sentimentmodel

April 26, 2023

[ ]:
```
!pip install emoji
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting emoji
  Downloading emoji-2.2.0.tar.gz (240 kB)
                          240.9/240.9

kB 4.4 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
Building wheels for collected packages: emoji
  Building wheel for emoji (setup.py) … done
  Created wheel for emoji: filename=emoji-2.2.0-py3-none-any.whl size=234926
sha256=18d4446f4a859d5d3f0238bed09923c84d703899ea67038af68f80095832c9d6
  Stored in directory: /root/.cache/pip/wheels/9a/b8/0f/f580817231cbf59f6ade9fd1
32ff60ada1de9f7dc85521f857
Successfully built emoji
Installing collected packages: emoji
Successfully installed emoji-2.2.0
```

[ ]:
```
!pip install h5py
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: h5py in /usr/local/lib/python3.9/dist-packages
(3.8.0)
Requirement already satisfied: numpy>=1.14.5 in /usr/local/lib/python3.9/dist-
packages (from h5py) (1.22.4)
```

[ ]:
```
import pandas as pd
import numpy as np
from keras.utils import to_categorical
from keras import models
from keras import layers
from keras.models import Sequential
from keras.optimizers import RMSprop,Adam
import tensorflow as tf
from sklearn.model_selection import train_test_split
```

```python
from keras import regularizers
from keras import backend as K
from keras.callbacks import ModelCheckpoint
import keras
import matplotlib.pyplot as plt
import re
import emoji
import pandas as pd
from itertools import groupby
from nltk.corpus import stopwords
import os
from keras.preprocessing.text import Tokenizer
from keras.utils import pad_sequences
```

[ ]:
```python
"""
Twitch tokenizer. As a code basis the NLTK TwitterTokenizer and the NLTK mark_negation()-method were used.
The basic logic is this:

1. Replace instances of type url, numbers, usernames, chatbot commands, mails with tags.

2. Tokenize text considering e.g. words, various emoticons and twitch emotes.

3. Lowercase tokens except of emoticons and tags.

4. Shortening: normalizing of words with chacters occuring more than twice in succession e.g. "loooooove" -> "loove"

5. "_NEG"-Tagging for negated words (see "mark_negation()" impl. for details)

6. Remove all non-alphabetical characters, keep line emoticons, unicode-emoji & emotes

"""

#pattern to match emoticons.
EMOTICONS = r"""
    (?:
      [<>3Oo0|]?
      [:;=8Xx%]                     # eyes
      [']?                        # optional tear
      [\-o\*\']?                 # optional nose
      [\)\]\(\[dDpP/\:\}\{@\|\\X><c3$LSÞ] # mouth
      |
      [\)\]\(\[dDpP/\:\}\{@\|\\X><c3$LSÞ] # mouth
      [\-o\*\']?                 # optional nose
```

```
      [']?                             # optional tear
      [:;=8Xx%]                          # eyes
      [<>OoO|]?
      |<3|<\/3|<\\3
      |
     \( °   °\)                   # lenny face
    |
    ¯\\_\( \)_/¯                     # meh
      |
      >_>|<_<
      |
      @};-|@}->--|@}-;-|@>-->--     #rose
      |
      O_O|o\-o|O_o|o_O|o_o|O\-O     #schock
      |
      >.<|v.v|>>|<<
      |
      \(>_<\)|\^\^|\^_\^|\(-__-\)|\(-_-\)|\(/  \)/|\(\^o\^\)
      |\('_'\)|\(/_;\)|\(T_T\)|\(;_;\)|\(=\^·\^=\)|\(\*_\*\)|\(\+_\+\)|\(@_@\)
      |\(  •̀_•́\)
    )"""

#pattern to match urls.
URL = r"(?:http(s)?:\/\/)?[\w.-]+(?:\.[\w\.-]+)+[\w\-\._~:/?#[\]@!\$&'\(\)\*\+,;
↪=.]+"

# The components of the tokenizer:
REGEXPS = (
    # ASCII Emoticons
    EMOTICONS
    ,
    # HTML tags:
    r"""<[^>\s]+>"""
    ,
    # ASCII Arrows
    r"""[\-]+>|<[\-]+"""
    ,
    # Twitter like hashtags:
    r"""(?:\#+[\w_]+[\w\'_\-]*[\w_]+)"""
    ,
    # Remaining word types:
    r"""
    #(?:[^\W\d_](?:[^\W\d_]|['\-_])+[^\W\d_]) # Words with apostrophes or␣
↪dashes.
        (?:[^\W_](?:[^\W\d_]|['\-_\d])+[^\W_]) # Words with apostrophes or␣
↪dashes. (modified)
    |
```

```
    (?:[+\-]?\d+[,/.:-]\d+[+\-]?)  # Numbers, including fractions, decimals.
    |
    (?:[\w_]+)                     # Words without apostrophes or dashes.
    |
    (?:\.(?:\s*\.){1,})            # Ellipsis dots.
    |
    (?:\S)                         # Everything else that isn't whitespace.
    """
    )

# Regular expression for negation by Christopher Potts
NEGATION = r"""
    (?:
        ^(?:never|no|nothing|nowhere|noone|none|not|
            havent|hasnt|hadnt|cant|couldnt|shouldnt|
            wont|wouldnt|dont|doesnt|didnt|isnt|arent|aint
        )$
    )
    |
    n't"""

URL_RE = re.compile(URL)
NUM = re.compile("(?<=^|(?<=\s)|(?<=\())#{,1}\d{1,}(?=$|(?=\s)|(?=\)))")
USERNAME = re.compile("(?<=^|(?<=\s))@\w+(?=$|(?=\s))")
COMMAND = re.compile("(?<=^|(?<=\s))!#?[a-zA-Z]+(?=$|(?=\s))")
MAIL = re.compile("[\w.+-]+@[\w-]+\.(?:[\w-]\.?)+[\w-]")

SHORTENING_OF =  re.compile("(.)\\1{2,}")

# pattern to find punctuation
CLAUSE_PUNCT = r'^[.:;!?]$'

# pattern to find non alphabetical chars
NON_ALPHABETICAL = re.compile('[^A-Za-z ]')

# create lexicon of stoppwords
#en_stopwords = set(stopwords.words('english'))
#en_stopwords.add("i'm")
#en_stopwords.add("i've")
#en_stopwords.add("can't")
#stripped_stopwords = [word.replace("'", "") for word in en_stopwords]  # add␣
 ↪stopwords without apostrophes
#negated_stopwords = [word+"_NEG" for word in en_stopwords] # add negated␣
 ↪stopwords
#[en_stopwords.add(word) for word in stripped_stopwords if word not in␣
 ↪en_stopwords]
#[en_stopwords.add(word) for word in negated_stopwords]
```

```python
# create lexicon of emoji
emoji_lexicon = emoji.EMOJI_DATA

######################################################################
# This is the core tokenizing regex:

WORD_RE = re.compile(r"""(%s)""" % "|".join(REGEXPS), re.VERBOSE | re.I
                     | re.UNICODE)

# WORD_RE performs poorly on these patterns:
HANG_RE = re.compile(r'([^a-zA-Z0-9])\1{3,}')

# The emoticon string gets its own regex so that we can preserve case for
# them as needed:
EMOTICON_RE = re.compile(EMOTICONS, re.VERBOSE | re.I | re.UNICODE)

# These are for regularizing HTML entities to Unicode:
ENT_RE = re.compile(r'&(#?(x?))([^&;\s]+);')

#negation and punctuation matching patterns
NEGATION_RE = re.compile(NEGATION, re.VERBOSE)
CLAUSE_PUNCT_RE = re.compile(CLAUSE_PUNCT)
######################################################################
# Functions for converting html entities
######################################################################

def load_labeled_emotes():
    emotes = set(pd.read_table("/content/drive/MyDrive/textanalytics/Project/
 ↪emote-controlled/lexica/emote_average.tsv")["word"])
    return emotes

######################################################################

class TwitchTokenizer:

    def __init__(self, preserve_case=True):
        self.preserve_case = preserve_case
        self.emotes = load_labeled_emotes()

    def tokenize(self, text):
        """
        :param text: str
        :rtype: list(str)
        :return: a tokenized list of strings; concatenating this list returns\
        the original string if `preserve_case=False`
        """
```

```python
        text = URL_RE.sub("URL", text)

        # Shorten problematic sequences of characters
        safe_text = HANG_RE.sub(r'\1\1\1', text)
        # Tokenize:
        words = WORD_RE.findall(safe_text)
        # Possibly alter the case, but avoid changing emoticons like :D into :d:
        if not self.preserve_case:
            words = list(map((lambda x : x if EMOTICON_RE.search(x) else
                              x.lower()), words))
        token_list = []
        for word in words:
            if word not in self.emotes and not re.match(EMOTICON_RE,word):
                if word not in ["URL", "NUM", "USERNAME", "COMMAND","MAIL"]: #␣
↪do not lowercase tags
                    word = word.lower()
                # shortening: normalizing of words with chacters occuring more␣
↪than twice in succession e.g. "loooooove" -> "loove"
                word = re.sub(SHORTENING_OF, r'\\1\\1', word)
            token_list.append(word)

        # remove all non-alphabetical characters, keep line emoticons,␣
↪unicode-emoji & emotes
        def keep_token(token):
            if re.match(NON_ALPHABETICAL,token) and not re.
↪match(EMOTICON_RE,token) and token not in self.emotes \
            and token not in emoji_lexicon:
                return False
            else:
                return True

        return token_list
```

[ ]:
```python
from nltk.tokenize.treebank import TreebankWordDetokenizer
def detokenize(text):
    return TreebankWordDetokenizer().detokenize(text)
```

cleaning text because out of nowhere the csv is full of semicolumns

[ ]:
```python
def preprocessdataframe(path):
  df = pd.read_csv(path)

  df = df[df['sentiment'] != "sentiment"]
  df = df.reset_index(drop=True)

  df = df[df['comment'] != "comment"]
  df = df.reset_index(drop=True)
```

```
  df = df.dropna()
  df.comment = df.comment.str.lower()

  tokenizer = TwitchTokenizer()
  df.comment = df.comment.apply(tokenizer.tokenize)

  df.comment = df.comment.apply(detokenize)

  return df
```

[ ]:
```
path = "/content/drive/MyDrive/textanalytics/Project/dataset/
 ↪labeled_dataset_augmented.csv"
df = preprocessdataframe(path)
#remove this comment to work on the entire dataset
#df = df.sample(frac=0.3, axis=0)
print(len(df))
```

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Handling sentiment label

[ ]:
```
labels = np.array(df['sentiment'])
y = []
for i in range(len(labels)):
    if labels[i] == -1:
        y.append(0)
    if labels[i] == 0:
        y.append(1)
    if labels[i] == 1:
        y.append(2)

y = np.array(y)
labels = tf.keras.utils.to_categorical(labels, 3, dtype="float32")
del y
# [neutral, positive, negative]
```

Vectorizing the dataset

[ ]:
```
df = df.comment.to_numpy()
max_words = 5000
max_len = 100

tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(df)
sequences = tokenizer.texts_to_sequences(df)
comments = pad_sequences(sequences, maxlen=max_len)
```

Create the embedding layer

```
[ ]: from keras.layers import Embedding
     embedding_layer = Embedding(1000, 64)
```

Splitting the dataset into train and test

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(comments,labels,␣
      ↪random_state=0)
     print (len(X_train),len(X_test),len(y_train),len(y_test))
```

```
83107 27703 83107 27703
```

Model 1 - LSTM

```
[ ]: model1 = Sequential()
     model1.add(layers.Embedding(max_words, 20))
     model1.add(layers.LSTM(15,dropout=0.5))
     model1.add(layers.Dense(3,activation='softmax'))

     model1.compile(optimizer='adam',loss='categorical_crossentropy',␣
      ↪metrics=['accuracy'])
     #Implementing model checkpoins to save the best metric and do not lose it on␣
      ↪training.
     checkpoint1 = ModelCheckpoint("best_model1_verAdam_tenepoch_2.hdf5",␣
      ↪monitor='val_accuracy', verbose=1,save_best_only=True,␣
      ↪mode='auto',save_weights_only=False)
     history = model1.fit(X_train, y_train, epochs=10,validation_data=(X_test,␣
      ↪y_test),callbacks=[checkpoint1])
```

```
Epoch 1/10
2597/2598 [============================>.] - ETA: 0s - loss: 0.3564 - accuracy:
0.8779
Epoch 1: val_accuracy improved from -inf to 0.92633, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 177s 67ms/step - loss: 0.3564 -
accuracy: 0.8779 - val_loss: 0.2301 - val_accuracy: 0.9263
Epoch 2/10
2597/2598 [============================>.] - ETA: 0s - loss: 0.2148 - accuracy:
0.9338
Epoch 2: val_accuracy improved from 0.92633 to 0.94062, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 162s 62ms/step - loss: 0.2148 -
accuracy: 0.9338 - val_loss: 0.2004 - val_accuracy: 0.9406
Epoch 3/10
2598/2598 [==============================] - ETA: 0s - loss: 0.1956 - accuracy:
0.9399
Epoch 3: val_accuracy improved from 0.94062 to 0.94192, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 154s 59ms/step - loss: 0.1956 -
```

```
accuracy: 0.9399 - val_loss: 0.1906 - val_accuracy: 0.9419
Epoch 4/10
2597/2598 [============================>.] - ETA: 0s - loss: 0.1829 - accuracy:
0.9429
Epoch 4: val_accuracy improved from 0.94192 to 0.94419, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 153s 59ms/step - loss: 0.1829 -
accuracy: 0.9429 - val_loss: 0.1842 - val_accuracy: 0.9442
Epoch 5/10
2597/2598 [============================>.] - ETA: 0s - loss: 0.1721 - accuracy:
0.9469
Epoch 5: val_accuracy improved from 0.94419 to 0.94780, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 150s 58ms/step - loss: 0.1721 -
accuracy: 0.9469 - val_loss: 0.1793 - val_accuracy: 0.9478
Epoch 6/10
2597/2598 [============================>.] - ETA: 0s - loss: 0.1698 - accuracy:
0.9482
Epoch 6: val_accuracy improved from 0.94780 to 0.94910, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 155s 60ms/step - loss: 0.1698 -
accuracy: 0.9482 - val_loss: 0.1795 - val_accuracy: 0.9491
Epoch 7/10
2597/2598 [============================>.] - ETA: 0s - loss: 0.1628 - accuracy:
0.9506
Epoch 7: val_accuracy did not improve from 0.94910
2598/2598 [==============================] - 153s 59ms/step - loss: 0.1628 -
accuracy: 0.9506 - val_loss: 0.1781 - val_accuracy: 0.9489
Epoch 8/10
2597/2598 [============================>.] - ETA: 0s - loss: 0.1585 - accuracy:
0.9519
Epoch 8: val_accuracy improved from 0.94910 to 0.94979, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 151s 58ms/step - loss: 0.1585 -
accuracy: 0.9519 - val_loss: 0.1776 - val_accuracy: 0.9498
Epoch 9/10
2598/2598 [==============================] - ETA: 0s - loss: 0.1564 - accuracy:
0.9530
Epoch 9: val_accuracy improved from 0.94979 to 0.95004, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 155s 60ms/step - loss: 0.1564 -
accuracy: 0.9530 - val_loss: 0.1758 - val_accuracy: 0.9500
Epoch 10/10
2598/2598 [==============================] - ETA: 0s - loss: 0.1541 - accuracy:
0.9534
Epoch 10: val_accuracy improved from 0.95004 to 0.95037, saving model to
best_model1_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 164s 63ms/step - loss: 0.1541 -
```

accuracy: 0.9534 - val_loss: 0.1751 - val_accuracy: 0.9504

Model 2 - BiLSTM

[ ]:
```
model2 = Sequential()
model2.add(layers.Embedding(max_words, 40, input_length=max_len))
model2.add(layers.Bidirectional(layers.LSTM(20,dropout=0.6)))
model2.add(layers.Dense(3,activation='softmax'))
model2.compile(optimizer='adam',loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])
#Implementing model checkpoins to save the best metric and do not lose it on␣
 ↪training.
checkpoint2 = ModelCheckpoint("best_model2_verAdam_tenepoch_2.hdf5",␣
 ↪monitor='val_accuracy', verbose=1,save_best_only=True,␣
 ↪mode='auto',save_weights_only=False)
history = model2.fit(X_train, y_train, epochs=5,validation_data=(X_test,␣
 ↪y_test),callbacks=[checkpoint2])
```

```
Epoch 1/5
2598/2598 [==============================] - ETA: 0s - loss: 0.3286 - accuracy:
0.8911
Epoch 1: val_accuracy improved from -inf to 0.93618, saving model to
best_model2_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 280s 106ms/step - loss: 0.3286 -
accuracy: 0.8911 - val_loss: 0.2133 - val_accuracy: 0.9362
Epoch 2/5
2598/2598 [==============================] - ETA: 0s - loss: 0.2080 - accuracy:
0.9351
Epoch 2: val_accuracy improved from 0.93618 to 0.94232, saving model to
best_model2_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 278s 107ms/step - loss: 0.2080 -
accuracy: 0.9351 - val_loss: 0.1890 - val_accuracy: 0.9423
Epoch 3/5
2598/2598 [==============================] - ETA: 0s - loss: 0.1826 - accuracy:
0.9436
Epoch 3: val_accuracy improved from 0.94232 to 0.94618, saving model to
best_model2_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 278s 107ms/step - loss: 0.1826 -
accuracy: 0.9436 - val_loss: 0.1826 - val_accuracy: 0.9462
Epoch 4/5
2598/2598 [==============================] - ETA: 0s - loss: 0.1717 - accuracy:
0.9477
Epoch 4: val_accuracy improved from 0.94618 to 0.94802, saving model to
best_model2_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 276s 106ms/step - loss: 0.1717 -
accuracy: 0.9477 - val_loss: 0.1788 - val_accuracy: 0.9480
Epoch 5/5
2598/2598 [==============================] - ETA: 0s - loss: 0.1631 - accuracy:
```

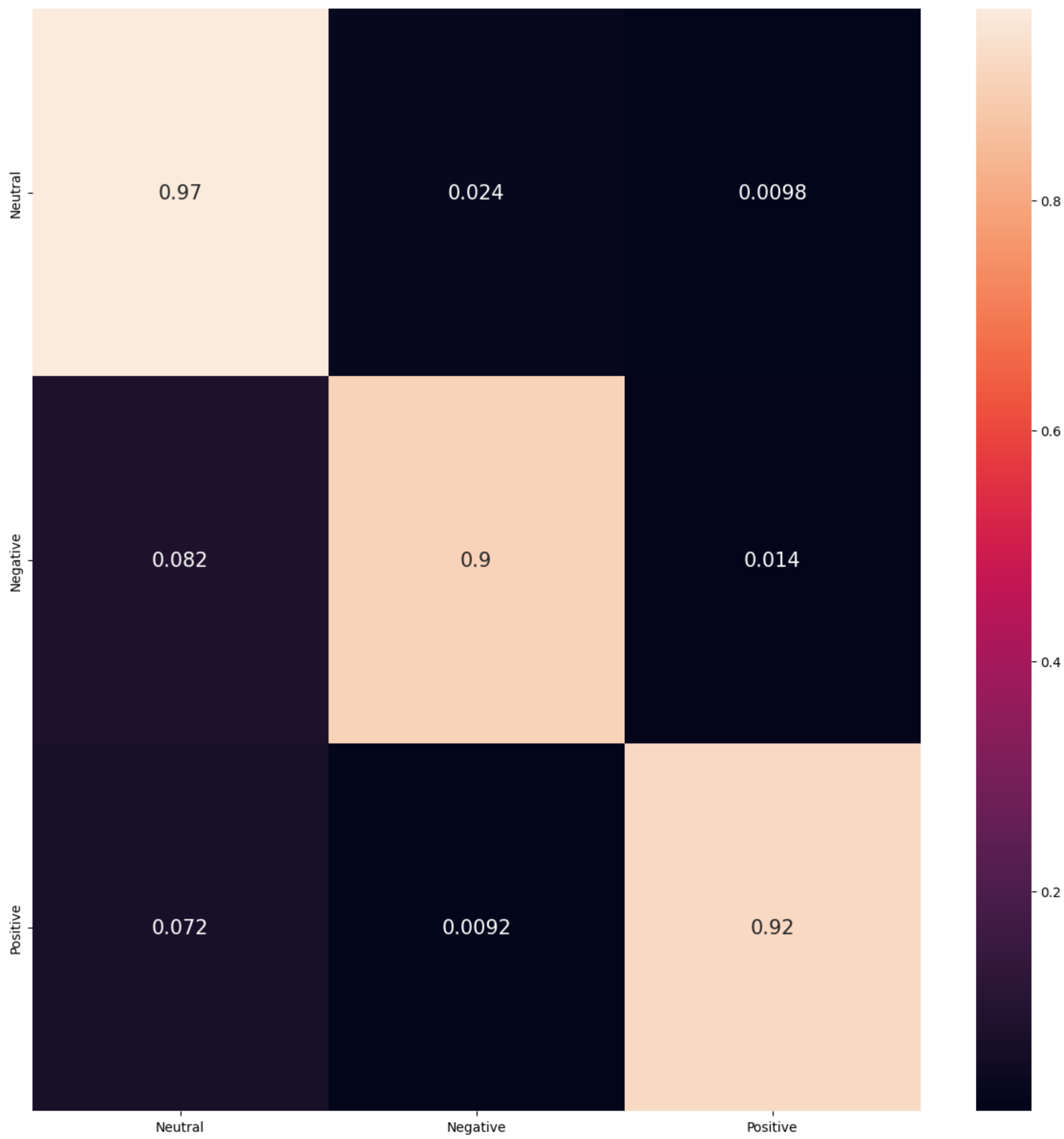
```
0.9508
Epoch 5: val_accuracy improved from 0.94802 to 0.94845, saving model to
best_model2_verAdam_tenepoch_2.hdf5
2598/2598 [==============================] - 272s 105ms/step - loss: 0.1631 -
accuracy: 0.9508 - val_loss: 0.1736 - val_accuracy: 0.9485
```

[ ]:

```
best_model = keras.models.load_model("/content/drive/MyDrive/textanalytics/
 ↪Project/best_model2_verAdam_tenepoch_2.hdf5")
test_loss, test_acc = best_model.evaluate(X_test, y_test, verbose=2)
print('Model accuracy: ',test_acc)
predictions = best_model.predict(X_test)
from sklearn.metrics import confusion_matrix
matrix = confusion_matrix(y_test.argmax(axis=1), np.around(predictions,␣
 ↪decimals=0).argmax(axis=1))
import seaborn as sns
conf_matrix = pd.DataFrame(matrix, index =␣
 ↪['Neutral','Negative','Positive'],columns =␣
 ↪['Neutral','Negative','Positive'])
#Normalizing
conf_matrix = conf_matrix.astype('float') / conf_matrix.sum(axis=1)[:, np.
 ↪newaxis]
plt.figure(figsize = (15,15))
img = sns.heatmap(conf_matrix, annot=True, annot_kws={"size": 15})
figure = img.get_figure()
```

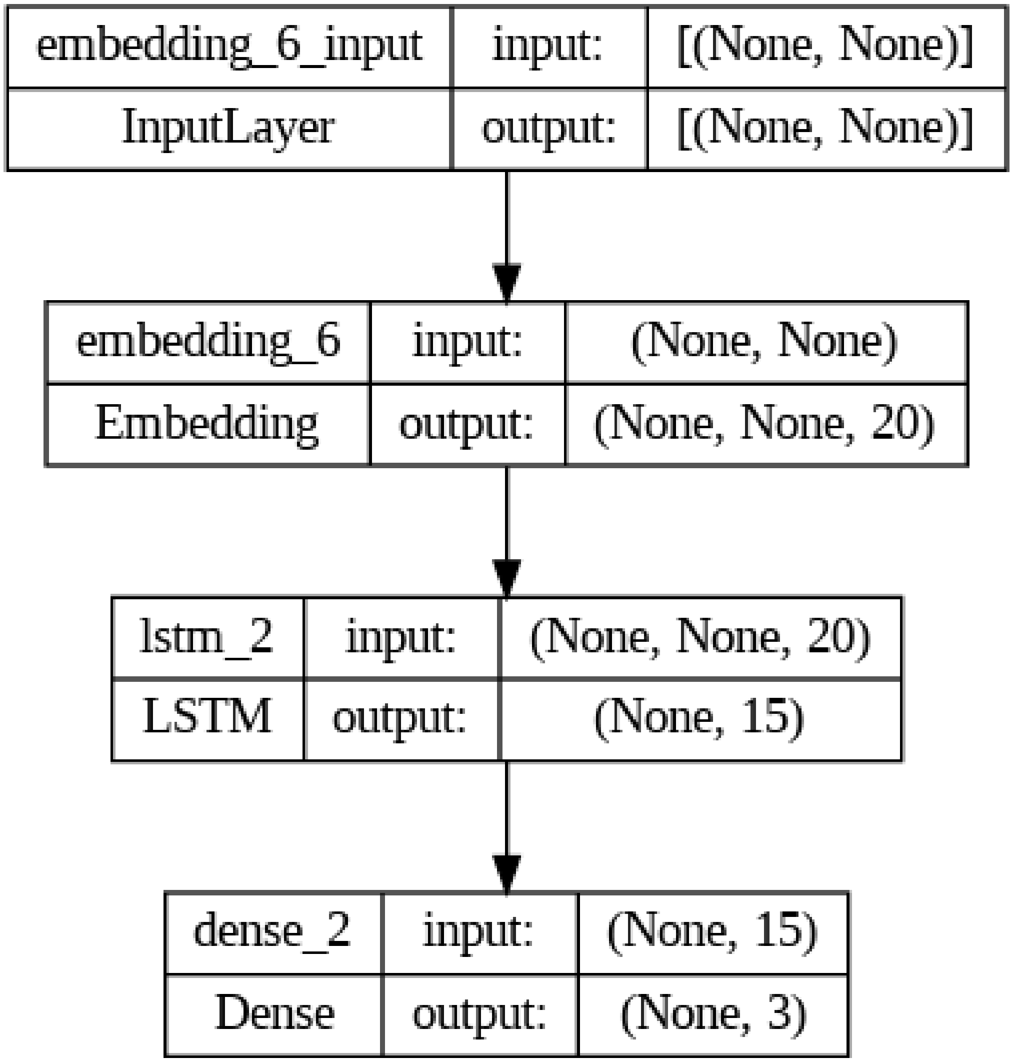
```
866/866 - 16s - loss: 0.1736 - accuracy: 0.9485 - 16s/epoch - 19ms/step
Model accuracy:  0.9484532475471497
866/866 [==============================] - 18s 20ms/step
```

```
<ipython-input-38-9fd87527aff6>:10: FutureWarning: Support for multi-dimensional
indexing (e.g. `obj[:, None]`) is deprecated and will be removed in a future
version.  Convert to a numpy array before indexing instead.
  conf_matrix = conf_matrix.astype('float') / conf_matrix.sum(axis=1)[:,
np.newaxis]
```

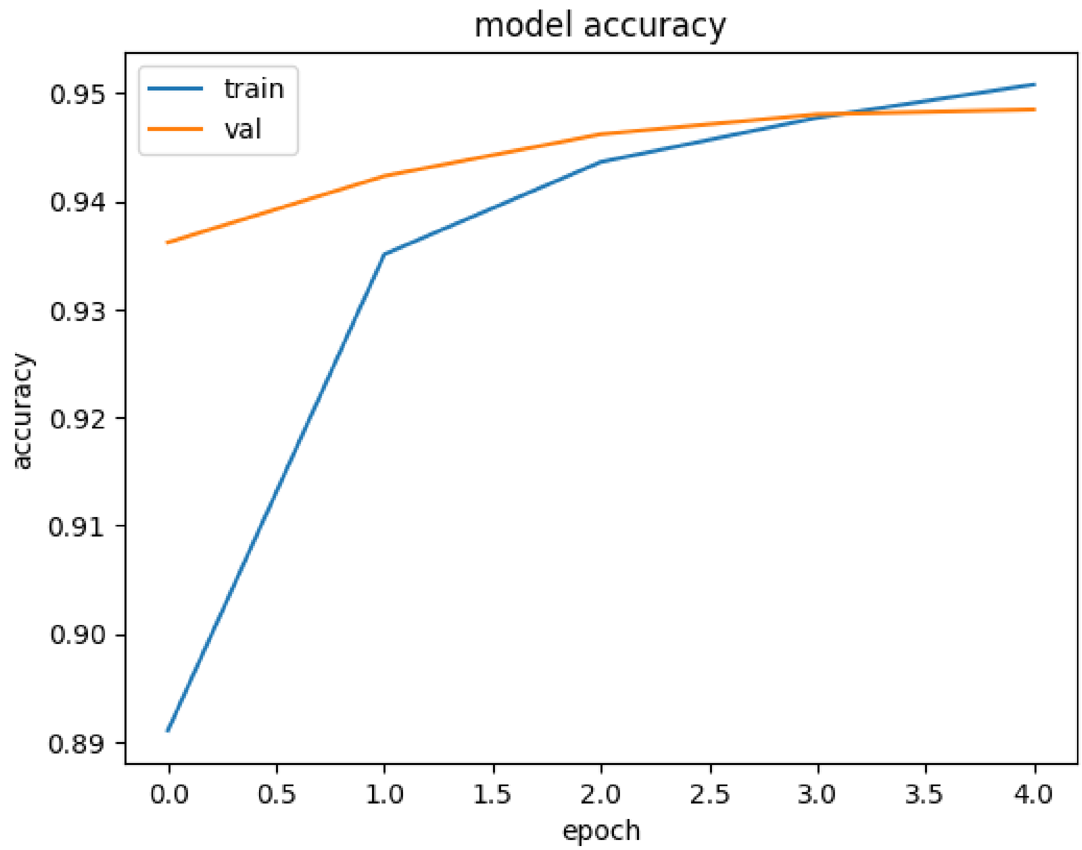


[ ]:
```
from keras.utils.vis_utils import plot_model
plot_model(best_model, to_file='/content/drive/MyDrive/textanalytics/Project/
 ↪model_plot_m1.png', show_shapes=True, show_layer_names=True)
```

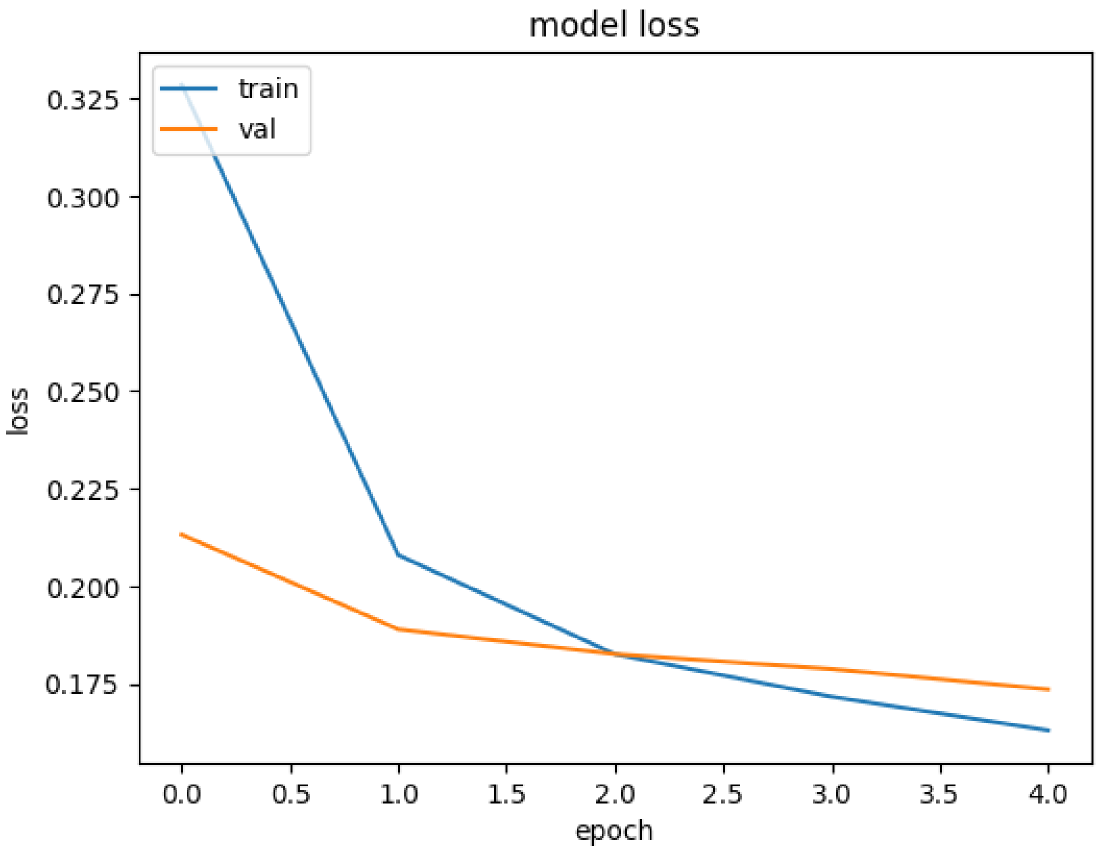
[ ]:



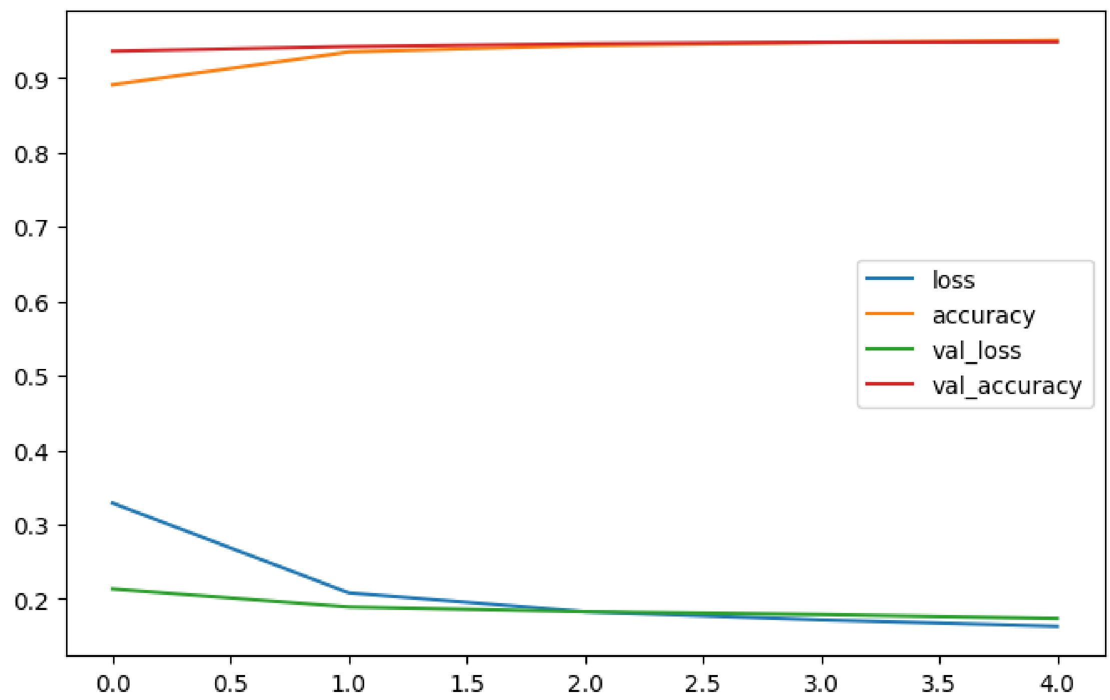
[ ]:
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.savefig("/content/drive/MyDrive/textanalytics/Project/acc_m2_ten_2.png")
plt.show()
```



[ ]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.savefig("/content/drive/MyDrive/textanalytics/Project/loss_m2_ten_2.png")
plt.show()
```



[ ]:
```
pd.DataFrame(history.history).plot(figsize=(8,5))
plt.savefig("/content/drive/MyDrive/textanalytics/Project/accloss_m2_ten_2.png")
plt.show()
```



let's predict the sentiment of a random twitch comment

[ ]:
```
sentiment = ["neutral", "positive", "negative"]
tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(df)
```

[ ]:
```
sequence = tokenizer.texts_to_sequences(['pepehands'])
test = pad_sequences(sequence, maxlen=max_len)
#print(np.around(best_model.predict(test), decimals=0).argmax(axis=1)[0])
sentiment[np.around(best_model.predict(test), decimals=0).argmax(axis=1)[0]]
```

```
1/1 [==============================] - 0s 45ms/step
```

[ ]: 'negative'

[ ]:
```
```