

## Setup

```
In [3]: # A dependency of the preprocessing for BERT inputs
!pip install -q tensorflow-text
```

```
|████████████████████████████████████████| 3.4MB 3.0MB/s
```

```
In [4]: # Using AdamW optimizer
!pip install -q tf-models-official==2.4
```

```
|████████████████████████████████████████| 1.1MB 2.9MB/s
|████████████████████████████████████████| 38.2MB 83kB/s
|████████████████████████████████████████| 358kB 36.3MB/s
|████████████████████████████████████████| 51kB 6.5MB/s
|████████████████████████████████████████| 102kB 9.7MB/s
|████████████████████████████████████████| 686kB 18.1MB/s
|████████████████████████████████████████| 1.2MB 34.6MB/s
|████████████████████████████████████████| 645kB 33.5MB/s
|████████████████████████████████████████| 174kB 39.2MB/s
```

```
Building wheel for sequeval (setup.py) ... done
```

```
Building wheel for py-cpuinfo (setup.py) ... done
```

```
In [5]: import os
import shutil

import tensorflow as tf
import tensorflow_hub as hub
import tensorflow_text as text
from official.nlp import optimization # to create AdamW optimizer

import matplotlib.pyplot as plt

tf.get_logger().setLevel('ERROR')
```

```
In [6]: url = 'https://github.com/ahlralf/point/blob/main/v1_emails.tar.gz?raw=true'
dataset = tf.keras.utils.get_file('v1_emails.tar.gz', url,
                                untar=True, cache_dir='.',
                                cache_subdir='')
```

```
Downloading data from https://github.com/ahlralf/point/blob/main/v1_emails.tar.gz?raw=true
```

```
475136/467631 [=====] - 0s 0us/step
```

```
In [7]: dataset_dir = os.path.join(os.path.dirname(dataset), 'v1_emails')
train_dir = os.path.join(dataset_dir, 'train')
```

```
In [8]: AUTOTUNE = tf.data.AUTOTUNE
batch_size = 32
seed = 42

raw_train_ds = tf.keras.preprocessing.text_dataset_from_directory(
    'v1_emails/train',
    batch_size=batch_size,
    validation_split=0.2,
    subset='training',
    seed=seed)

class_names = raw_train_ds.class_names
train_ds = raw_train_ds.cache().prefetch(buffer_size=AUTOTUNE)

val_ds = tf.keras.preprocessing.text_dataset_from_directory(
    'v1_emails/train',
    batch_size=batch_size,
    validation_split=0.2,
    subset='validation',
```

```

seed=seed)

val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)

test_ds = tf.keras.preprocessing.text_dataset_from_directory(
    'v1_emails/test',
    batch_size=batch_size)

test_ds = test_ds.cache().prefetch(buffer_size=AUTOTUNE)

```

Found 1238 files belonging to 2 classes.  
 Using 991 files for training.  
 Found 1238 files belonging to 2 classes.  
 Using 247 files for validation.  
 Found 308 files belonging to 2 classes.

Looking at a few emails:

Preprocessing email text data:

```

In [9]: import re
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords

```

[nltk\_data] Downloading package stopwords to /root/nltk\_data...  
 [nltk\_data] Unzipping corpora/stopwords.zip.

```

In [10]: regex_tokenizer = nltk.RegexpTokenizer("\w+")
def text_preprocessing(content):
    content = str(content)
    content = re.sub("[^a-zA-Z]", " ", content)
    content = content.lower()
    content = content.encode("utf-8", "ignore").decode()
    content = " ".join(regex_tokenizer.tokenize(content))
    for c in content:
        c.replace('\n', ' ')
    words = content.split()
    stops = set(stopwords.words("english"))
    words = [w for w in words if not w in stops]

    return ' '.join(words)

train_2 = train_ds
for text_batch, label_batch in train_2:
    text_batch = text_preprocessing(text_batch)

for text_batch, label_batch in train_2.take(1):
    for i in range(10):
        print(f'Email: {text_batch.numpy()[i]}')
        label = label_batch.numpy()[i]
        print(f'Label: {label} ({class_names[label]})')

```

Email: b"Hi Ulf,\n\nOn Fri, 2018-04-20 at 09:35 +0200, Ulf Hansson wrote:\n\nPrevious multi slot implementation was removed as nobody used it and\nnobody tested it. There are lots of mistakes in previous implementation\nwhich are not related to request serialization\nlike lack of slot switch / lack of adding slot id to CIU commands / e\n\nSo obviously it was never tested and never used at real multi slot hardware.\n\nIn current implementation data transfers and commands to different\n\nhosts (slots) are serialized internally in the dw\_mmc driver. We have\n\nrequest queue and when .request() is called we add new request to the\n\nqueue. We take new request from the queue only if the previous one\n\nhas already finished.\n\nSo although hosts (slots) have separate locks (mmc\_claim|release\_host())\n\nthe requests to different slots are serialized by driver.\n\nIsn't that enough?\n\nI'm not very familiar with SD/SDIO/(e)MMC specs so my assumptions might be wrong\n\nin that case please correct me.\n\nNevertheless we had to deal somehow with existing hardware which\n\nhas multislot dw mmc controller and both slots are used...\n\nThis patch at least shouldn't break anything for current users (which use\n\nnit in single slot mode)\n\nMoreover we tested this dual



```

map_name_to_handle = {
    'bert_en_uncased_L-12_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_uncased_L-12_H-768_A-12/3',
    'bert_en_cased_L-12_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_cased_L-12_H-768_A-12/3',
    'bert_multi_cased_L-12_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_multi_cased_L-12_H-768_A-12/3',
    'small_bert/bert_en_uncased_L-2_H-128_A-2':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-2_H-128_A-2/1',
    'small_bert/bert_en_uncased_L-2_H-256_A-4':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-2_H-256_A-4/1',
    'small_bert/bert_en_uncased_L-2_H-512_A-8':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-2_H-512_A-8/1',
    'small_bert/bert_en_uncased_L-2_H-768_A-12':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-2_H-768_A-12/1',
    'small_bert/bert_en_uncased_L-4_H-128_A-2':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-4_H-128_A-2/1',
    'small_bert/bert_en_uncased_L-4_H-256_A-4':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-4_H-256_A-4/1',
    'small_bert/bert_en_uncased_L-4_H-512_A-8':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-4_H-512_A-8/1',
    'small_bert/bert_en_uncased_L-4_H-768_A-12':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-4_H-768_A-12/1',
    'small_bert/bert_en_uncased_L-6_H-128_A-2':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-6_H-128_A-2/1',
    'small_bert/bert_en_uncased_L-6_H-256_A-4':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-6_H-256_A-4/1',
    'small_bert/bert_en_uncased_L-6_H-512_A-8':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-6_H-512_A-8/1',
    'small_bert/bert_en_uncased_L-6_H-768_A-12':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-6_H-768_A-12/1',
    'small_bert/bert_en_uncased_L-8_H-128_A-2':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-8_H-128_A-2/1',
    'small_bert/bert_en_uncased_L-8_H-256_A-4':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-8_H-256_A-4/1',
    'small_bert/bert_en_uncased_L-8_H-512_A-8':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-8_H-512_A-8/1',
    'small_bert/bert_en_uncased_L-8_H-768_A-12':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-8_H-768_A-12/1',
    'small_bert/bert_en_uncased_L-10_H-128_A-2':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-10_H-128_A-2/1',
    'small_bert/bert_en_uncased_L-10_H-256_A-4':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-10_H-256_A-4/1',
    'small_bert/bert_en_uncased_L-10_H-512_A-8':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-10_H-512_A-8/1',
    'small_bert/bert_en_uncased_L-10_H-768_A-12':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-10_H-768_A-12/1',
    'small_bert/bert_en_uncased_L-12_H-128_A-2':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-12_H-128_A-2/1',
    'small_bert/bert_en_uncased_L-12_H-256_A-4':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-12_H-256_A-4/1',
    'small_bert/bert_en_uncased_L-12_H-512_A-8':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-12_H-512_A-8/1',
    'small_bert/bert_en_uncased_L-12_H-768_A-12':
        'https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-12_H-768_A-12/1',
    'albert_en_base':
        'https://tfhub.dev/tensorflow/albert_en_base/2',
    'electra_small':
        'https://tfhub.dev/google/electra_small/2',
    'electra_base':
        'https://tfhub.dev/google/electra_base/2',
    'experts_pubmed':
        'https://tfhub.dev/google/experts/bert/pubmed/2',
    'experts_wiki_books':
        'https://tfhub.dev/google/experts/bert/wiki_books/2',

```

```

'talking-heads_base':
    'https://tfhub.dev/tensorflow/talkheads_ggelu_bert_en_base/1',
}

map_model_to_preprocess = {
    'bert_en_uncased_L-12_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'bert_en_cased_L-12_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_cased_preprocess/3',
    'small_bert/bert_en_uncased_L-2_H-128_A-2':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-2_H-256_A-4':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-2_H-512_A-8':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-2_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-4_H-128_A-2':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-4_H-256_A-4':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-4_H-512_A-8':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-4_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-6_H-128_A-2':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-6_H-256_A-4':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-6_H-512_A-8':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-6_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-8_H-128_A-2':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-8_H-256_A-4':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-8_H-512_A-8':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-8_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-10_H-128_A-2':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-10_H-256_A-4':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-10_H-512_A-8':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-10_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-12_H-128_A-2':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-12_H-256_A-4':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-12_H-512_A-8':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'small_bert/bert_en_uncased_L-12_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'bert_multi_cased_L-12_H-768_A-12':
        'https://tfhub.dev/tensorflow/bert_multi_cased_preprocess/3',
    'albert_en_base':
        'https://tfhub.dev/tensorflow/albert_en_preprocess/3',
    'electra_small':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
    'electra_base':
        'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',

```

```

'experts_pubmed':
    'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
'experts_wiki_books':
    'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
'talking-heads_base':
    'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3',
}

```

```

tfhub_handle_encoder = map_name_to_handle[bert_model_name]
tfhub_handle_preprocess = map_model_to_preprocess[bert_model_name]

```

```

print(f'BERT model selected          : {tfhub_handle_encoder}')
print(f'Preprocess model auto-selected: {tfhub_handle_preprocess}')

```

```

BERT model selected          : https://tfhub.dev/tensorflow/small_bert/bert_en_unca
sed_L-4_H-512_A-8/1
Preprocess model auto-selected: https://tfhub.dev/tensorflow/bert_en_uncased_preproc
ess/3

```

Preprocessing model

```
In [12]: bert_preprocess_model = hub.KerasLayer(tfhub_handle_preprocess)
```

```
In [13]: text_test = ["The driver is looking good!\n\nIt looks like you've done some kind of
text_preprocessed = bert_preprocess_model(text_test)
```

```

print(f'Keys          : {list(text_preprocessed.keys())}')
print(f'Shape         : {text_preprocessed["input_word_ids"].shape}')
print(f'Word Ids      : {text_preprocessed["input_word_ids"][0, :12]}')
print(f'Input Mask    : {text_preprocessed["input_mask"][0, :12]}')
print(f'Type Ids      : {text_preprocessed["input_type_ids"][0, :12]}')

```

```

Keys          : ['input_word_ids', 'input_mask', 'input_type_ids']
Shape         : (1, 128)
Word Ids      : [ 101 1996 4062 2003 2559 2204  999 2009 3504 2066 2017 1005]
Input Mask    : [1 1 1 1 1 1 1 1 1 1 1 1]
Type Ids      : [0 0 0 0 0 0 0 0 0 0 0 0]

```

Using BERT model

```
In [14]: bert_model = hub.KerasLayer(tfhub_handle_encoder)
```

```
In [15]: bert_results = bert_model(text_preprocessed)
```

```

print(f'Loaded BERT: {tfhub_handle_encoder}')
print(f'Pooled Outputs Shape:{bert_results["pooled_output"].shape}')
print(f'Pooled Outputs Values:{bert_results["pooled_output"][0, :12]}')
print(f'Sequence Outputs Shape:{bert_results["sequence_output"].shape}')
print(f'Sequence Outputs Values:{bert_results["sequence_output"][0, :12]}')

```

```

Loaded BERT: https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-4_H-512_A-8/1
Pooled Outputs Shape:(1, 512)
Pooled Outputs Values:[ 0.8474724  0.9954415 -0.2801296  0.12758732  0.31347966
 0.9054938
 0.51660323 -0.9968071 -0.056826  -0.9988778  0.1418411 -0.98870677]
Sequence Outputs Shape:(1, 128, 512)
Sequence Outputs Values:[[ 0.39939636 -0.39085585  0.9385306  ... 0.28003708 0.033
86177
 -0.40618864]
[-0.2922875  0.40331358 -1.0200567  ... -0.57538235 0.06500234
 0.86555874]
[-0.836157  0.07805508  0.6440214  ... 0.6109729  0.54963326
 0.5941912 ]
...
[-0.3181702 -1.1716307 -1.4007791  ... 0.5933541 -0.54000527
 -0.59103113]
[-0.40100214 0.1862419 -0.2739593  ... 0.6435037  0.38049644

```



```

    0.5307539 ]
[-0.17033839  0.25949234  0.619225    ... -0.47313017  0.668039
 0.0198222  ]]

```

The BERT models return a map with 3 important keys: pooled\_output, sequence\_output, encoder\_outputs:

"pooled\_output" represents each input sequence as a whole. The shape is [batch\_size, H]. [~ Embedding for the entire email] "sequence\_output" represents each input token in the context. The shape is [batch\_size, seq\_length, H]. [~ contextual embedding for every token in the email] "encoder\_outputs" are the intermediate activations of the L Transformer blocks. outputs["encoder\_outputs"][i] is a Tensor of shape [batch\_size, seq\_length, 1024] with the outputs of the i-th Transformer block, for  $0 \leq i < L$ . The last value of the list is equal to sequence\_output.

For the fine-tuning we use the pooled\_output array.

## Defining model

Fine-tuned model comprising preprocessing model + selected BERT model + 1 dense + 1 dropout layer

```

In [16]: def build_classifier_model():
    text_input = tf.keras.layers.Input(shape=(), dtype=tf.string, name='text')
    preprocessing_layer = hub.KerasLayer(tfhub_handle_preprocess, name='preprocessing')
    encoder_inputs = preprocessing_layer(text_input)
    encoder = hub.KerasLayer(tfhub_handle_encoder, trainable=True, name='BERT_encoder')
    outputs = encoder(encoder_inputs)
    net = outputs['pooled_output']
    net = tf.keras.layers.Dropout(0.1)(net)
    net = tf.keras.layers.Dense(1, activation=None, name='classifier')(net)
    return tf.keras.Model(text_input, net)

```

```

In [17]: classifier_model = build_classifier_model()
bert_raw_result = classifier_model(tf.constant(text_test))
print(tf.sigmoid(bert_raw_result))

tf.Tensor([[0.66126657]], shape=(1, 1), dtype=float32)

```

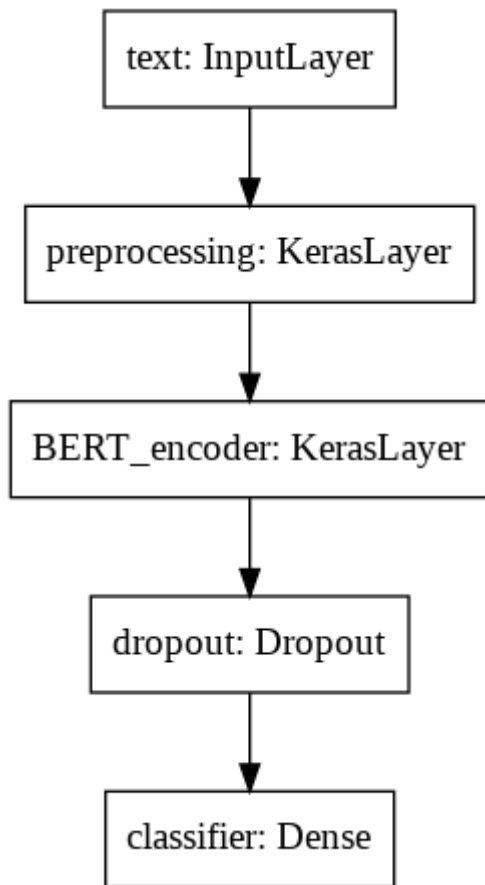
Model structure

```

In [18]: tf.keras.utils.plot_model(classifier_model)

```

Out[18]:



## Model training

Loss function: binary cross entropy loss function (binary classification, model outs a probability)

```
In [19]: loss = tf.keras.losses.BinaryCrossentropy(from_logits=True)
         metrics = tf.metrics.BinaryAccuracy()
```

Optimizer: AdamW

For the learning rate (init\_lr), we use the same schedule as BERT pre-training: linear decay of a notional initial learning rate, prefixed with a linear warm-up phase over the first 10% of training steps (num\_warmup\_steps). In line with the BERT paper, the initial learning rate is smaller for fine-tuning (best of 5e-5, 3e-5, 2e-5).

```
In [20]: epochs = 5
         steps_per_epoch = tf.data.experimental.cardinality(train_ds).numpy()
         num_train_steps = steps_per_epoch * epochs
         num_warmup_steps = int(0.1*num_train_steps)

         init_lr = 3e-5
         optimizer = optimization.create_optimizer(init_lr=init_lr,
                                                    num_train_steps=num_train_steps,
                                                    num_warmup_steps=num_warmup_steps,
                                                    optimizer_type='adamw')
```

Loading BERT model and training

```
In [21]: classifier_model.compile(optimizer=optimizer,
                                loss=loss,
                                metrics=metrics)
```

```
In [22]: print(f'Training model with {tfhub_handle_encoder}')
         history = classifier_model.fit(x=train_ds,
```



```
validation_data=val_ds,
epochs=epochs)
```

Training model with [https://tfhub.dev/tensorflow/small\\_bert/bert\\_en\\_uncased\\_L-4\\_H-512\\_A-8/1](https://tfhub.dev/tensorflow/small_bert/bert_en_uncased_L-4_H-512_A-8/1)

Epoch 1/5

31/31 [=====] - 22s 471ms/step - loss: 0.4728 - binary\_accuracy: 0.6542 - val\_loss: 0.2743 - val\_binary\_accuracy: 0.9150

Epoch 2/5

31/31 [=====] - 14s 442ms/step - loss: 0.3257 - binary\_accuracy: 0.8911 - val\_loss: 0.2535 - val\_binary\_accuracy: 0.9231

Epoch 3/5

31/31 [=====] - 14s 443ms/step - loss: 0.3018 - binary\_accuracy: 0.8985 - val\_loss: 0.2684 - val\_binary\_accuracy: 0.9069

Epoch 4/5

31/31 [=====] - 14s 445ms/step - loss: 0.2657 - binary\_accuracy: 0.8957 - val\_loss: 0.2605 - val\_binary\_accuracy: 0.9150

Epoch 5/5

31/31 [=====] - 14s 445ms/step - loss: 0.2476 - binary\_accuracy: 0.9030 - val\_loss: 0.2491 - val\_binary\_accuracy: 0.9352

Evaluating model

```
In [23]: loss, accuracy = classifier_model.evaluate(test_ds)
```

```
print(f'Loss: {loss}')
print(f'Accuracy: {accuracy}')
```

10/10 [=====] - 2s 168ms/step - loss: 0.2824 - binary\_accuracy: 0.8961

Loss: 0.2824189066886902

Accuracy: 0.8961039185523987

Plotting accuracy, loss over time:

```
In [24]: history_dict = history.history
print(history_dict.keys())

acc = history_dict['binary_accuracy']
val_acc = history_dict['val_binary_accuracy']
loss = history_dict['loss']
val_loss = history_dict['val_loss']

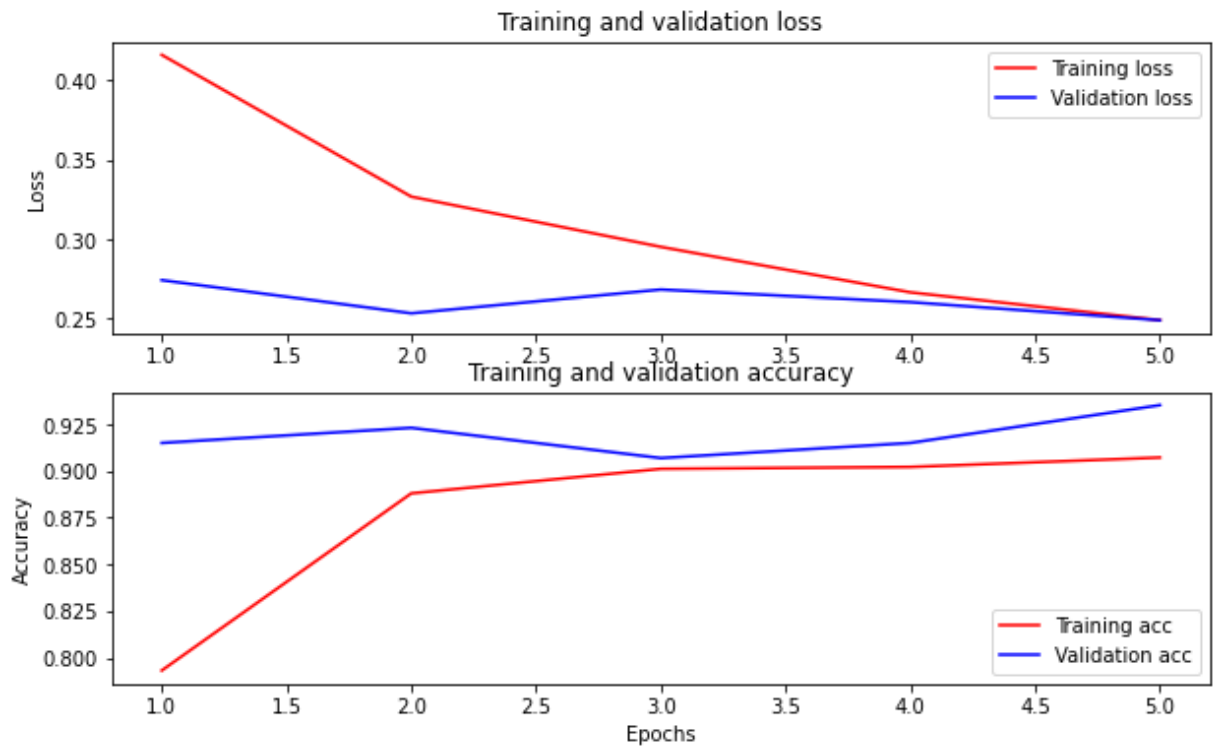
epochs = range(1, len(acc) + 1)
fig = plt.figure(figsize=(10, 6))
fig.tight_layout()

plt.subplot(2, 1, 1)
# "bo" is for "blue dot"
plt.plot(epochs, loss, 'r', label='Training loss')
# b is for "solid blue line"
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
# plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.subplot(2, 1, 2)
plt.plot(epochs, acc, 'r', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
```

```
dict_keys(['loss', 'binary_accuracy', 'val_loss', 'val_binary_accuracy'])
```

```
Out[24]: <matplotlib.legend.Legend at 0x7f97af55bed0>
```



```
In [34]: # testing:
examples = ["Was looking for that. Thanks. Speaking of that, recent lksctp-tools \
got some defines to help knowing which features the available kernel headers \
have as it now probes if specific struct members are available or not. \
Though yeah, it also wouldn't help in this case, just mentioning it.", \
"Sorry but I don't like imposing a run-time check on everybody \
when stack-based requests are the odd ones out. If we're going to make \
this a run-time check (I'd much prefer a compile-time check, but I \
understand that this may involve too much churn), then please do it \
for stack-based request users only.", "And I was just reminded about huge \
pages. But still, my point of finding a compromise still stands.", \
"Since when is the cover letter \
mandatory? I understand that is helps for a complicated patch set \
to explain the problem and solution in the cover letter, but for this \
simple test case addition what's the point? And there is nothing \
forcing a cover letter in", "I'm not exactly sure how Linux switch driver \
works, but from DT perspective I think we should rather have \
*hardware* described instead of a common Linux case. If I'm right, \
we should rather have all 3 switch ports described (5, 7,8) and have \
Linux just use the one it needs."]
# technical, non-technical, technical, non-technical, technical

def print_results(inputs, results):
    for i in range(len(inputs)):
        prediction = "Non-technical"
        if results[i][0]>=0.5:
            prediction = "Technical"
        print("Input:", inputs[i], "\nScore:", results[i][0], "\nPrediction:", prediction)

results = tf.sigmoid(classifier_model(tf.constant(examples)))
print_results(examples, results)
```

Input: Was looking for that. Thanks. Speaking of that, recent lksctp-tools got some defines to help knowing which features the available kernel headers have as it now probes if specific struct members are available or not. Though yeah, it also wouldn't help in this case, just mentioning it.

Score: tf.Tensor(0.9106656, shape=(), dtype=float32)

Prediction: Technical

Input: Sorry but I don't like imposing a run-time check on everybody when stack-based requests are the odd ones out. If we're going to make this a run-time check (I'd much prefer a compile-time check, but I understand that this may involve too much ch

urn), then please do it for stack-based request users only.

Score: tf.Tensor(0.7932073, shape=(), dtype=float32)

Prediction: Technical

Input: And I was just reminded about huge pages. But still, my point of finding a compromise still stands.

Score: tf.Tensor(0.89355475, shape=(), dtype=float32)

Prediction: Technical

Input: Since when is the cover letter mandatory? I understand that it helps for a complicated patch set to explain the problem and solution in the cover letter, but for this simple test case addition what's the point? And there is nothing forcing a cover letter in

Score: tf.Tensor(0.8910215, shape=(), dtype=float32)

Prediction: Technical

Input: I'm not exactly sure how Linux switch driver works, but from DT perspective I think we should rather have \*hardware\* described instead of a common Linux case. If I'm right, we should rather have all 3 switch ports described (5, 7,8) and have Linux just use the one it needs.

Score: tf.Tensor(0.96671313, shape=(), dtype=float32)

Prediction: Technical