AADARSH KUMAR GUPTA · 2H AGO · 198 VIEWS

Milestone Neural Network

Python · Twitter Sentiment Analysis

Run
4172.9s

In [1]:
```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load


import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version u
sing "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/twitter-entity-sentiment-analysis/twitter_validation.csv
/kaggle/input/twitter-entity-sentiment-analysis/twitter_training.csv
```

In [2]:
```
# Import pandas
import pandas as pd

# Import training data
df_train = pd.read_csv('/kaggle/input/twitter-entity-sentiment-analysis/twitter_training.csv')

# Print few random entries
df_train.sample(5)
```

Out[2]:

	2401	Borderlands	Positive	im getting on borderlands and i will murder you all ,
24878	4672	Google	Neutral	"Can't say freely about what an marvelous expe...
29799	724	ApexLegends	Neutral	Ooooo la la der GGs insane wraith and mirage i...
59196	3347	Facebook	Irrelevant	All white Americans on my Facebook page compla...
42262	10050	PlayerUnknownsBattlegrounds(PUBG)	Positive	also just played pubg with someone yang cantik...
50586	6284	FIFA	Negative	Something is wrong with the settings

In [3]:
```
df_train.rename(columns={'2401': 'id', 'Borderlands': 'game','Positive':'sentiment','im getting on borderlands and i will murd
er you all ,':'text'}, inplace=True)
```

In [4]:
```
df_train.sample(5)
```

Out[4]:

	id	game	sentiment	text
50325	6239	FIFA	Negative	While I constantly hate restrictions, it's all...
1981	2748	Borderlands	Positive	Nice.
71828	11104	TomClancysGhostRecon	Negative	Hey RhandlerR, RhandlerR & RhandlerR - Am I go...
60723	4804	GrandTheftAuto(GTA)	Negative	Hahah some GTA for shit that
7078	9217	Overwatch	Negative	mm guess not ordered but recommended.. • NieR:...

EDA

In [5]:

```
# Checking the number of rows and columns
print("The DataFrame has " + str(df_train.shape[0]) + " samples and " + str(df_train.shape[1]) + " columns")
```

```
The DataFrame has 74681 samples and 4 columns
```

In [6]:

```
# Check duplicates
print("Duplicate entries in the dataset: " + str(df_train.duplicated().sum()))
```

```
Duplicate entries in the dataset: 2700
```

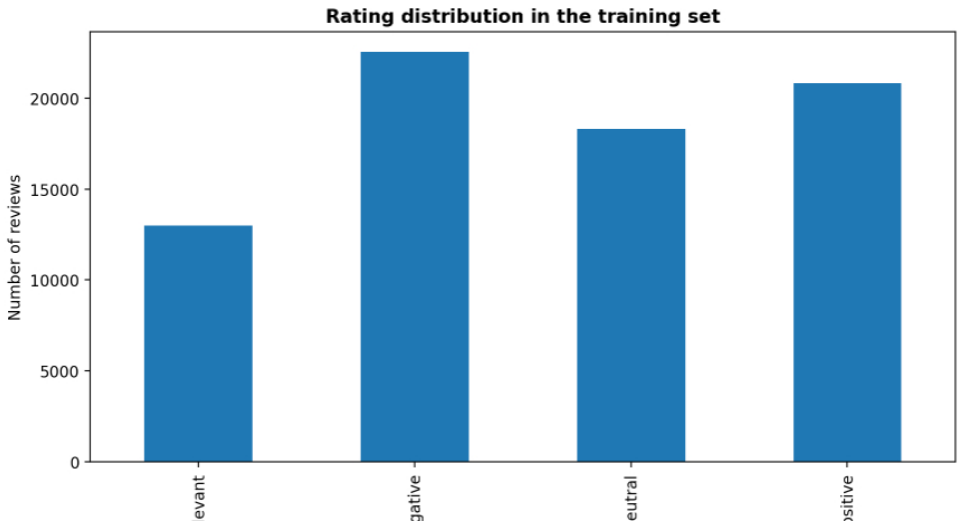
In [7]:

```
# Check null values and data type of each column
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74681 entries, 0 to 74680
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   id         74681 non-null  int64 
 1   game       74681 non-null  object
 2   sentiment  74681 non-null  object
 3   text       73995 non-null  object
dtypes: int64(1), object(3)
memory usage: 2.3+ MB
```

In [8]:

```
import matplotlib.pyplot as plt
%matplotlib inline
%config InlineBackend.figure_format = 'retina'

# Check target balance
df_train['sentiment'].value_counts().sort_index().plot.bar(figsize=(10,5))
plt.title('Rating distribution in the training set', fontweight="bold")
plt.xlabel('Target')
plt.ylabel('Number of reviews')
plt.show()
```



In [9]:
```
# Drop few columns
df_train = df_train.drop(['id'],axis=1)
```

In [10]:
```
import re
from nltk.corpus import stopwords

# Create a stopwords set adding some personal 'words'
stopwords_english = set(stopwords.words('english'))
my_stopwords = set(["http", "'s", "n't", "'m", "'re", "'ve"])
stopwords_english.update(my_stopwords)

def preprocess_review(text):
    # Convert to lower case
    text = text.lower()

    # Remove numbers
    text = re.sub(r'\d+', '', text)

    # Remove punctuation
    text = re.sub(r'[^\w\s]', '', text)

    # Split text into tokens
    tokens = text.split()

    # Filter tokens
    clean_tokens = [tok for tok in tokens if tok not in stopwords_english and len(tok) > 1]

    # Join tokens into a string
    clean_text = ' '.join(clean_tokens)

    return clean_text
```

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is requir
ed for this version of SciPy (detected version 1.23.5
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

There are multiple ways to clean text, including stemming and lemmatization. Although these techniques can enhance the outcome, they also slow down the function considerably, especially for larger datasets like this one. For instance, my previous function using these techniques took more than an hour to train the dataset, whereas the new solution takes a little over a minute. Therefore, I opted for a faster function even though it may result in slightly less accuracy.

Let's check it out:

In [11]:
```
# Get one review as sample
sample = df_train['text'][5]

print('ORIGINAL REVIEW:   ' + sample + '\n')
print('---------------------------------------------------------------------------- \n')
print('WITH PROCESSING:    ' + preprocess_review(sample))
```

```
ORIGINAL REVIEW:   So I spent a few hours making something for fun. . . If you don't know I am a HUGE @Borderlands fan and
Maya is one of my favorite characters. So I decided to make myself a wallpaper for my PC. . Here is the original image ver
sus the creation I made :) Enjoy! pic.twitter.com/mLsI5wf9Jg

----------------------------------------------------------------------------

WITH PROCESSING:    spent hours making something fun dont know huge borderlands fan maya one favorite characters decided m
ake wallpaper pc original image versus creation made enjoy pictwittercommlsiwfjg
```

In [12]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74681 entries, 0 to 74680
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype
```

```
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   game       74681 non-null  object
 1   sentiment  74681 non-null  object
 2   text       73995 non-null  object
dtypes: object(3)
memory usage: 1.7+ MB
```

In [13]:

```
df_train.dropna(subset=['text'],inplace=True)
```

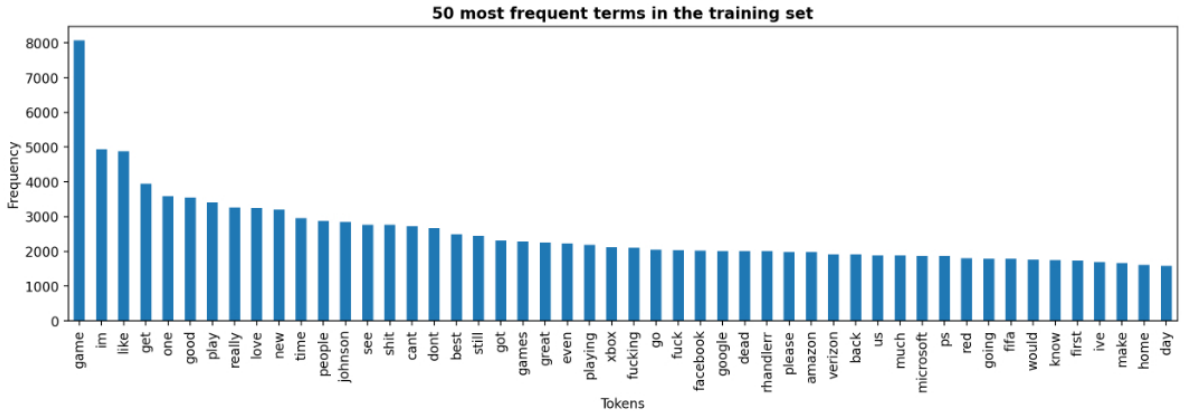
In [14]:

```
%%time

# Preprocess training data adding new column
df_train["clean_text"] = df_train["text"].apply(preprocess_review)
```

```
CPU times: user 1.61 s, sys: 10.4 ms, total: 1.62 s
Wall time: 1.62 s
```

In [15]:

```
# Get 50 most frequent words in the training set
frequent_words = pd.Series(' '.join(df_train.clean_text).split()).value_counts()[:50]
frequent_words.plot.bar(figsize=(15,4))
plt.title('50 most frequent terms in the training set', fontweight="bold")
plt.xlabel('Tokens')
plt.ylabel('Frequency')
plt.show()
```



In [16]:

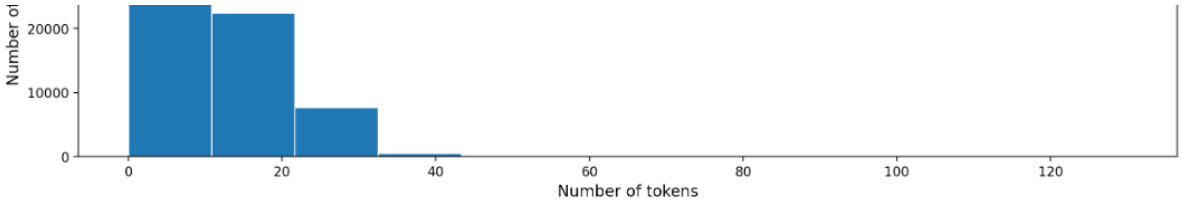
```
# I found that the variable 'frequent_words' takes up about 6 Gb of RAM! Better clean it up!
import gc

del frequent_words

gc.collect()
```

Out[16]:

```
10566
```

In [17]:

```
# Plot the number of tokens in cleaned reviews
plt.figure(figsize=(15,4))
plt.hist(df_train['clean_text'].apply(lambda x:len(x.split())), bins=12, edgecolor='white')
plt.xlabel('Number of tokens', fontsize=12)
plt.ylabel('Number of reviews',fontsize=12)
plt.title('Distribution of token counts in reviews', fontsize=14)
plt.show()
```



In [18]:

```
# Filter rows with less than 250 tokens
less_than_250 = df_train['clean_text'].apply(lambda x: len(x.split())) < 250  # Check by getting True and False values

# Print percentage
print(f"{(sum(less_than_250) / len(df_train) * 100):.2f}% of rows have less than 250 tokens.")
```

```
100.00% of rows have less than 250 tokens.
```

In [19]:

```
# Remove original text column
df_train = df_train.drop(columns=['text'])
# Get few entries to check operation
df_train.head()
```

Out[19]:

	game	sentiment	clean_text
0	Borderlands	Positive	coming borders kill
1	Borderlands	Positive	im getting borderlands kill
2	Borderlands	Positive	im coming borderlands murder
3	Borderlands	Positive	im getting borderlands murder
4	Borderlands	Positive	im getting borderlands murder

Test Set

Importing and processing the text data as did in the training set

In [20]:

```
# Import training data
df_test = pd.read_csv('/kaggle/input/twitter-entity-sentiment-analysis/twitter_validation.csv')

# Print a random row
df_test.sample()
```

Out[20]:

	3364	Facebook	Irrelevant	I mentioned on Facebook that I was struggling for motivation to go for a run the other day, which has been translated by Tom's great auntie as 'Hayley can't get out of bed' and told to his grandma, who now thinks I'm a lazy, terrible person 🤣
716	7366	LeagueOfLegends	Negative	the implication that seraphine has witnessed j...

In [21]:

```
df_test.rename(columns={'3364': 'id', 'Facebook': 'game','Irrelevant':'sentiment','I mentioned on Facebook that I was struggli
ng for motivation to go for a run the other day, which has been translated by Tom's great auntie as 'Hayley can't get out of b
ed' and told to his grandma, who now thinks I'm a lazy, terrible person 🤣':'text'}, inplace=True)
```

In [22]:

```
%%time

# Remove unceccessary columns
df_test = df_test.drop(['id'],axis=1)

# Preprocess training data adding new column
df_test["clean_text"] = df_test["text"].apply(preprocess_review)

# Remove original text column
df_test = df_test.drop(columns=['text'])

# Get few entries to check cleaning operation
df_test.head()
```

```
CPU times: user 30.4 ms, sys: 1.78 ms, total: 32.1 ms
Wall time: 31.7 ms
```

Out[22]:

	game	sentiment	clean_text
0	Amazon	Neutral	bbc news amazon boss jeff bezos rejects claims...
1	Microsoft	Negative	microsoft pay word functions poorly samsungus ...
2	CS-GO	Negative	csgo matchmaking full closet hacking truly awf...
3	Google	Neutral	president slapping americans face really commi...
4	FIFA	Negative	hi eahelp ive madeleine mccann cellar past yea...

In [23]:

```
#Label_encoding For sentimens.
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
df_train['sentiment']=label_encoder.fit_transform(df_train['sentiment'])
df_test['sentiment']=label_encoder.fit_transform(df_test['sentiment'])
```

Split the data

In [24]:

```
# Create X, y arrays
from sklearn.model_selection import train_test_split

# Training data
X_train = df_train["clean_text"].values
y_train = df_train["sentiment"].values

# Split into train/test sets
X_tr, X_va, y_tr, y_va = train_test_split(X_train, y_train, test_size=0.2, random_state=0)

# Test data
X_te = df_test["clean_text"].values

print("Training data:", X_tr.shape, y_tr.shape)
print("Validation data:", X_va.shape, y_va.shape)
print("Test data:", X_te.shape)
```

```
Training data: (59196,) (59196,)
Validation data: (14799,) (14799,)
Test data: (999,)
```

Model Part

Given the dataset's size and my preference for using a Neural Network model, it's certainly worthwhile to employ an accelerator. Below are the default setup settings for enabling the TPU (Tensor Processing Unit).

In [25]:

```
import warnings
warnings.filterwarnings("ignore")

import tensorflow as tf

try:
    tpu = tf.distribute.cluster_resolver.TPUClusterResolver()
    tf.config.experimental_connect_to_cluster(tpu)
    tf.tpu.experimental.initialize_tpu_system(tpu)

    strategy = tf.distribute.experimental.TPUStrategy
except ValueError:
    strategy = tf.distribute.get_strategy()
    print('Number of replicas:', strategy.num_replicas_in_sync)
```

```
Number of replicas: 1
```

In [26]:

```
try:
    tpu = tf.distribute.cluster_resolver.TPUClusterResolver() # TPU detection
except ValueError:
```

```
except ValueError:
    tpu = None
    gpus = tf.config.experimental.list_logical_devices("GPU")

if tpu:
    tf.tpu.experimental.initialize_tpu_system(tpu)
    strategy = tf.distribute.experimental.TPUStrategy(tpu,)
    print('Running on TPU ', tpu.cluster_spec().as_dict()['worker'])
elif len(gpus) > 1:
    strategy = tf.distribute.MirroredStrategy([gpu.name for gpu in gpus])
    print('Running on multiple GPUs ', [gpu.name for gpu in gpus])
elif len(gpus) == 1:
    strategy = tf.distribute.get_strategy()
    print('Running on single GPU ', gpus[0].name)
else:
    strategy = tf.distribute.get_strategy()
    print('Running on CPU')
print("Number of accelerators: ", strategy.num_replicas_in_sync)
```

```
Running on CPU
Number of accelerators:  1
```

Now, this code uses the Keras module from TensorFlow to preprocess text data. Specifically, it uses the 'Tokenizer' function to convert the text into a sequence of integers, and the 'pad_sequences' function to ensure that each sequence has the same length.

In [27]:

```
%%time

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Tokenize and pad the sequences
tokenizer = Tokenizer(num_words=20000)
tokenizer.fit_on_texts(X_tr)

max_seq_length = 250

X_tr_seq = tokenizer.texts_to_sequences(X_tr)
X_tr_seq = pad_sequences(X_tr_seq, maxlen=max_seq_length)

X_va_seq = tokenizer.texts_to_sequences(X_va)
X_va_seq = pad_sequences(X_va_seq, maxlen=max_seq_length)

X_te_seq = tokenizer.texts_to_sequences(X_te)
X_te_seq = pad_sequences(X_te_seq, maxlen=max_seq_length)
```

```
CPU times: user 3.19 s, sys: 52.4 ms, total: 3.24 s
Wall time: 3.24 s
```

In [28]:

```
X_tr_seq
```

Out[28]:

```
array([[    0,     0,     0, ...,   557,   141, 19845],
       [    0,     0,     0, ...,     0,     0,   236],
       [    0,     0,     0, ...,  3696,   252,    34],
       ...,
       [    0,     0,     0, ...,    80,    49,   204],
       [    0,     0,     0, ...,   721,   721, 10729],
       [    0,     0,     0, ...,    23,  3238,  4410]], dtype=int32)
```

In [29]:

```
X_va_seq
```

Out[29]:

```
array([[   0,    0,    0, ...,   54, 3294,  864],
       [   0,    0,    0, ...,  140,   17, 4517],
       [   0,    0,    0, ...,   80,  469, 5948],
       ...,
       [   0,    0,    0, ...,  394,  125, 1296],
       [   0,    0,    0, ..., 1442,  658, 2281],
       [   0,    0,    0, ...,    0,    0,  238]], dtype=int32)
```

In [30]:
```
X_te_seq
```

Out[30]:
```
array([[    0,     0,     0, ...,  1821,  8296, 15319],
       [    0,     0,     0, ...,  2364, 13835,  6435],
       [    0,     0,     0, ...,   568,  1131,     1],
       ...,
       [    0,     0,     0, ...,   152,    51,   382],
       [    0,     0,     0, ...,    58,   577,   675],
       [    0,     0,     0, ...,    36,   713,  4820]], dtype=int32)
```

Let's build the model. There are various approaches available, but I decided to experiment with a combination of several different layers, including a convolutional layer and a bidirectional LTSM layers. Probably these ones may be responsible for slowing down the training time more than the other layers. Anyway, let's evaluate it afterwards:

In [31]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Conv1D, MaxPooling1D, LSTM, Bidirectional, Dense, BatchNormalization, Dropout
from tensorflow.keras.optimizers import Adam

with strategy.scope():
    model = Sequential()
    model.add(Embedding(input_dim=20000, output_dim=128, input_length=250))

    model.add(Conv1D(filters=64, kernel_size=3, activation='relu'))
    model.add(MaxPooling1D(pool_size=2))

    model.add(Bidirectional(LSTM(units=64, return_sequences=True)))
    model.add(BatchNormalization())
    model.add(Dropout(0.2))

    model.add(Bidirectional(LSTM(units=128)))
    model.add(BatchNormalization())
    model.add(Dropout(0.2))

    model.add(Dense(units=32, activation='relu'))
    model.add(BatchNormalization())
    model.add(Dropout(0.2))

    model.add(Dense(units=6, activation='softmax'))

    model.compile(optimizer=Adam(learning_rate = 1e-4),
                  loss = 'sparse_categorical_crossentropy',
                  metrics=['acc']
                 )

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 250, 128)          2560000

 conv1d (Conv1D)             (None, 248, 64)           24640

 max_pooling1d (MaxPooling1D  (None, 124, 64)          0
 )

 bidirectional (Bidirectiona  (None, 124, 128)         66048
 l)

 batch_normalization (BatchN  (None, 124, 128)         512
 ormalization)

 dropout (Dropout)           (None, 124, 128)          0

 bidirectional_1 (Bidirectio  (None, 256)              263168
 nal)

 batch_normalization_1 (Batc  (None, 256)              1024
 hNormalization)
```

```
dropout_1 (Dropout)          (None, 256)               0

dense (Dense)                (None, 32)                8224

batch_normalization_2 (Batc  (None, 32)                128
hNormalization)

dropout_2 (Dropout)          (None, 32)                0

dense_1 (Dense)              (None, 6)                 198

=================================================================
Total params: 2,923,942
Trainable params: 2,923,110
Non-trainable params: 832
_________________________________________________________________
```

In [32]:

```
from tensorflow.keras.callbacks import EarlyStopping

# Creates 'EarlyStopping' callback
earlystopping_cb = EarlyStopping(patience=4, restore_best_weights=True)
```

In [33]:

```
X_tr_seq.shape
```

Out[33]:

```
(59196, 250)
```

In [34]:

```
y_tr.shape
```

Out[34]:

```
(59196,)
```

In [35]:

```
X_va_seq.shape
```

Out[35]:

```
(14799, 250)
```

In [36]:

```
%%time

history = model.fit(X_tr_seq,
                    y_tr,
                    validation_data=(X_va_seq, y_va),
                    callbacks=[earlystopping_cb],
                    batch_size=70,
                    epochs=9,
                    verbose=1,
                   )
```

```
Epoch 1/9
846/846 [==============================] - 494s 572ms/step - loss: 1.7143 - acc: 0.3735 - val_loss: 1.2680 - val_acc: 0.55
00
Epoch 2/9
846/846 [==============================] - 487s 576ms/step - loss: 0.8888 - acc: 0.6934 - val_loss: 1.8329 - val_acc: 0.49
97
Epoch 3/9
846/846 [==============================] - 491s 580ms/step - loss: 0.4873 - acc: 0.8393 - val_loss: 1.5714 - val_acc: 0.56
02
Epoch 4/9
846/846 [==============================] - 498s 589ms/step - loss: 0.3046 - acc: 0.8995 - val_loss: 1.0545 - val_acc: 0.66
63
Epoch 5/9
846/846 [==============================] - 502s 593ms/step - loss: 0.2162 - acc: 0.9274 - val_loss: 1.8065 - val_acc: 0.54
63
Epoch 6/9
846/846 [==============================] - 497s 587ms/step - loss: 0.1744 - acc: 0.9411 - val_loss: 2.5314 - val_acc: 0.51
10
Epoch 7/9
846/846 [==============================] - 501s 592ms/step - loss: 0.1473 - acc: 0.9486 - val_loss: 1.5927 - val_acc: 0.63
```

```
76
Epoch 8/9
846/846 [==============================] - 509s 602ms/step - loss: 0.1349 - acc: 0.9521 - val_loss: 1.6542 - val_acc: 0.60
94
CPU times: user 3h 36min 2s, sys: 11min 7s, total: 3h 47min 10s
Wall time: 1h 6min 20s
```

In [37]:

```
import pickle
pickle.dump(model,open('model.pkl','wb'))
```

```
Keras weights file (<HDF5 file "variables.h5" (mode r+)>) saving:
...layers
......batch_normalization
.........vars
............0
............1
............2
............3
......batch_normalization_1
.........vars
............0
............1
............2
............3
......batch_normalization_2
.........vars
............0
............1
............2
............3
......bidirectional
.........backward_layer
............cell
..............vars
................0
................1
................2
............vars
.........forward_layer
............cell
..............vars
................0
................1
................2
............vars
.........layer
............cell
..............vars
............vars
.........vars
......bidirectional_1
.........backward_layer
............cell
..............vars
................0
................1
................2
............vars
.........forward_layer
............cell
..............vars
................0
................1
................2
............vars
.........layer
............cell
..............vars
............vars
.........vars
......conv1d
.........vars
............0
            1
```

```
.............
......dense
.........vars
............0
............1
......dense_1
.........vars
............0
............1
......dropout
.........vars
......dropout_1
.........vars
......dropout_2
.........vars
......embedding
.........vars
............0
......max_pooling1d
.........vars
...metrics
......mean
.........vars
............0
............1
......mean_metric_wrapper
.........vars
............0
............1
...optimizer
......vars
.........0
.........1
.........10
.........11
.........12
.........13
.........14
.........15
.........16
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.........37
.........38
.........39
.........4
.........40
.........41
.........42
.........43
.........44
.........45
.........46
.........47
.........48
.........49
```

```
.........5
.........50
.........6
.........7
.........8
.........9
...vars
Keras model archive saving:
File Name                                     Modified             Size
config.json                              2023-08-14 09:11:09         7025
variables.h5                             2023-08-14 09:11:10     35167568
metadata.json                            2023-08-14 09:11:09           64
```

In [38]:

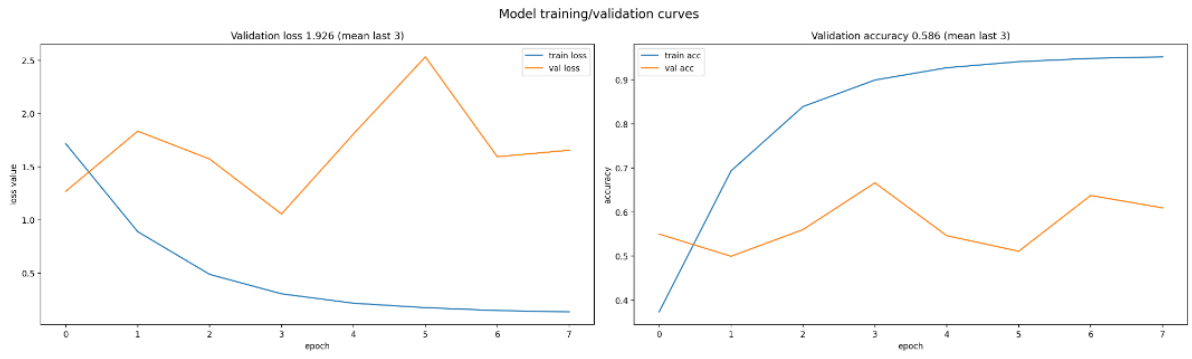
```
import numpy as np

# Create two plots: one for the loss value, one for the accuracy
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

plt.suptitle('Model training/validation curves', size=15)

# Plot loss values
ax1.plot(history.history["loss"], label="train loss")
ax1.plot(history.history["val_loss"], label="val loss")
ax1.set_title(
    "Validation loss {:.3f} (mean last 3)".format(
        np.mean(history.history["val_loss"][-3:])  # last three values
    )
)
ax1.set_xlabel("epoch")
ax1.set_ylabel("loss value")
ax1.legend()

# Plot accuracy values
ax2.plot(history.history["acc"], label="train acc")
ax2.plot(history.history["val_acc"], label="val acc")
ax2.set_title(
    "Validation accuracy {:.3f} (mean last 3)".format(
        np.mean(history.history["val_acc"][-3:])  # last three values
    )
)
ax2.set_xlabel("epoch")
ax2.set_ylabel("accuracy")
ax2.legend()
plt.tight_layout()
plt.show()
```



In [39]:

```
test_loss, test_acc = model.evaluate(X_va_seq,y_va)

print('Validation loss:', test_loss)
print('Validation accuracy:', test_acc)
```

```
463/463 [==============================] - 52s 112ms/step - loss: 1.0545 - acc: 0.6663
Validation loss: 1.0545268058776855
Validation accuracy: 0.6662612557411194
```

In [40]:

```
# Compute validation set predictions
pred = [np.argmax(i) for i in model.predict(X_va_seq)]
```

```
463/463 [==============================] - 54s 112ms/step
```

In [41]:

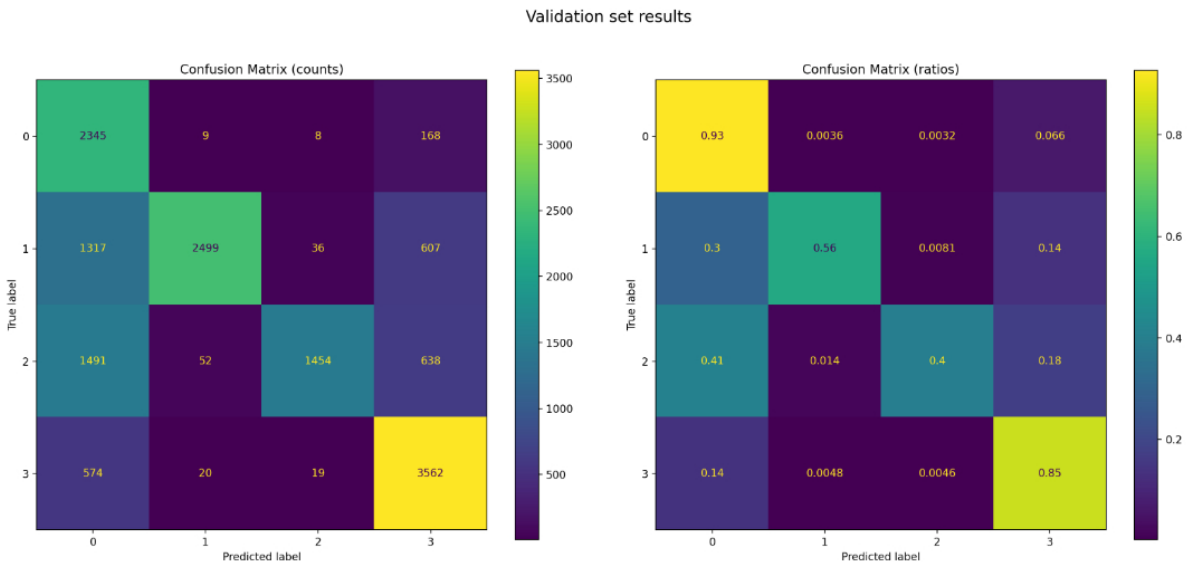
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Compute confusion matrix for raw counts
cm_raw = confusion_matrix(y_va, pred)

# Compute confusion matrix for normalized ratios
cm_norm = confusion_matrix(y_va, pred, normalize='true')

# Create confusion matrix plots
disp_raw = ConfusionMatrixDisplay(confusion_matrix=cm_raw)
disp_norm = ConfusionMatrixDisplay(confusion_matrix=cm_norm)

# Plot confusion matrices side by side
fig, axs = plt.subplots(1, 2, figsize=(20, 8), gridspec_kw={"width_ratios": [10, 10], "wspace": 0.1}, subplot_kw={"aspect":"eq
ual"})
plt.suptitle('Validation set results', size = 15)
disp_raw.plot(ax=axs[0])
axs[0].set_title('Confusion Matrix (counts)')
disp_norm.plot(ax=axs[1])
axs[1].set_title('Confusion Matrix (ratios)')
plt.show()
```



Based on the confusion matrices in the validation set, we can see that the model performed better with 4 and 5-star ratings. This is not surprising given that these ratings had the largest number of samples available for the training.

Concerning the errors, overall the model tends to predict ratings that are close to each other, for instance often mistakenly predicting a rating of 2 for a rating of 3, or vice versa.

Make predictions

In [42]:

```
# Compute test set predictions
predictions = [np.argmax(i) for i in model.predict(X_te_seq)]

# Create a new DataFrame to merge review ids and the model predictions
submission = pd.DataFrame({'sentiment': df_test.sentiment, 'rating': predictions})

# Check few random entries
submission.sample(10)
```

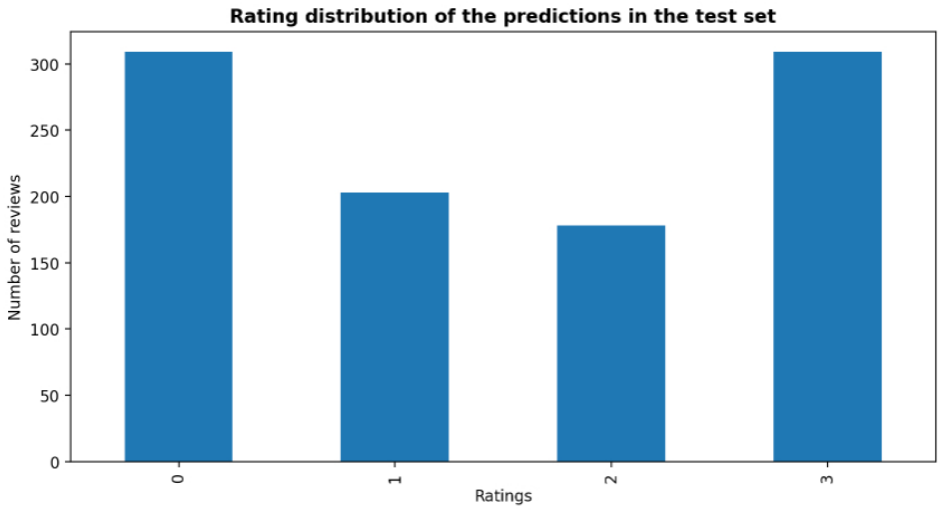
```
32/32 [==============================] - 3s 107ms/step
```

Out[42]:

	sentiment	rating
233	0	0
108	2	2
858	0	0
188	2	2
487	1	0
985	3	3
365	3	3
388	3	3
134	0	0
205	1	1

In [43]:

```
# Check target balance
submission['rating'].value_counts().sort_index().plot.bar(figsize=(10,5))
plt.title('Rating distribution of the predictions in the test set', fontweight="bold")
plt.xlabel('Ratings')
plt.ylabel('Number of reviews')
plt.show()
```



The target distribution in the test set is similar to the one in training set.

In [44]:

```
# Export predictions
submission.to_csv("submission.csv", index=None)
```

In [ ]:

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Output
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Logs →

4172.9 second run - successful

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0 comments