

4.Roberta

January 7, 2022

```
[ ]: from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

```
[ ]: import os
import pathlib
from pathlib import Path
os.chdir("/content/drive/My Drive/Akarshan/BERT")
!ls -l
```

```
total 51350
-rw----- 1 root root 8388432 Dec 26 21:48 BERT5.hdf5
drwx----- 2 root root 4096 Dec 3 16:27 clr
-rw----- 1 root root 488058 Dec 25 21:03 Compare.ipynb
-rw----- 1 root root 258091 Dec 26 21:52 'Copy of Distllbert400000.ipynb'
-rw----- 1 root root 76810 Dec 26 21:53 'Copy of Roberta.ipynb'
drwx----- 2 root root 4096 Dec 3 16:27 Data
-rw----- 1 root root 8306584 Dec 24 07:57 DBert1hk.hdf5
-rw----- 1 root root 12719136 Dec 24 07:57 DBert4hk.hdf5
-rw----- 1 root root 251068 Dec 26 21:28 Distllbert400000.ipynb
-rw----- 1 root root 476335 Dec 26 21:08 'EDA on results.ipynb'
drwx----- 2 root root 4096 Dec 18 07:14 'misc model'
-rw----- 1 root root 78553 Dec 26 21:47 model.png
drwx----- 2 root root 4096 Dec 3 16:27 papers
-rw----- 1 root root 8306584 Dec 19 08:56 Rbert4.hdf5
-rw----- 1 root root 203164 Dec 26 21:29 Retraining.ipynb
-rw----- 1 root root 86347 Dec 19 06:43 Roberta.ipynb
-rw----- 1 root root 12719160 Dec 25 10:35 SBert.hdf5
-rw----- 1 root root 203507 Dec 25 10:50 SciBert400k.ipynb
```

```
[ ]: from psutil import virtual_memory
ram_gb = virtual_memory().total / 1e9
print('Your runtime has {:.1f} gigabytes of available RAM\n'.format(ram_gb))

if ram_gb < 20:
```

```

print('Not using a high-RAM runtime')
else:
    print('You are using a high-RAM runtime!')

```

Your runtime has 27.3 gigabytes of available RAM

You are using a high-RAM runtime!

```

[!]: gpu_info = !nvidia-smi
gpu_info = '\n'.join(gpu_info)
if gpu_info.find('failed') >= 0:
    print('Not connected to a GPU')
else:
    print(gpu_info)

```

Sun Dec 26 21:54:03 2021

```

+-----+
| NVIDIA-SMI 495.44                Driver Version: 460.32.03    CUDA Version: 11.2     |
+-----+-----+-----+-----+-----+-----+
| GPU   Name           Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf    Pwr:Usage/Cap|      Memory-Usage | GPU-Util  Compute M. |
|                                           MIG M. |
+-----+-----+-----+-----+-----+-----+
|   0   Tesla P100-PCIE...    Off  | 00000000:00:04.0 Off |             0        |
| N/A   30C    P0      26W / 250W |      0MiB / 16280MiB |           0%      Default |
|                                           N/A |
+-----+-----+-----+-----+-----+

```

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+-----+
| Processes: |
| GPU   GI    CI          PID    Type    Process name                      GPU Memory |
|          ID    ID                                   Usage |
+-----+-----+-----+-----+-----+
| No running processes found |
+-----+

```

```

[!]: !pip install transformers
    !pip install pympler
    !pip install tensorflow-addons

```

Collecting transformers

Downloading transformers-4.15.0-py3-none-any.whl (3.4 MB)

|| 3.4 MB 4.1 MB/s

Requirement already satisfied: importlib-metadata in

/usr/local/lib/python3.7/dist-packages (from transformers) (4.8.2)

Collecting pyyaml>=5.1

```

    Downloading PyYAML-6.0-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_12_x86_64.manylinux2010_x86_64.whl (596 kB)
      || 596 kB 92.1 MB/s
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.7/dist-packages (from transformers) (4.62.3)
Collecting tokenizers<0.11,>=0.10.1
  Downloading tokenizers-0.10.3-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_12_x86_64.manylinux2010_x86_64.whl (3.3 MB)
    || 3.3 MB 65.0 MB/s
Collecting sacremoses
  Downloading sacremoses-0.0.46-py3-none-any.whl (895 kB)
    || 895 kB 90.4 MB/s
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from transformers) (2.23.0)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.7/dist-packages (from transformers) (1.19.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.7/dist-packages (from transformers) (21.3)
Collecting huggingface-hub<1.0,>=0.1.0
  Downloading huggingface-hub-0.2.1-py3-none-any.whl (61 kB)
    || 61 kB 673 kB/s
Requirement already satisfied: filelock in /usr/local/lib/python3.7/dist-packages (from transformers) (3.4.0)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.7/dist-packages (from transformers) (2019.12.20)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.7/dist-packages (from huggingface-hub<1.0,>=0.1.0->transformers) (3.10.0.2)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/python3.7/dist-packages (from packaging>=20.0->transformers) (3.0.6)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packages (from importlib-metadata->transformers) (3.6.0)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from requests->transformers) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests->transformers) (2.10)
Requirement already satisfied: urllib3!=1.25.0,!1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.7/dist-packages (from requests->transformers) (1.24.3)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (from requests->transformers) (2021.10.8)
Requirement already satisfied: click in /usr/local/lib/python3.7/dist-packages (from sacremoses->transformers) (7.1.2)
Requirement already satisfied: joblib in /usr/local/lib/python3.7/dist-packages (from sacremoses->transformers) (1.1.0)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from sacremoses->transformers) (1.15.0)
Installing collected packages: pyyaml, tokenizers, sacremoses, huggingface-hub,

```

```

transformers
  Attempting uninstall: pyyaml
    Found existing installation: PyYAML 3.13
    Uninstalling PyYAML-3.13:
      Successfully uninstalled PyYAML-3.13
Successfully installed huggingface-hub-0.2.1 pyyaml-6.0 sacremoses-0.0.46
tokenizers-0.10.3 transformers-4.15.0
Collecting pympler
  Downloading Pympler-1.0.1-py3-none-any.whl (164 kB)
    || 164 kB 4.1 MB/s
Installing collected packages: pympler
Successfully installed pympler-1.0.1
Collecting tensorflow_addons
  Downloading tensorflow_addons-0.15.0-cp37-cp37m-
manylinux_2_12_x86_64.manylinux2010_x86_64.whl (1.1 MB)
    || 1.1 MB 4.3 MB/s
Requirement already satisfied: typeguard>=2.7 in /usr/local/lib/python3.7
/dist-packages (from tensorflow_addons) (2.7.1)
Installing collected packages: tensorflow-addons
Successfully installed tensorflow-addons-0.15.0

```

```

[ ]: import numpy as np
import pickle
import pandas as pd
import pickle
import time
import matplotlib.pyplot as plt
import seaborn as sns
from pympler import asizeof
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
import transformers
from transformers import pipeline
from tensorflow.keras.layers import concatenate
from transformers import TFAutoModel, AutoTokenizer,
    ↳AutoConfig, TFAutoModelForSequenceClassification
from tensorflow.keras.callbacks import ModelCheckpoint
from clr import clr_callback
import tensorflow_addons as tfa

```

```

[ ]: csvfile = 'Data//data.csv'
dropna = 'Data//datadropna.csv'
sent_data_file = 'Data//sent_data.csv'
label_file = 'Data//label.csv'
vocab_file = 'Data//vocab_tr_w.txt'

```

```
[ ]: df = pd.read_csv(dropna,usecols = ['SBE','Label'])
# df.dropna(inplace=True)
print(df.head())
print(df.shape)
```

```

      Label
0         1  To facilitate an easier notation throughout th...
1         0  Therefore _MATH_ defines a special order of ti...
2         0  This is important since only _MATH_ is the rea...
3         0  Note that in all contour time-integrals we ess...
4         0  Theorem _REF_ proves the equivalence of ensemb...
(1189321, 2)
```

0.1 Generating Embeddings

```
[ ]: # Hyperparameters form paper
```

```
epoch = 30
patience = 10
lr = 1e-6
batch_size = 32
vocab = 30526 #will have to retrain Bert so not using
MAX_LEN = 128 #not enough ram for 256
```

```
[ ]: model_name = 'roberta-base'
config = AutoConfig.from_pretrained(model_name,training =False, num_labels=2 )
config.output_hidden_states = False

BERT = TFAutoModel.from_pretrained(model_name,config = config)

tokenizer = AutoTokenizer.from_pretrained(model_name,
                                          do_lower_case=True,
                                          use_fast=True,
                                          max_length=MAX_LEN,
                                          truncation=True,
                                          pad_to_max_length=True)

pipe = pipeline('feature-extraction', model=BERT,
               tokenizer=tokenizer,device=1)
```

```
Downloading: 0%|          | 0.00/481 [00:00<?, ?B/s]
```

```
Downloading: 0%|          | 0.00/627M [00:00<?, ?B/s]
```

Some layers from the model checkpoint at roberta-base were not used when initializing TFRobertaModel: ['lm_head']

- This IS expected if you are initializing TFRobertaModel from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing TFRobertaModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model). All the layers of TFRobertaModel were initialized from the model checkpoint at roberta-base.

If your task is similar to the task the model of the checkpoint was trained on, you can already use TFRobertaModel for predictions without further training.

Downloading: 0%| | 0.00/878k [00:00<?, ?B/s]

Downloading: 0%| | 0.00/446k [00:00<?, ?B/s]

Downloading: 0%| | 0.00/1.29M [00:00<?, ?B/s]

```
[ ]: batch=500
df = df.iloc[300000:400000,:]
step = int(df.shape[0]/batch)
step
```

```
[ ]: 200
```

```
[ ]: #### getting embedding vectors as bert output ####
# pipe returns embeddings for every token in a sent
# so features[x][0] is of shape (y,768) with y tokens in xth sentence
# taking the mean for y tokens give the embedding for the xth sent in total
# saving a batch of features as feature_matrix with 768 zeors as head
import pickle
import time
count = 500+500+500
for part in range(batch):
    i = part+count
    strt = time.time()
    indx = step*part
    indy = step*(part+1)
    # print(indx,indy)
    feature_matrix = array = np.empty(768, dtype=object)
    lst = []
    features = np.array(pipe(df['SBE'].iloc[indx:indy].to_list()))

    for idx in range(np.shape(features)[0]):
        sent_mean = np.mean(features[idx][0],axis =0)
        lst.append(sent_mean)
    # print(np.shape(lst))
    feature_matrix= np.array(lst)
```

```

# print(np.shape(feature_matrix))
# print(feature_matrix)

with open('Data//embeddingRo//embeddings'+str(i),'wb') as f:
    pickle.dump(feature_matrix,f)

print(f'Part {part+1} of {batch} done. in {(time.time()-strt)/60:.2f} min')

```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:17:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths
or shapes) is deprecated. If you meant to do this, you must specify
'dtype=object' when creating the ndarray

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Part 308 of 500 done. in 1.16 min
Part 309 of 500 done. in 1.19 min
Part 310 of 500 done. in 1.15 min
Part 311 of 500 done. in 1.16 min
Part 312 of 500 done. in 1.13 min
Part 313 of 500 done. in 1.17 min
Part 314 of 500 done. in 1.20 min
Part 315 of 500 done. in 1.16 min
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Part 323 of 500 done. in 1.15 min
Part 324 of 500 done. in 1.17 min
Part 325 of 500 done. in 1.14 min
Part 326 of 500 done. in 1.13 min
Part 327 of 500 done. in 1.20 min
Part 328 of 500 done. in 1.20 min
Part 329 of 500 done. in 1.24 min
Part 330 of 500 done. in 1.20 min
Part 331 of 500 done. in 1.18 min
Part 332 of 500 done. in 1.24 min
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Part 335 of 500 done. in 1.22 min
Part 336 of 500 done. in 1.25 min
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Part 338 of 500 done. in 1.20 min
Part 339 of 500 done. in 1.19 min
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Part 347 of 500 done. in 1.19 min
Part 348 of 500 done. in 1.18 min
Part 349 of 500 done. in 1.17 min
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Part 351 of 500 done. in 1.19 min
Part 352 of 500 done. in 1.18 min
Part 353 of 500 done. in 1.25 min
Part 354 of 500 done. in 1.26 min
Part 355 of 500 done. in 1.20 min
Part 356 of 500 done. in 1.20 min
Part 357 of 500 done. in 1.22 min
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Part 362 of 500 done. in 1.23 min
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Part 371 of 500 done. in 1.20 min
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Part 485 of 500 done. in 1.25 min
Part 486 of 500 done. in 1.29 min
Part 487 of 500 done. in 1.28 min
Part 488 of 500 done. in 1.26 min
Part 489 of 500 done. in 1.26 min
Part 490 of 500 done. in 1.22 min
Part 491 of 500 done. in 1.20 min
Part 492 of 500 done. in 1.23 min
Part 493 of 500 done. in 1.22 min
Part 494 of 500 done. in 1.23 min
Part 495 of 500 done. in 1.25 min
Part 496 of 500 done. in 1.23 min
Part 497 of 500 done. in 1.23 min
Part 498 of 500 done. in 1.18 min
Part 499 of 500 done. in 1.18 min
Part 500 of 500 done. in 1.20 min

```
[ ]: num = len(os.listdir('Data//embeddingRo//'))

with open('Data//embeddingRo//embeddings'+str(0),'rb') as f:
    dataD = pickle.load(f)

for idx in range(1,num):

    with open('Data//embeddingRo//embeddings'+str(idx),'rb') as f:
        mat = pickle.load(f)
        dataD=np.concatenate([dataD,mat],axis=0)

[ ]: np.shape(dataD)
```

```
[ ]: (400000, 768)
```

```
[ ]: df = df.iloc[:400000,:]
```

```
[ ]: train_text, temp_text, train_labels, temp_labels = train_test_split(dataD,
    →df['Label'],
    →random_state=2018,
    →3,
    →stratify=df['Label'])

# we will use temp_text and temp_labels to create validation and test set
val_text, test_text, val_labels, test_labels = train_test_split(temp_text,
    →temp_labels,
    →random_state=2018,
    →stratify=temp_labels)
```

```
[ ]: train_labels = tf.keras.utils.to_categorical(train_labels)
val_labels = tf.keras.utils.to_categorical(val_labels)
test_labels = tf.keras.utils.to_categorical(test_labels)
```

```
[ ]: train_data = tf.data.Dataset.from_tensor_slices((train_text, train_labels))
train_data = train_data.batch(128)
```

```
val_data = tf.data.Dataset.from_tensor_slices((val_text, val_labels))
val_data = val_data.batch(128)
```

```
[ ]: input = tf.keras.layers.Input(shape=(768,), name='input_token', dtype='int32')
X = tf.keras.layers.Dense(768, activation='relu')(input)
X = tf.keras.layers.Dropout(0.2)(X)
X = tf.keras.layers.Dense(512, activation='relu')(input)
X = tf.keras.layers.Dropout(0.2)(X)
X = tf.keras.layers.Dense(128, activation='relu')(X)
X = tf.keras.layers.Dropout(0.2)(X)
X = tf.keras.layers.Dense(2, activation='softmax')(X)
model = tf.keras.Model(inputs=input, outputs = X)
```

```
[ ]: model.summary()
```

Model: "model_5"

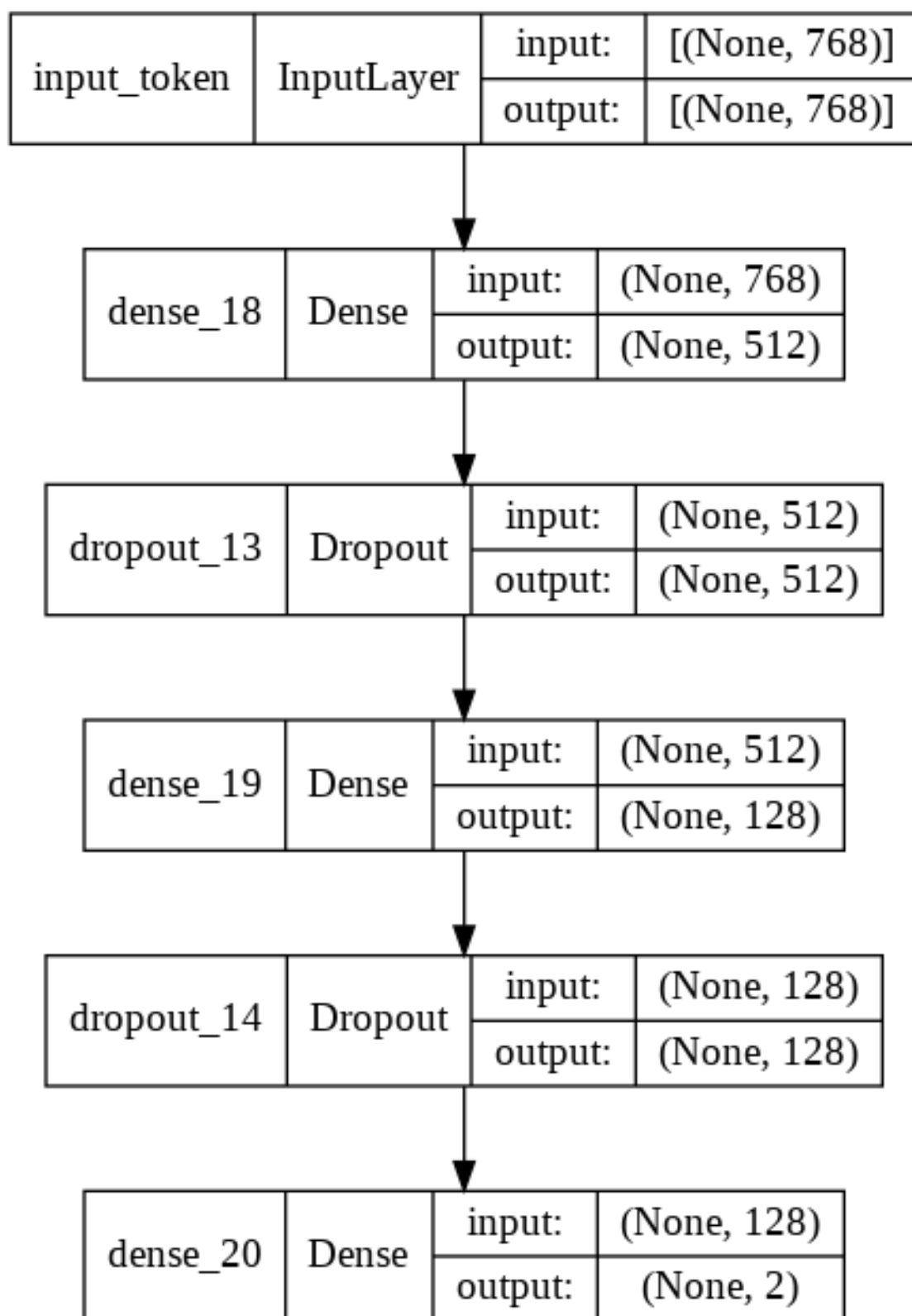
Layer (type)	Output Shape	Param #
input_token (InputLayer)	[(None, 768)]	0

dense_18 (Dense)	(None, 512)	393728
dropout_13 (Dropout)	(None, 512)	0
dense_19 (Dense)	(None, 128)	65664
dropout_14 (Dropout)	(None, 128)	0
dense_20 (Dense)	(None, 2)	258

```
=====
Total params: 459,650
Trainable params: 459,650
Non-trainable params: 0
-----
```

```
[ ]: from keras.utils.vis_utils import plot_model
plot_model(model, show_shapes=True, show_layer_names=True)
```

```
[ ]:
```



```
[ ]: filepath="roBERT.hdf5"
checkpoint = ModelCheckpoint(filepath,
    ↳monitor='val_loss',verbose=1,save_best_only=True, mode='min')
ES =tf.keras.callbacks.
    ↳EarlyStopping(monitor="val_loss",patience=patience,verbose=1,mode="min",restore_best_weight
# pre = tf.keras.metrics.Precision()
f1 = tfa.metrics.F1Score(num_classes=2, average="macro")
callbacks_list = [checkpoint,ES]
model.compile(loss='binary_crossentropy', optimizer='adam' ,metrics=[f1])

[ ]: history = model.fit(train_data, validation_data=val_data,
    ↳epochs=epoch,verbose=1, callbacks = callbacks_list)
```

```
Epoch 1/30
2185/2188 [=====>.] - ETA: 0s - loss: 0.6529 - f1_score:
0.4582
Epoch 00001: val_loss improved from inf to 0.65063, saving model to roBERT.hdf5
2188/2188 [=====] - 8s 4ms/step - loss: 0.6529 -
f1_score: 0.4582 - val_loss: 0.6506 - val_f1_score: 0.4436
Epoch 2/30
2180/2188 [=====>.] - ETA: 0s - loss: 0.6506 - f1_score:
0.4540
Epoch 00002: val_loss improved from 0.65063 to 0.64889, saving model to
roBERT.hdf5
2188/2188 [=====] - 8s 4ms/step - loss: 0.6506 -
f1_score: 0.4540 - val_loss: 0.6489 - val_f1_score: 0.4474
Epoch 3/30
2187/2188 [=====>.] - ETA: 0s - loss: 0.6502 - f1_score:
0.4530
Epoch 00003: val_loss improved from 0.64889 to 0.64838, saving model to
roBERT.hdf5
2188/2188 [=====] - 9s 4ms/step - loss: 0.6502 -
f1_score: 0.4530 - val_loss: 0.6484 - val_f1_score: 0.4510
Epoch 4/30
2186/2188 [=====>.] - ETA: 0s - loss: 0.6501 - f1_score:
0.4527
Epoch 00004: val_loss improved from 0.64838 to 0.64780, saving model to
roBERT.hdf5
2188/2188 [=====] - 8s 4ms/step - loss: 0.6501 -
f1_score: 0.4527 - val_loss: 0.6478 - val_f1_score: 0.4539
Epoch 5/30
2173/2188 [=====>.] - ETA: 0s - loss: 0.6500 - f1_score:
0.4546
Epoch 00005: val_loss improved from 0.64780 to 0.64767, saving model to
roBERT.hdf5
2188/2188 [=====] - 8s 4ms/step - loss: 0.6499 -
f1_score: 0.4549 - val_loss: 0.6477 - val_f1_score: 0.4487
Epoch 6/30
```

2178/2188 [=====>.] - ETA: 0s - loss: 0.6498 - f1_score: 0.4555
Epoch 00006: val_loss did not improve from 0.64767
2188/2188 [=====] - 8s 3ms/step - loss: 0.6498 - f1_score: 0.4556 - val_loss: 0.6477 - val_f1_score: 0.4505
Epoch 7/30
2176/2188 [=====>.] - ETA: 0s - loss: 0.6497 - f1_score: 0.4548
Epoch 00007: val_loss did not improve from 0.64767
2188/2188 [=====] - 8s 4ms/step - loss: 0.6497 - f1_score: 0.4551 - val_loss: 0.6481 - val_f1_score: 0.4557
Epoch 8/30
2179/2188 [=====>.] - ETA: 0s - loss: 0.6496 - f1_score: 0.4562
Epoch 00008: val_loss did not improve from 0.64767
2188/2188 [=====] - 8s 4ms/step - loss: 0.6496 - f1_score: 0.4562 - val_loss: 0.6478 - val_f1_score: 0.4495
Epoch 9/30
2172/2188 [=====>.] - ETA: 0s - loss: 0.6495 - f1_score: 0.4551
Epoch 00009: val_loss did not improve from 0.64767
2188/2188 [=====] - 8s 3ms/step - loss: 0.6495 - f1_score: 0.4552 - val_loss: 0.6480 - val_f1_score: 0.4476
Epoch 10/30
2174/2188 [=====>.] - ETA: 0s - loss: 0.6498 - f1_score: 0.4550
Epoch 00010: val_loss did not improve from 0.64767
2188/2188 [=====] - 8s 3ms/step - loss: 0.6497 - f1_score: 0.4551 - val_loss: 0.6478 - val_f1_score: 0.4493
Epoch 11/30
2178/2188 [=====>.] - ETA: 0s - loss: 0.6496 - f1_score: 0.4531
Epoch 00011: val_loss did not improve from 0.64767
2188/2188 [=====] - 8s 3ms/step - loss: 0.6495 - f1_score: 0.4532 - val_loss: 0.6478 - val_f1_score: 0.4504
Epoch 12/30
2178/2188 [=====>.] - ETA: 0s - loss: 0.6496 - f1_score: 0.4551
Epoch 00012: val_loss did not improve from 0.64767
2188/2188 [=====] - 8s 4ms/step - loss: 0.6495 - f1_score: 0.4552 - val_loss: 0.6479 - val_f1_score: 0.4495
Epoch 13/30
2177/2188 [=====>.] - ETA: 0s - loss: 0.6495 - f1_score: 0.4555
Epoch 00013: val_loss did not improve from 0.64767
2188/2188 [=====] - 8s 3ms/step - loss: 0.6495 - f1_score: 0.4558 - val_loss: 0.6478 - val_f1_score: 0.4529
Epoch 14/30

2171/2188 [=====>.] - ETA: 0s - loss: 0.6494 - f1_score: 0.4551
Epoch 00014: val_loss improved from 0.64767 to 0.64759, saving model to roBERT.hdf5
2188/2188 [=====] - 8s 4ms/step - loss: 0.6494 - f1_score: 0.4552 - val_loss: 0.6476 - val_f1_score: 0.4509
Epoch 15/30
2181/2188 [=====>.] - ETA: 0s - loss: 0.6493 - f1_score: 0.4555
Epoch 00015: val_loss did not improve from 0.64759
2188/2188 [=====] - 8s 3ms/step - loss: 0.6493 - f1_score: 0.4555 - val_loss: 0.6477 - val_f1_score: 0.4512
Epoch 16/30
2181/2188 [=====>.] - ETA: 0s - loss: 0.6495 - f1_score: 0.4553
Epoch 00016: val_loss did not improve from 0.64759
2188/2188 [=====] - 8s 3ms/step - loss: 0.6495 - f1_score: 0.4554 - val_loss: 0.6476 - val_f1_score: 0.4508
Epoch 17/30
2177/2188 [=====>.] - ETA: 0s - loss: 0.6493 - f1_score: 0.4572
Epoch 00017: val_loss improved from 0.64759 to 0.64740, saving model to roBERT.hdf5
2188/2188 [=====] - 8s 4ms/step - loss: 0.6493 - f1_score: 0.4572 - val_loss: 0.6474 - val_f1_score: 0.4475
Epoch 18/30
2184/2188 [=====>.] - ETA: 0s - loss: 0.6492 - f1_score: 0.4561
Epoch 00018: val_loss did not improve from 0.64740
2188/2188 [=====] - 8s 3ms/step - loss: 0.6492 - f1_score: 0.4561 - val_loss: 0.6477 - val_f1_score: 0.4513
Epoch 19/30
2173/2188 [=====>.] - ETA: 0s - loss: 0.6493 - f1_score: 0.4555
Epoch 00019: val_loss did not improve from 0.64740
2188/2188 [=====] - 8s 3ms/step - loss: 0.6493 - f1_score: 0.4556 - val_loss: 0.6479 - val_f1_score: 0.4494
Epoch 20/30
2172/2188 [=====>.] - ETA: 0s - loss: 0.6493 - f1_score: 0.4554
Epoch 00020: val_loss did not improve from 0.64740
2188/2188 [=====] - 8s 3ms/step - loss: 0.6492 - f1_score: 0.4555 - val_loss: 0.6476 - val_f1_score: 0.4496
Epoch 21/30
2179/2188 [=====>.] - ETA: 0s - loss: 0.6493 - f1_score: 0.4557
Epoch 00021: val_loss did not improve from 0.64740
2188/2188 [=====] - 8s 3ms/step - loss: 0.6492 -

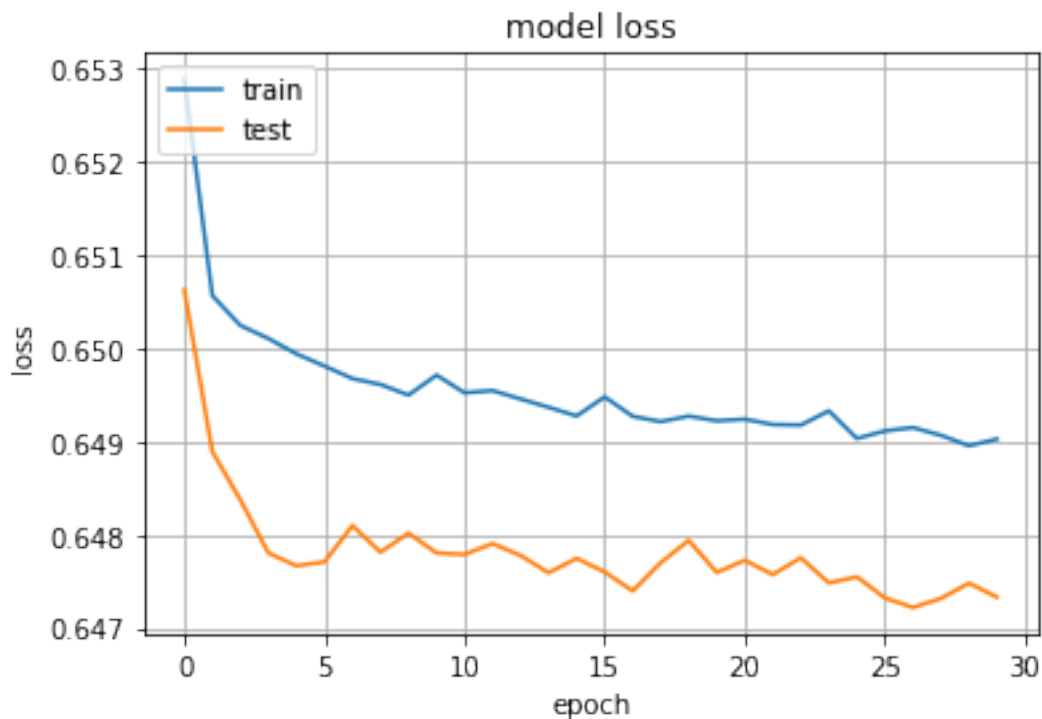
```

f1_score: 0.4558 - val_loss: 0.6477 - val_f1_score: 0.4491
Epoch 22/30
2173/2188 [=====>.] - ETA: 0s - loss: 0.6493 - f1_score:
0.4554
Epoch 00022: val_loss did not improve from 0.64740
2188/2188 [=====] - 8s 3ms/step - loss: 0.6492 -
f1_score: 0.4555 - val_loss: 0.6476 - val_f1_score: 0.4487
Epoch 23/30
2187/2188 [=====>.] - ETA: 0s - loss: 0.6492 - f1_score:
0.4546
Epoch 00023: val_loss did not improve from 0.64740
2188/2188 [=====] - 8s 3ms/step - loss: 0.6492 -
f1_score: 0.4546 - val_loss: 0.6478 - val_f1_score: 0.4500
Epoch 24/30
2183/2188 [=====>.] - ETA: 0s - loss: 0.6494 - f1_score:
0.4537
Epoch 00024: val_loss did not improve from 0.64740
2188/2188 [=====] - 8s 3ms/step - loss: 0.6493 -
f1_score: 0.4537 - val_loss: 0.6475 - val_f1_score: 0.4483
Epoch 25/30
2185/2188 [=====>.] - ETA: 0s - loss: 0.6490 - f1_score:
0.4568
Epoch 00025: val_loss did not improve from 0.64740
2188/2188 [=====] - 8s 4ms/step - loss: 0.6490 -
f1_score: 0.4568 - val_loss: 0.6475 - val_f1_score: 0.4491
Epoch 26/30
2182/2188 [=====>.] - ETA: 0s - loss: 0.6491 - f1_score:
0.4577
Epoch 00026: val_loss improved from 0.64740 to 0.64732, saving model to
roBERT.hdf5
2188/2188 [=====] - 8s 4ms/step - loss: 0.6491 -
f1_score: 0.4577 - val_loss: 0.6473 - val_f1_score: 0.4492
Epoch 27/30
2183/2188 [=====>.] - ETA: 0s - loss: 0.6492 - f1_score:
0.4546
Epoch 00027: val_loss improved from 0.64732 to 0.64722, saving model to
roBERT.hdf5
2188/2188 [=====] - 8s 4ms/step - loss: 0.6492 -
f1_score: 0.4547 - val_loss: 0.6472 - val_f1_score: 0.4493
Epoch 28/30
2179/2188 [=====>.] - ETA: 0s - loss: 0.6491 - f1_score:
0.4542
Epoch 00028: val_loss did not improve from 0.64722
2188/2188 [=====] - 8s 3ms/step - loss: 0.6491 -
f1_score: 0.4542 - val_loss: 0.6473 - val_f1_score: 0.4467
Epoch 29/30
2180/2188 [=====>.] - ETA: 0s - loss: 0.6490 - f1_score:
0.4547

```


Epoch 00029: val_loss did not improve from 0.64722
 2188/2188 [=====] - 8s 3ms/step - loss: 0.6490 -
 f1_score: 0.4548 - val_loss: 0.6475 - val_f1_score: 0.4517
 Epoch 30/30
 2183/2188 [=====>.] - ETA: 0s - loss: 0.6490 - f1_score:
 0.4552
 Epoch 00030: val_loss did not improve from 0.64722
 2188/2188 [=====] - 8s 3ms/step - loss: 0.6490 -
 f1_score: 0.4552 - val_loss: 0.6473 - val_f1_score: 0.4470

```
[ ]: plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.grid()
plt.show()
```



```
[ ]: from keras.models import load_model
model = load_model("roBERT.hdf5")

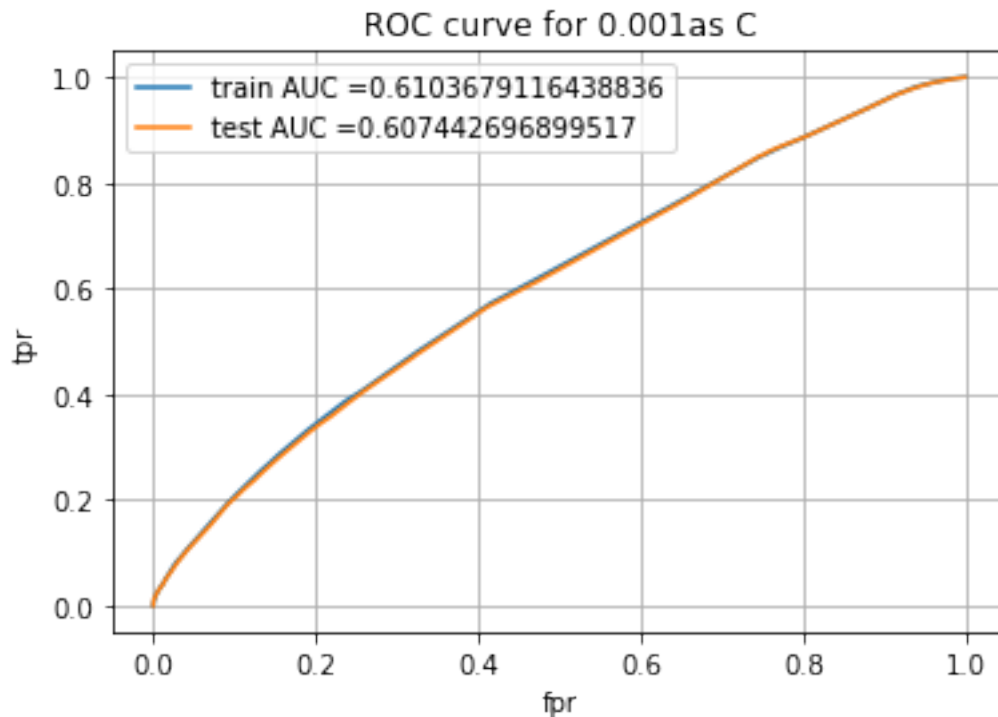
[ ]: test_data = tf.data.Dataset.from_tensor_slices((test_text))
test_data = test_data.shuffle(5000).batch(128)
```

```

[:]: y_pr_ts = model.predict(test_data)[:,:]
y_pred_tr = model.predict(train_data)[:,:]
y_ts = test_labels[:,0]
y_tr = train_labels[:,0]
from sklearn.metrics import
    →roc_curve, auc, confusion_matrix, accuracy_score, precision_score, recall_score, f1_score

train_fpr, train_tpr, tr_thresholds = roc_curve(y_tr, y_pred_tr)
test_fpr, test_tpr, te_thresholds = roc_curve(y_ts, y_pr_ts)
plt.plot(train_fpr, train_tpr, label="train AUC")
    →="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC "+str(auc(test_fpr, test_tpr)))
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.title('ROC curve for '+str(0.001)+'as C')
plt.legend()
plt.grid()
plt.show()

```



```

[:]: # This section of code where ever implemented is taken from sample kNN python
    →notebook

def find_best_threshold(threshold, fpr, tpr):
    t = threshold[np.argmax(tpr*(1-fpr))]

```

```

    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very
    →high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for
    →threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshold):
    predictions = []
    for i in proba:
        if i>=threshold:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions

print('test')
best_ts_thres = find_best_threshold(te_thresholds, test_fpr, test_tpr)

print('train')
best_tr_thres = find_best_threshold(tr_thresholds, train_fpr, train_tpr)

```

```

test
the maximum value of tpr*(1-fpr) 0.33247305148634676 for threshold 0.663
train
the maximum value of tpr*(1-fpr) 0.3344086594483335 for threshold 0.667

```

```

[:]: print('Train Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_tr, predict_with_best_t(y_pred_tr,
    →best_tr_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')

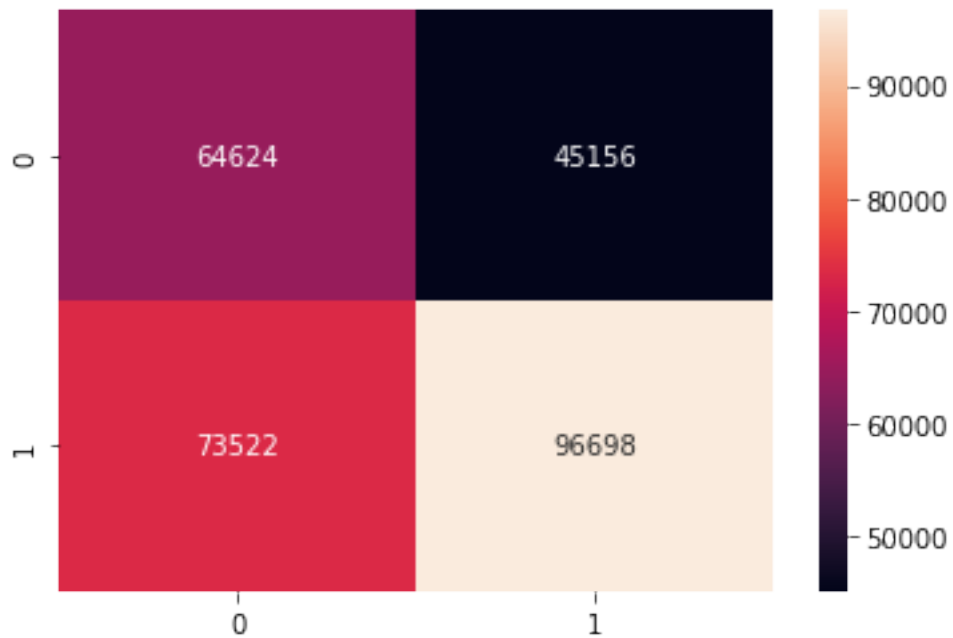
```

Train Confusion Matrix

```

[:]: <matplotlib.axes._subplots.AxesSubplot at 0x7f694651d8d0>

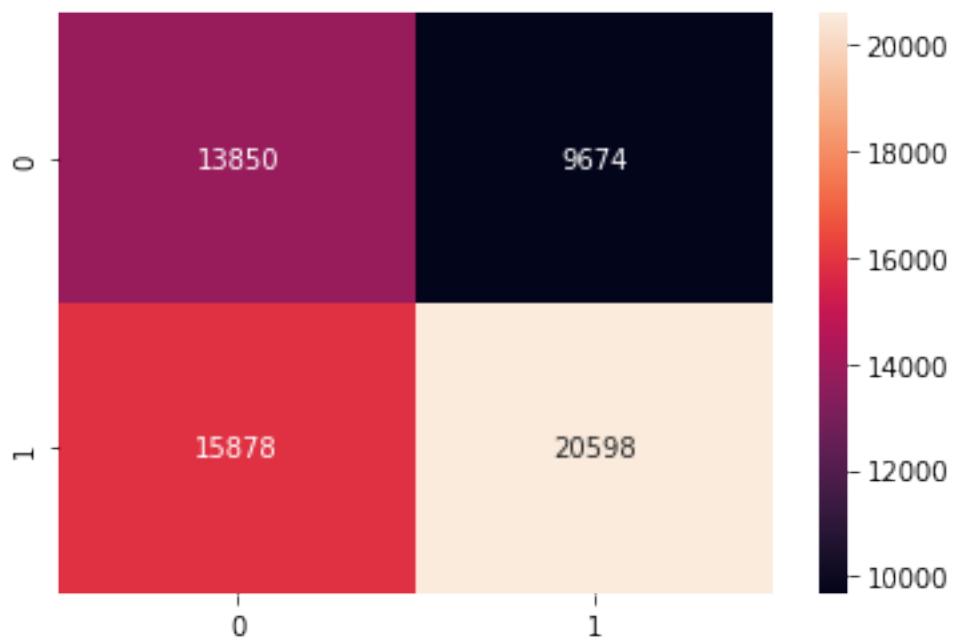
```



```
[ ]: print('Test Confusion Matrix')
cm2 = pd.DataFrame(confusion_matrix(y_ts, predict_with_best_t(y_pr_ts,
↪best_ts_thres)), range(2),range(2))
sns.heatmap(cm2, annot=True,fmt='g')
```

Test Confusion Matrix

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f69463d2410>
```



```
[ ]: acc=accuracy_score(y_ts, predict_with_best_t(y_pr_ts, best_ts_thres))*100
ps=precision_score(y_ts, predict_with_best_t(y_pr_ts, best_ts_thres))*100
rc=recall_score(y_ts, predict_with_best_t(y_pr_ts, best_ts_thres))*100
f1=f1_score(y_ts, predict_with_best_t(y_pr_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

Accuracy on test set: 57.41%
Precision on test set: 68.04%
recall score on test set: 56.47%
f1 score on test set: 61.72%

```
[ ]: acc=accuracy_score(y_ts, predict_with_best_t(y_pr_ts, best_ts_thres))*100
ps=precision_score(y_ts, predict_with_best_t(y_pr_ts, best_ts_thres))*100
rc=recall_score(y_ts, predict_with_best_t(y_pr_ts, best_ts_thres))*100
f1=f1_score(y_ts, predict_with_best_t(y_pr_ts, best_ts_thres))*100

print("Accuracy on test set: %0.2f%%"%(acc))
print("Precision on test set: %0.2f%%"%(ps))
print("recall score on test set: %0.2f%%"%(rc))
print("f1 score on test set: %0.2f%%"%(f1))
```

Accuracy on test set: 57.41%
Precision on test set: 68.04%
recall score on test set: 56.47%
f1 score on test set: 61.72%

```
[ ]:
```