urges governments to act	1	1.0000
1	Fighting poverty and global warming in Africa	1	1.0000
2	Carbon offsets: How a Vatican forest failed to	1	0.8786
3	Carbon offsets: How a Vatican forest failed to	1	1.0000
4	URUGUAY: Tools Needed for Those Most Vulnerabl	1	0.8087

In [5]:

```
# Split the data randomly into a test and a training set (70/30 % of the observations)
# Using random_state as seed for reproducibility
train_df, test_df = train_test_split(df_tweets, test_size=0.3, random_state=42)
# Display the first 5 rows of the dataframe to check if the data is loaded correctly
train_df.head()
```

Out[5]:

	tweet	existence	existence.confidence
230	Ocean Saltiness Shows Global Warming Is Intens	1	1.0000
498	RT @panteraonca07: Slideshow of Alaska Before	1	1.0000
2510	@prismsinc Worlds Greenest Celebrity: Limos, P	1	0.6499
5115	FRIDAY AFTERNOON IGNORANCE-OFF: Virginia GOP (1	0.6717
3370	RT @mmfa: Brain Freeze: Conservative media sti	1	0.6969

2. Fine-tune a BERT model to predict non-climate sceptic language using the Augmented Social Scientist package

```
In [6]:
```

```
# Preprocess the data so it can be handled by the BERT model
train_dataloader = bert.encode(train_df['tweet'].values, train_df['existence'].values)

label ids: {0: 0, 1: 1}

In [7]:
test_dataloader = bert.encode(test_df['tweet'].values, test_df['existence'].values)
```

The next step is to train the model using the training data. Various learning rates and numbers of epochs have been tested to optimize the model's performance. This thorough analysis aims to achieve the best possible Area Under the Curve (AUC), ensuring the model's predictive accuracy is maximized.

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label ids: {0: 0, 1: 1}

```
TII [Q]:
# Train the model
scores = bert.run training(train dataloader,
                          test dataloader,
                          n epochs=3,
                          lr=4e-5,
                          random state=42,
                          save model as="climate scepticism model")
Some weights of BertForSequenceClassification were not initialized from the model checkpo
int at bert-base-cased and are newly initialized: ['classifier.bias', 'classifier.weight'
You should probably TRAIN this model on a down-stream task to be able to use it for predi
ctions and inference.
/opt/conda/lib/python3.10/site-packages/transformers/optimization.py:457: FutureWarning:
This implementation of AdamW is deprecated and will be removed in a future version. Use t
he PyTorch implementation torch.optim.AdamW instead, or set `no_deprecation_warning=True`
to disable this warning
 warnings.warn(
====== Epoch 1 / 3 ======
Training...
 Batch 40 of
                    93.
                         Elapsed: 0:00:10.
          80 of
 Batch
                    93.
                          Elapsed: 0:00:20.
 Average training loss: 0.47
 Training took: 0:00:24
Running Validation...
 Average test loss: 0.40
 Validation took: 0:00:03
                        recall f1-score support
             precision
                  0.72
                           0.43
                                     0.53
          \cap
                                                327
                           0.94
                                     0.88
          1
                  0.82
                                                941
   accuracy
                                     0.81
                                               1268
                  0.77
  macro avg
                            0.68
                                     0.71
                                               1268
weighted avg
                  0.80
                            0.81
                                     0.79
                                               1268
===== Epoch 2 / 3 ======
Training...
                   93. Elapsed: 0:00:10.
 Batch 40 of
 Batch
         80 of
                    93.
                          Elapsed: 0:00:20.
 Average training loss: 0.28
 Training took: 0:00:23
Running Validation...
 Average test loss: 0.47
 Validation took: 0:00:03
             precision recall f1-score support
                  0.72
                           0.56
                                     0.63
                                                327
                           0.93
                                     0.89
                  0.86
                                                941
                                     0.83
                                              1268
   accuracy
                                    0.76
                                              1268
                  0.79
                       0.74
  macro avg
weighted avg
                 0.82
                           0.83
                                    0.82
                                              1268
```

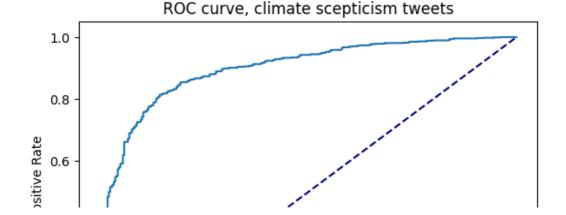
====== Epoch 3 / 3 ======

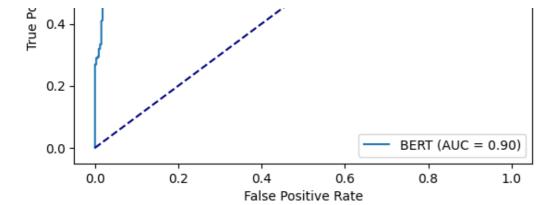
Training...

Batch 40 of 93. Elapsed: 0:00:10. Batch 80 of 93. Elapsed: 0:00:20.

Average training loss: 0.17 Training took: 0:00:23

```
Running Validation...
  Average test loss: 0.45
  Validation took: 0:00:03
              precision
                          recall f1-score
                                              support
                             0.72
           0
                                       0.70
                                                   327
                   0.69
           1
                   0.90
                             0.89
                                       0.89
                                                   941
    accuracy
                                       0.84
                                                  1268
                   0.80
                             0.80
                                       0.80
                                                  1268
   macro avg
                             0.84
                                       0.85
weighted avg
                   0.85
                                                  1268
Training complete!
In [9]:
# Display the scores
scores
Out[9]:
(array([0.69230769, 0.9
 array([0.71559633, 0.88947928]),
 array([0.7037594 , 0.89470871]),
 array([327, 941]))
In [10]:
# Predict using the trained model on the test data
pred prob test = bert.predict with model(test dataloader, model path="./models/climate sc
epticism model")
# Make the original existence column into an array
y = np.array(test df['existence'])
fpr, tpr, thresholds = roc curve(y, pred prob test[:, 1])
/opt/conda/lib/python3.10/site-packages/torch/_utils.py:831: UserWarning: TypedStorage is
deprecated. It will be removed in the future and UntypedStorage will be the only storage
class. This should only matter to you if you are using storages directly. To access Unty
pedStorage directly, use tensor.untyped storage() instead of tensor.storage()
  return self.fget. get (instance, owner)()
label ids: {0: 0, 1: 1}
In [11]:
# Create the ROC graph
plt.figure()
plt.plot(fpr,tpr, label='BERT (AUC = %0.2f)' % roc auc score(y, pred prob test[:, 1]))
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC curve, climate scepticism tweets')
plt.legend(loc="lower right")
plt.show()
```





In [12]:

```
# Compute the AUC score
auc = roc_auc_score(y, pred_prob_test[:, 1])
print(f"AUC: {auc}")
AUC: 0.8994855495650083
```

An AUC (Area Under the Curve) of about 0.90 means the model is excellent at telling the difference between positive and negative cases. In simple terms, there's a 90% chance the model will rank a positive case higher than a negative one. This high AUC shows the model works very well overall.

To test the model further, we will use a custom tweet. The cutoff value is set at 0.75 because this is where the ROC curve flattens out, showing a good balance between sensitivity and specificity. This cutoff helps the model effectively tell positive and negative cases apart.

```
In [13]:
```

```
def predict climate scepticism(tweet, model path="./models/climate scepticism model", cut
off=0.75):
    # Create a DataFrame with the tweet
    tweet df = pd.DataFrame([tweet], columns=['tweet'])
    # Preprocess the data so it can be handled by the BERT model
    processed tweet df = bert.encode(tweet df['tweet'])
    # Predict using the trained model
   pred_prob_tweet = bert.predict_with_model(processed_tweet_df, model_path=model_path)
    # Interpret the output and set limit. Set the cut-off to the specified threshold
    not_climate_sceptic = pred prob tweet[0, 1] > cutoff
    # Prepare the result message
    result message = f"\nTweet: {tweet}\n"
    if not climate sceptic:
       result message += f"Predicted probability of not being climate sceptic: {pred pro
b tweet[0, 1]:.2f}n"
       result message += "The tweet is not climate sceptic."
    else:
       result message += f"Predicted probability of being climate sceptic: {pred prob tw
eet[0, 0]:.2f}\n"
       result message += "The tweet is climate sceptic."
    return result message
```

In [14]:

```
label ids: {0: 0, 1: 1}

Tweet: Climate change is a hoax. The earth is not warming up. #climatechange #globalwarming #hoax

Predicted probability of being climate sceptic: 0.96

The tweet is climate sceptic.

label ids: {0: 0, 1: 1}

Tweet: The earth is warming up. We need to take action now. #climatechange #globalwarming #action

Predicted probability of not being climate sceptic: 0.98
```

The results show what the model thinks about two tweets.

The tweet is not climate sceptic.

print(predict_climate_scepticism(tweet))

- 1. The first tweet says climate change isn't real, and the model is pretty sure (96%) it's climate sceptic.
- 2. The second tweet says the earth is warming and we need to do something. The model is quite sure (98%) it's not climate sceptic.

In simple terms, the model seems to understand whether tweets doubt climate change or not, and it's doing a good job at it.