(2)

BERT tutorial: Classify spam vs no spam emails

```
import tensorflow as tf
import tensorflow_hub as hub
import tensorflow_text as text
```

Import the dataset (Dataset is taken from kaggle)

```
import pandas as pd

df = pd.read_csv("spam.csv")
df.head(5)
```

Category		Message
0	ham	Go until jurong point, crazy Available only
1	ham	Ok lar Joking wif u oni
2	spam	Free entry in 2 a wkly comp to win FA Cup fina
3	ham	U dun say so early hor U c already then say
4	ham	Nah I don't think he goes to usf, he lives aro

df.groupby('Category').describe()

Message

	count	unique	top	freq
Category				
ham	4825	4516	Sorry, I'll call later	30
spam	747	641	Please call our customer service representativ	4

```
df['Category'].value_counts()
```

ham 4825 spam 747

Name: Category, dtype: int64

747/4825

0.15481865284974095

15% spam emails, 85% ham emails: This indicates class imbalance

```
df_spam = df[df['Category']=='spam']
df_spam.shape
     (747, 2)
df_ham = df[df['Category']=='ham']
df_ham.shape
     (4825, 2)
df_ham_downsampled = df_ham.sample(df_spam.shape[0])
df_ham_downsampled.shape
     (747, 2)
df_balanced = pd.concat([df_ham_downsampled, df_spam])
df_balanced.shape
     (1494, 2)
df_balanced['Category'].value_counts()
     spam
             747
     Name: Category, dtype: int64
```

m	spa	Message	Category	
C		We can go 4 e normal pilates after our intro	ham	4925
1		accordingly. I repeat, just text the word ok o	spam	4249
C		Guess which pub im in? Im as happy as a pig in	ham	5006
C		You in your room? I need a few	ham	2567
C		I HAVE A DATE ON SUNDAY WITH WILL!!	ham	14

Split it into training and test data set

Now lets import BERT model and get embeding vectors for few sample statements

Get embeding vectors for few sample words. Compare them using cosine similarity

```
e = get_sentence_embeding([
    "banana",
    "grapes",
    "mango",
    "jeff bezos",
    "elon musk",
    "bill gates"
]
)
from sklearn.metrics.pairwise import cosine_similarity
cosine_similarity([e[0]],[e[1]])
    array([[0.9911089]], dtype=float32)
```

Values near to 1 means they are similar. 0 means they are very different. Above you can use comparing "banana" vs "grapes" you get 0.99 similarity as they both are fruits

Comparing banana with jeff bezos you still get 0.84 but it is not as close as 0.99 that we got with grapes

Jeff bezos and Elon musk are more similar then Jeff bezos and banana as indicated above

Build Model

There are two types of models you can build in tensorflow.

(1) Sequential (2) Functional

So far we have built sequential model. But below we will build functional model. More information on these two is here: https://becominghuman.ai/sequential-vs-functional-model-in-keras-20684f766057

```
# Bert layers
text_input = tf.keras.layers.Input(shape=(), dtype=tf.string, name='text')
preprocessed_text = bert_preprocess(text_input)
outputs = bert_encoder(preprocessed_text)

# Neural network layers
1 = tf.keras.layers.Dropout(0.1, name="dropout")(outputs['pooled_output'])
1 = tf.keras.layers.Dense(1, activation='sigmoid', name="output")(1)

# Use inputs and outputs to construct a final model
model = tf.keras.Model(inputs=[text_input], outputs = [1])
```

https://stackoverflow.com/questions/47605558/importerror-failed-to-import-pydot-you-must-install-pydot-and-graphviz-for-py

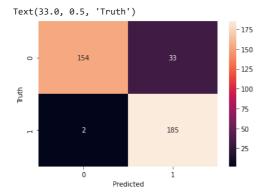
```
model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
text (InputLayer)	[(None,)]	0	
keras_layer (KerasLayer)	{'input_mask': (Nor	text[0][0]	
keras_layer_1 (KerasLayer)	{'default': (None,	7 109482241	keras_layer[0][0] keras_layer[0][1] keras_layer[0][2]
dropout (Dropout)	(None, 768)	0	keras_layer_1[0][13]
output (Dense)	(None, 1)	769	dropout[0][0]

Train the model

```
Enoch 2/10
   Epoch 3/10
   Epoch 4/10
   35/35 [=====
            Epoch 5/10
   35/35 [============ ] - 7s 187ms/step - loss: 0.2837 - accuracy: 0.9098 - precision: 0.9076 - recall: 0.9125
   Epoch 6/10
   35/35 [=====
           Epoch 7/10
   Epoch 8/10
   35/35 [=====
            Epoch 9/10
   Epoch 10/10
            <tensorflow.python.keras.callbacks.History at 0x1db822fcf70>
model.evaluate(X_test, y_test)
   [0.2599719762802124,
   0.9064171314239502.
   0.8486238718032837.
   0.98930484056472781
y_predicted = model.predict(X_test)
y_predicted = y_predicted.flatten()
import numpy as np
y_predicted = np.where(y_predicted > 0.5, 1, 0)
y_predicted
   1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1,
       1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0,
       0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0,
       0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0,
       1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0,
       1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1,
       1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1,
       1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0,
       0,\ 0,\ 1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 0,\ 0,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,
       1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1,
       0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1,
       1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0,
       0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0,
       1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1,
       0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0])
from sklearn.metrics import confusion_matrix, classification_report
cm = confusion_matrix(y_test, y_predicted)
cm
   array([[154, 33],
       [ 2, 185]], dtype=int64)
from matplotlib import pyplot as plt
import seaborn as sn
sn.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```



print(classification_report(y_test, y_predicted))

	precision	recall	f1-score	support
0	0.99	0.82	0.90	187
1	0.85	0.99	0.91	187
			0.01	274
accuracy			0.91	374
macro avg	0.92	0.91	0.91	374
weighted avg	0.92	0.91	0.91	374

Inference