Movie Classifier using Augmented Data: Overview

1. Data Augmentation:
    - To handle Data Imbalance
    - Method 1: Converted text to 16 different languages and re-translated the text back to English. This created variations in the text descriptions.
    - Method 2: Created a Markov Chain using the entire training data. Generated text description samples from this chain.
    - Generated the title for the augmented Movie Descriptions randomly.
    - Picked 100 Augmented samples(from method1 and method2 datasets collectively) for selected Genres
    - Integrated the Augmented data with the Train Data¶

1. Indexing the Vocabulary:

    - Used TextVectorization to index the vocabulary found in the dataset. Later, we use the same layer instance to vectorize the samples. Our layer will only consider the top 20,000 words, and will truncate or pad sequences to be actually 200 tokens long.

1. Data Pre-Processing:
    - Did traditional pre-processing of the data: Lowercasing, Removing twitter handles, stopwords, URLs, extra spaces, etc.
    - Encoded the categories

1. Embedding:
    - Used pre-trained GLOVE Embeddings. Found 400000 word vectors
    - Created the Embedding Matrix: Words not found in embedding index will be all-zeros. This includes the representation for "padding" and "OOV".
    - Created tensorflow.keras.layers.Embedding layer and embedded the text sequences.

1. Modelling:
    - Creating the Model

- Vectoring the Data
- Fitting the Model
- Model Summary:
  - input_1 (InputLayer)
  - embedding (Embedding Layer)
  - bidirectional (Bidirectional LSTM layer)
  - dense (Dense)
  - dropout (Dropout)
  - dense_1 (Dense)

1. Evaluation:
   - Test Accuracy: 57.91%
   - After augmenting the data for classes which had less samples, the accuracy increases for these classes.

Bi-directional LSTM				
genre	precision	recall	f1-score	support
adventure	0.22	0.14	**0.17**	237
comedy	0.57	0.58	**0.58**	2439
crime	0.20	0.03	**0.06**	183
family	0.41	0.11	**0.18**	236
history	0.20	0.01	**0.02**	79
romance	0.25	0.02	**0.03**	238
short	0.47	0.40	**0.43**	1725
talk-show	0.46	0.26	**0.33**	128
action	0.40	0.39	0.40	431
adult	0.56	0.45	0.50	171
animation	0.32	0.21	0.26	159
biography	0.00	0.00	0.00	94
documentary	0.73	0.80	0.76	4351
drama	0.58	0.74	0.65	4489
fantasy	0.29	0.06	0.11	109
game-show	0.79	0.48	0.60	64
horror	0.52	0.79	0.63	687
music	0.63	0.48	0.55	247
musical	0.50	0.02	0.04	91
mystery	0.00	0.00	0.00	98
news	0.00	0.00	0.00	52
reality-tv	0.39	0.20	0.27	295
sci-fi	0.46	0.37	0.41	238
sport	0.73	0.29	0.42	154
thriller	0.31	0.27	0.29	517
war	0.00	0.00	0.00	49
western	0.92	0.75	0.83	330
accuracy			**0.59**	17891
macro avg	0.40	0.29	0.31	17891
weighted avg	0.56	0.59	0.57	17891

Bi-directional LSTM with Data Augmentation				
genre	precision	recall	f1-score	support
adventure	0.55	0.78	**0.64**	2674
comedy	0.71	0.82	**0.76**	2629
crime	0.46	0.56	**0.50**	162
family	0.36	0.41	**0.38**	285
history	0.36	0.31	**0.33**	126
romance	0.23	0.10	**0.14**	186
short	0.84	0.78	**0.81**	204
talk-show	0.63	0.62	**0.62**	472
action	0.17	0.21	0.19	75
adult	0.00	0.00	0.00	72
animation	0.00	0.00	0.00	47
biography	0.50	0.02	0.04	55
documentary	0.29	0.05	0.09	153
drama	0.48	0.30	0.37	1004
fantasy	0.00	0.00	0.00	68
game-show	0.81	0.33	0.47	39
horror	0.33	0.09	0.15	308
music	0.50	0.52	0.51	86
musical	0.00	0.00	0.00	30
mystery	0.00	0.00	0.00	100
news	0.00	0.00	0.00	46
reality-tv	0.20	0.10	0.13	94
sci-fi	0.00	0.00	0.00	137
sport	0.17	0.01	0.02	166
thriller	0.45	0.22	0.29	120
war	0.00	0.00	0.00	36
western	0.55	0.59	0.57	1469
accuracy			**0.58**	10843
macro avg	0.32	0.25	0.26	10843
weighted avg	0.53	0.58	0.54	10843

I. Data Augmention

In [1]:
```
import tensorflow as tf
from tensorflow.keras.layers import Embedding
```

```
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.text import one_hot
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Bidirectional

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import nltk
import re
import random
from nltk.stem.porter import PorterStemmer
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
from imblearn.under_sampling import RandomUnderSampler
import warnings
warnings.filterwarnings("ignore")
```

Method 1: Converting Descriptions to different languages and re-converting back to English

In [2]:
```
from textblob import TextBlob
from textblob.translate import NotTranslated
import random


def data_augmentation(message,no_aug, intent,title):
    sr = random.SystemRandom()
    language = ["es", "de", "fr", "ar", "te", "hi", "ja", "fa", "sq", "bg", "nl", "gu", "ig", "kk", "mt", "ps"]
    text = TextBlob(message)
    lang=sr.choice(language)
    text = text.translate(from_lang='en', to=lang)   ## Converting to random langauge for meaningful variation
    text = text.translate(from_lang=lang, to="en")
    #file = open('Final_augmented_data.txt','a')
    file.write(str(no_aug)+' :::'+title+':::'+intent+'::: '+str(text)+"\n")
    #file.close()
```

In [3]:
```
train_df=pd.read_csv('train_df.csv')
```

In [4]:
```
Genre_count = train_df.Genre.value_counts().to_dict()
Genre_count
```

Out[4]:
```
{' drama ': 10939,
 ' documentary ': 10467,
 ' comedy ': 5978,
 ' short ': 4069,
 ' horror ': 1732,
 ' thriller ': 1283,
 ' action ': 1030,
 ' western ': 828,
 ' reality-tv ': 698,
 ' family ': 631,
 ' adventure ': 609,
 ' music ': 569,
 ' romance ': 535,
 ' sci-fi ': 521,
 ' adult ': 470,
 ' crime ': 405,
 ' animation ': 404,
 ' sport ': 346,
 ' talk-show ': 316,
 ' mystery ': 251,
 ' fantasy ': 251,
 ' musical ': 222,
 ' biography ': 219,
 ' history ': 196,
 ' game-show ': 155,
 ' news ': 145,
 ' war ': 102}
```

Selecting the less populated categories for Augmentation

In [11]:
```
mov = [' war ',' musical ',' biography ',' new ',' history ',' mystery ',' fantasy ', ' animation ']
```

In [1]:
```
## Loop to interate all messages
import numpy as np
import math

max_intent_count=10939
no_aug=1
for intent, count in Genre_count.items():
```

```
    count_diff = max_intent_count - count
    file = open('Final_augmented_data.txt','a')
    if intent in mov:#count_diff>5000:
        for i in range(0,1000):
            random_number = random.randint(0, count-1)
            x=train_df[train_df['Genre']==intent]
            x=x.reset_index(drop=True)
            text=x['Description'][random_number]
            title=x['Title'][random_number]
            data_augmentation(text, no_aug, intent,title)
            no_aug = no_aug+1
    file.close()
```

Method 2: Data Augmentation Using Markov Chain

In [1]:
```
## Import python library
import pandas as pd
import nltk

pd.set_option('display.max_colwidth', 5000)
## Read file
file_name = 'train_df.csv'
## Read file using pandas
train_df = pd.read_csv(file_name)
```

In [3]:
```
Genre_count = train_df.Genre.value_counts().to_dict()
Genre_count
```

Out[3]:
```
{' drama ': 10939,
 ' documentary ': 10467,
 ' comedy ': 5978,
 ' short ': 4069,
 ' horror ': 1732,
 ' thriller ': 1283,
 ' action ': 1030,
 ' western ': 828,
 ' reality-tv ': 698,
 ' family ': 631,
 ' adventure ': 609,
 ' music ': 569,
 ' romance ': 535,
 ' sci-fi ': 521,
 ' adult ': 470,
 ' crime ': 405,
 ' animation ': 404,
 ' sport ': 346,
 ' talk-show ': 316,
 ' mystery ': 251,
 ' fantasy ': 251,
 ' musical ': 222,
 ' biography ': 219,
 ' history ': 196,
 ' game-show ': 155,
 ' news ': 145,
 ' war ': 102}
```

In [7]:
```
def data_augmentation_markovify(text, no_aug, genre,title):
    file = open('augmented_data_markovify.txt','a')
    file.write(str(no_aug)+' ::: '+title+' :::'+genre+'::: '+text+"\n")
    file.close()
```

Generating the title of the Movie Descriptions randomly

In [128…
```
from random_word import RandomWords
r = RandomWords()

max_genre_count=10939
no_aug=34728
for genre, count in Genre_count.items():
    count_diff = max_genre_count - count
```

```
    if count_diff>10715:
        print(genre)
        for i in range(0,2000):
            try:
                corpus=train_df[train_df['Genre']==genre]['Description'].to_string(index=False)
                text_model = markovify.Text(corpus, state_size=3)
                new_text=[]
                for i in range(5):
                    new_text.append(text_model.make_short_sentence(280))
                new_text=" ".join(new_text)
                title = r.get_random_word()
                data_augmentation_markovify(new_text, no_aug, genre,title)
                no_aug = no_aug+1
            except:
                pass
```

Integrating the Augmented data with the Train Data

In [3]:

```
train_df=pd.read_csv('train_df.csv')
animation_df=pd.read_csv('augmented_data_animation.txt',sep=':::',names=['Index','Title','Genre','Description'])
family_df=pd.read_csv('augmented_data_crime_family.txt',sep=':::',names=['Index','Title','Genre','Description'])
romance_df=pd.read_csv('augmented_data_romance.txt',sep=':::',names=['Index','Title','Genre','Description'])
thriller_df=pd.read_csv('augmented_data_thriller.txt',sep=':::',names=['Index','Title','Genre','Description'])
short_df=pd.read_csv('augmented_data_short.txt',sep=':::',names=['Index','Title','Genre','Description'])
mystery_df=pd.read_csv('augmented_data_mystery_fantasy_musical_history_biography.txt',sep=':::',names=['Index','Title
music_df=pd.read_csv('augmented_data_music.txt',sep=':::',names=['Index','Title','Genre','Description'])
scifi_df=pd.read_csv('augmented_data_scifi.txt',sep=':::',names=['Index','Title','Genre','Description'])
war_df=pd.read_csv('augmented_data_adult_war.txt',sep=':::',names=['Index','Title','Genre','Description'])
game_df=pd.read_csv('game_show_augmented_data.txt',sep=':::',names=['Index','Title','Genre','Description'])
markov_aug_df=pd.read_csv('markov_aug_df.csv')
aug_df = pd.concat([animation_df,family_df,romance_df,thriller_df,short_df,mystery_df,music_df,scifi_df,war_df,game_d
#aug_df = pd.read_csv('markov_aug_df.csv')

aug_df = aug_df.sample(frac = 1).reset_index(drop=True)
```

In [5]:

```
aug_df.head()
```

Out[5]:

	Index	Title	Genre	Description	Unnamed: 0
0	44543	shahs	war	Intense bonds between man and horse developed...	44542.0
1	1361	Final Fantasy XI: Wings of the Goddess (2007)	fantasy	The fourth expanse to the final immortal imag...	NaN
2	1007	"Timeline Alpha" (2017)	sci-fi	Schedule alphabet is an event series. What is...	NaN
3	17314	whiter	music	In the aftermath of Esbjorn Svenssons untimel...	17313.0
4	39554	disagreeably	history	General Ludendorf, who used to be the greates...	39553.0

In [6]:
```
train_df.head()
```

Out[6]:

	Unnamed: 0.1	Unnamed: 0	Index	Title	Genre	Description
0	0	23699	23700	"NigaHiga" (2007)	comedy	Jeremy Lin retires from basketball, not to pl...
1	1	24841	24842	Popat (2013)	drama	Based in a village in Kolhapur, Popat is a st...
2	2	37358	37359	Maestri (2014)	documentary	For young conductors the opportunity to get t...
3	3	48000	48001	Me vs. Comic-Con: Who's Better? (2007)	short	San Diego Comic-Con International is the larg...
4	4	53004	53005	Plumb and Dumber (1995)	adult	Barney's wife, Maggie, kicks him out of their...

In [7]:
```
aug_df = aug_df[['Title','Genre','Description']]
train_df = train_df.iloc[:,3:6]
```

In [8]:
```
print("Shape of train data: ",train_df.shape)
print("Shape of augmented data: ",aug_df.shape)
```

```
Shape of train data:  (43371, 3)
Shape of augmented data:  (61675, 3)
```

In [10]:
```
#Value Counts in Original Data
cnt_org= dict(train_df.Genre.value_counts())
print(cnt_org)

#Value Counts in Augmented Data
cnt_aug= dict(aug_df.Genre.value_counts())
print(cnt_aug)

max_records= 11000
```

```
genre_to_augment = [' comedy ',' western ',' horror ',' talk-show ',' short ',' family ',' sport ',' adult ',' war ',
new_df=pd.DataFrame()
for key,val in cnt_org.items():
    if val>max_records:
        gen_df= train_df[train_df['Genre']==key][0:max_records]
        new_df= pd.concat([new_df,gen_df],ignore_index=True)
    else:
        diff = max_records-val
        count_in_aug = aug_df[aug_df['Genre']==key].shape[0]
        max_cnt= min(count_in_aug,diff)
        gen_df_1= train_df[train_df['Genre']==key][0:val]
        if key in genre_to_augment:
            gen_df_2= aug_df[aug_df['Genre']==key][0:100]
        else:
            gen_df_2=pd.DataFrame()
        new_df = pd.concat([new_df,gen_df_1,gen_df_2],ignore_index=True)


new_df.shape
```

```
{' drama ': 10939, ' documentary ': 10467, ' comedy ': 5978, ' short ': 4069, ' horror ': 1732, ' thriller ': 1283, '
action ': 1030, ' western ': 828, ' reality-tv ': 698, ' family ': 631, ' adventure ': 609, ' music ': 569, ' romance
': 535, ' sci-fi ': 521, ' adult ': 470, ' crime ': 405, ' animation ': 404, ' sport ': 346, ' talk-show ': 316, ' my
stery ': 251, ' fantasy ': 251, ' musical ': 222, ' biography ': 219, ' history ': 196, ' game-show ': 155, ' news ':
145, ' war ': 102}
{' talk-show ': 3161, ' family ': 3000, ' music ': 3000, ' adult ': 3000, ' animation ': 3000, ' game-show ': 3000, '
fantasy ': 2999, ' mystery ': 2999, ' biography ': 2997, ' musical ': 2995, ' history ': 2989, ' war ': 2962, ' short
': 2885, ' sci-fi ': 2768, ' thriller ': 2402, ' romance ': 2380, ' crime ': 2052, ' horror ': 2000, ' adventure ': 2
000, ' western ': 2000, ' reality-tv ': 2000, ' action ': 2000, ' news ': 1672, ' sport ': 1414}
```

Out[10]:
```
(44271, 3)
```

In [11]:
```
print(new_df['Genre'].value_counts())
```

```
Genre
 drama          10939
 documentary    10467
 comedy          5978
 short           4169
 horror          1832
 thriller        1283
 action          1030
 western          928
 family           731
 reality-tv       698
 adventure        609
 adult            570
 music            569
 romance          535
 sci-fi           521
 sport            446
 talk-show        416
 crime            405
 animation        404
 musical          322
 mystery          251
 fantasy          251
 biography        219
 war              202
 history          196
 game-show        155
 news             145
Name: count, dtype: int64
```

In [12]:
```
df=new_df.copy()
```

Test Data

In [13]:
```
test_df=pd.read_csv('test_df.csv')
```

In [14]:
```
test_df.head()
```

Out[14]:

	Unnamed: 0.1	Unnamed: 0	Index	Title	Genre	Description
0	0	50377	50378	Die Flaschenpostinsel (2018)	adventure	An old, worn-out photo album - Laini had cert...
1	1	1426	1427	Román pro zeny (2005)	comedy	This romantic comedy presents a story of two ...
2	2	9349	9350	The Combat (1926)	western	Tough lumberjack Blaze Burke is told he'll be...
3	3	41416	41417	Zeitgeist Protest (2017)	drama	Omar, an awkward, melancholic man, is stuck i...
4	4	24673	24674	"Redfern Now" (2012)	drama	A young indigenous boy Joel (or joely) obtain...

II. Data Preprocessing

In [15]:
```
mov = df.copy()
#mov = mov.iloc[0:105046,:]
```

In [16]:
```
mov['Description'][0]
```

Out[16]:
```
' Based in a village in Kolhapur, Popat is a story of four friends Raghunath Hiwale, Bakul Chinchukey and Mukund Bora
te all three in their early twenties and Janardan Shingre in his forties. Four friends come together and decide to ma
ke a film on HIV/AIDS. The only knowledge they have about films is that Raghu is a junior actor. With the help of lit
tle knowledge they get from sources in the village through government awareness program and basic documents, Mukund b
egins writing a story as he is the only literate out of the three. They bump into Janardan Shingre who has a video ca
mera as he is a photographer by profession and also shoots local marriages. The journey begins and all of a sudden th
ese friends find themselves in middle of a life threatening situation. A roller coaster ride, a humorous take on HIV/
AIDS, Popat shows how life is not full of laughter fun and free lunch.'
```

In [17]:
```
mov.shape[0]
```

Out[17]:
```
44271
```

Data pre-processing

In [18]:
```
import string
def clean_text(text):
    text = text.lower()                                # lower-case all characters
    text =  re.sub(r'@\S+', '',text)                   # remove twitter handles
    text =  re.sub(r'http\S+', '',text)                # remove urls
    text =  re.sub(r'pic.\S+', '',text)
    text =  re.sub(r"[^a-zA-Z+']", ' ',text)           # only keeps characters
```

```
    text = re.sub(r'\s+[a-zA-Z]\s+', ' ', text+' ')      # keep words with length>1 only
    text = "".join([i for i in text if i not in string.punctuation])
    words = nltk.tokenize.word_tokenize(text)
    stopwords = nltk.corpus.stopwords.words('english')   # remove stopwords
    text = " ".join([i for i in words if i not in stopwords and len(i)>2])
    text= re.sub("\s[\s]+", " ",text).strip()            # remove repeated/leading/trailing spaces
    return text
```

In [19]:
```
#Applying the above clean_text method for cleaning and preprocessing the Description column of the dataset that is bei
mov['clean_description'] = mov['Description'].apply(clean_text)
test_df['clean_description'] = test_df['Description'].apply(clean_text)
```

Encoding the Categories

In [21]:
```
# Create a new column 'category_id' with encoded categories
mov['category_id'] = mov['Genre'].factorize()[0]
```

In [22]:
```
# Dictionaries for future use
category_id_df = mov[['Genre', 'category_id']].drop_duplicates()
category_to_id = dict(category_id_df.values)
id_to_category = dict(category_id_df[['category_id', 'Genre']].values)
```

In [23]:
```
print(category_to_id)
```

```
{' drama ': 0, ' documentary ': 1, ' comedy ': 2, ' short ': 3, ' horror ': 4, ' thriller ': 5, ' action ': 6, ' west
ern ': 7, ' reality-tv ': 8, ' family ': 9, ' adventure ': 10, ' music ': 11, ' romance ': 12, ' sci-fi ': 13, ' adul
t ': 14, ' crime ': 15, ' animation ': 16, ' sport ': 17, ' talk-show ': 18, ' mystery ': 19, ' fantasy ': 20, ' musi
cal ': 21, ' biography ': 22, ' history ': 23, ' game-show ': 24, ' news ': 25, ' war ': 26}
```

X and Y

In [24]:
```
## Get the Dependent and Independent features
y=mov['category_id']
X=mov['clean_description']
#X=np.array(corpus)
```

In [25]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

III. Creating a vocabulary index

In [27]:
```
#Let's use the TextVectorization to index the vocabulary found in the dataset.
#Later, we'll use the same layer instance to vectorize the samples.
#Our layer will only consider the top 20,000 words, and will truncate or pad sequences
#to be actually 200 tokens long.

from tensorflow.keras.layers import TextVectorization
vectorizer = TextVectorization(max_tokens=20000, output_sequence_length=200)
text_ds = tf.data.Dataset.from_tensor_slices(X_train).batch(128)
vectorizer.adapt(text_ds)
```

```
2023-11-16 16:48:03.796820: I metal_plugin/src/device/metal_device.cc:1154] Metal device set to: Apple M2
2023-11-16 16:48:03.796868: I metal_plugin/src/device/metal_device.cc:296] systemMemory: 8.00 GB
2023-11-16 16:48:03.796875: I metal_plugin/src/device/metal_device.cc:313] maxCacheSize: 2.67 GB
2023-11-16 16:48:03.797157: I tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:303] Could
not identify NUMA node of platform GPU ID 0, defaulting to 0. Your kernel may not have been built with NUMA support.
2023-11-16 16:48:03.797193: I tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:269] Create
d TensorFlow device (/job:localhost/replica:0/task:0/device:GPU:0 with 0 MB memory) -> physical PluggableDevice (devi
ce: 0, name: METAL, pci bus id: <undefined>)
2023-11-16 16:48:03.876382: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin opti
mizer for device_type GPU is enabled.
```

In [28]:
```
vectorizer.get_vocabulary()[:5]
```

Out[28]:
```
['', '[UNK]', 'life', 'one', 'film']
```

In [29]:
```
voc = vectorizer.get_vocabulary()
word_index = dict(zip(voc, range(len(voc))))
```

In [32]:
```
output = vectorizer([["the cat sat on the mat"]])
output.numpy()[0, :6]
```

Out[32]:
```
array([    1,  1568,  6511,     1,     1, 17746])
```

IV. Embedding: Using pre-trained Glove Embeddings

Loading the pre-trained GLOVE Embeddings

In [33]:
```
import os
path_to_glove_file = os.path.join(
    os.path.expanduser("~"), "/Users/dibyanshu/Documents/Jupyter Codes/NLP/glove.6B/glove.6B.200d.txt"
)

embeddings_index = {}
with open(path_to_glove_file) as f:
    for line in f:
        word, coefs = line.split(maxsplit=1)
        coefs = np.fromstring(coefs, "f", sep=" ")
        embeddings_index[word] = coefs

print("Found %s word vectors." % len(embeddings_index))
```

```
Found 400000 word vectors.
```

Creating the Embedding Matrix

In [34]:
```
num_tokens = len(voc) + 2
embedding_dim = 200
hits = 0
misses = 0

# Prepare embedding matrix
embedding_matrix = np.zeros((num_tokens, embedding_dim))
for word, i in word_index.items():
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        # Words not found in embedding index will be all-zeros.
        # This includes the representation for "padding" and "OOV"
        embedding_matrix[i] = embedding_vector
        hits += 1
    else:
        misses += 1
print("Converted %d words (%d misses)" % (hits, misses))
```

```
Converted 19766 words (234 misses)
```

Creating the Embedding Layer

In [35]:
```
from tensorflow.keras.layers import Embedding
import keras
embedding_layer = Embedding(
    num_tokens,
    embedding_dim,
    embeddings_initializer=keras.initializers.Constant(embedding_matrix),
    trainable=True,
)
```

V. Modelling

In [36]:
```
from tensorflow.keras import layers

# Creating model
int_sequences_input = keras.Input(shape=(None,), dtype="int64")
embedded_sequences = embedding_layer(int_sequences_input)
x = layers.Bidirectional(LSTM(100))(embedded_sequences)
#x = layers.Dropout(0.5)(x)
x = layers.Dense(32, activation="relu")(x)
x = layers.Dropout(0.5)(x)
preds = layers.Dense(27, activation="softmax")(x)
model = keras.Model(int_sequences_input, preds)
print(model.summary())
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, None)]            0

 embedding (Embedding)       (None, None, 200)         4000400

 bidirectional (Bidirection  (None, 200)               240800
 al)

 dense (Dense)               (None, 32)                6432

 dropout (Dropout)           (None, 32)                0

 dense_1 (Dense)             (None, 27)                891

=================================================================
Total params: 4248523 (16.21 MB)
Trainable params: 4248523 (16.21 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
```

Vectorising the data

In [37]:

```
x_train = vectorizer(np.array([[s] for s in X_train])).numpy()
x_val = vectorizer(np.array([[s] for s in X_test])).numpy()

y_train = np.array(y_train)
y_val = np.array(y_test)
```

Fitting the Model

In [38]:

```
model.compile(
    loss="sparse_categorical_crossentropy", optimizer="rmsprop", metrics=["acc"]
)
model.fit(x_train, y_train, batch_size=128, epochs=5, validation_data=(x_val, y_val))
```

```
Epoch 1/5
```

```
2023-11-16 16:48:41.911717: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
2023-11-16 16:48:42.414783: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
2023-11-16 16:48:42.443128: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
2023-11-16 16:48:44.902817: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
2023-11-16 16:48:44.916973: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
232/232 [==============================] - ETA: 0s - loss: 2.1997 - acc: 0.4065
2023-11-16 16:50:09.182693: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
2023-11-16 16:50:09.333550: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
2023-11-16 16:50:09.346827: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
232/232 [==============================] - 94s 373ms/step - loss: 2.1997 - acc: 0.4065 - val_loss: 1.8128 - val_acc: 0.5047
Epoch 2/5
232/232 [==============================] - 72s 311ms/step - loss: 1.8058 - acc: 0.5022 - val_loss: 1.6289 - val_acc: 0.5298
Epoch 3/5
232/232 [==============================] - 63s 271ms/step - loss: 1.6108 - acc: 0.5537 - val_loss: 1.5547 - val_acc: 0.5521
Epoch 4/5
232/232 [==============================] - 58s 251ms/step - loss: 1.4569 - acc: 0.5940 - val_loss: 1.5013 - val_acc: 0.5651
Epoch 5/5
232/232 [==============================] - 54s 231ms/step - loss: 1.3271 - acc: 0.6310 - val_loss: 1.4575 - val_acc: 0.5821
```

Out[38]:
```
<keras.src.callbacks.History at 0x2ce7875b0>
```

VI. Evaluation

Test Data Validation

In [39]:
```
#test_df=pd.read_csv('test_df.csv')
```

In [40]:
```
def category_test(Genre):
    for key, val in category_to_id.items():
        if Genre==key:
            return val
```

In [41]:
```
test_df['category_id']  = test_df['Genre'].apply(category_test)
```

In [42]:
```
test_df.head()
```

Out[42]:

	Unnamed: 0.1	Unnamed: 0	Index	Title	Genre	Description	clean_description	category_id
0	0	50377	50378	Die Flaschenpostinsel (2018)	adventure	An old, worn-out photo album - Laini had cert...	old worn photo album laini certainly wanted tw...	10
1	1	1426	1427	Román pro zeny (2005)	comedy	This romantic comedy presents a story of two ...	romantic comedy presents story two women twent...	2
2	2	9349	9350	The Combat (1926)	western	Tough lumberjack Blaze Burke is told he'll be...	tough lumberjack blaze burke told hell made lu...	7
3	3	41416	41417	Zeitgeist Protest (2017)	drama	Omar, an awkward, melancholic man, is stuck i...	omar awkward melancholic man stuck past remain...	0
4	4	24673	24674	"Redfern Now" (2012)	drama	A young indigenous boy Joel (or joely) obtain...	young indigenous boy joel joely obtains schola...	0

In [43]:
```
test_df = test_df.iloc[:,3:8]
```

In [44]:
```
y_test=np.array(test_df['category_id'])
X_test=np.array(test_df['clean_description'])
X_test = vectorizer(np.array([[s] for s in X_test])).numpy()
```

In [45]:
```
y_pred=model.predict(X_test)
#y_pred=model.predict(x_val)
```

```
2023-11-16 16:55:02.924025: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin opti
mizer for device_type GPU is enabled.
2023-11-16 16:55:03.063621: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin opti
mizer for device_type GPU is enabled.
2023-11-16 16:55:03.077796: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin opti
mizer for device_type GPU is enabled.
```

```
339/339 [==============================] - 8s 20ms/step
```

In [46]:
```python
y_pred
```

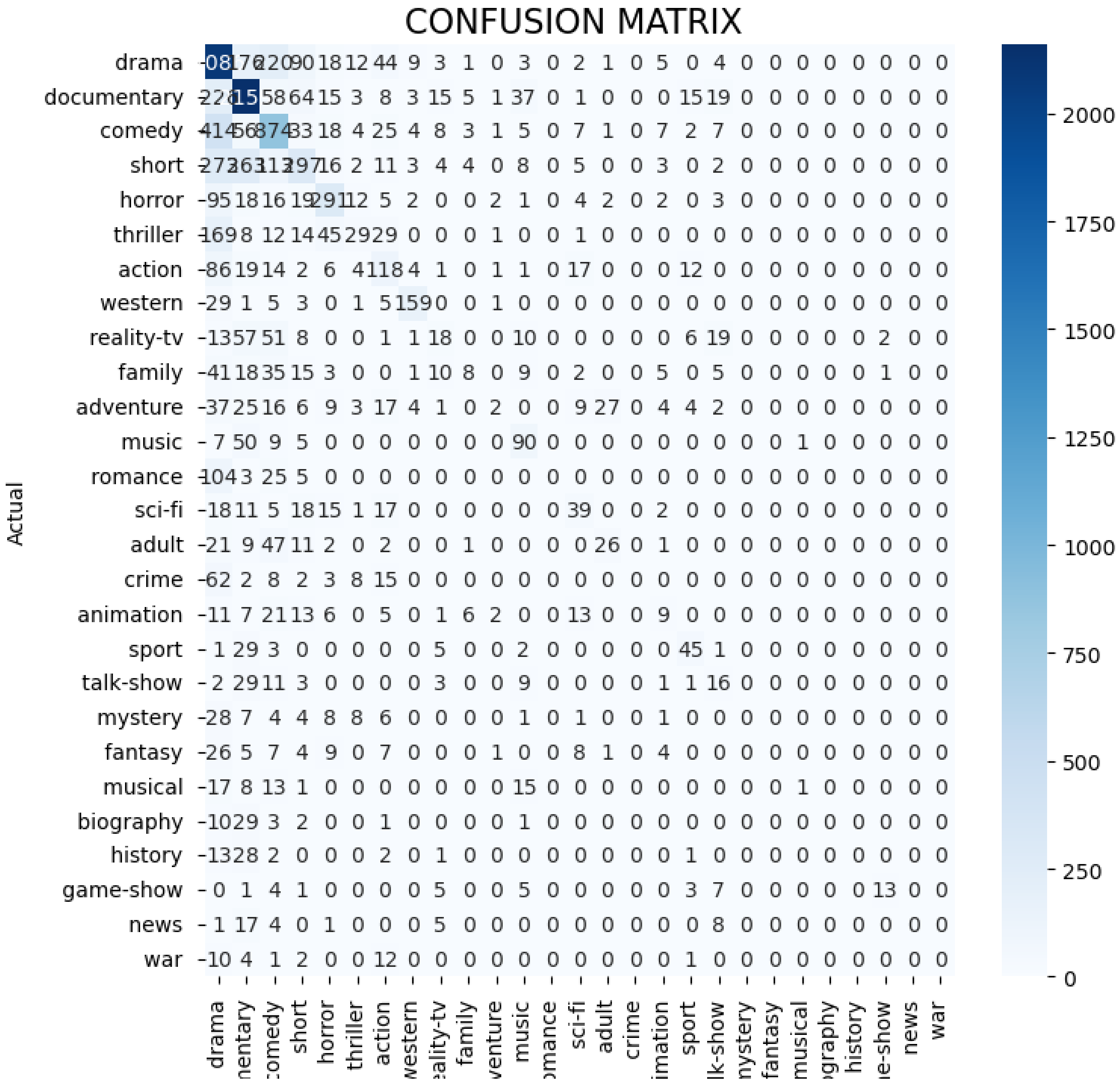
Out[46]:
```
array([[8.4040225e-02, 1.3797465e-01, 1.7794773e-02, ..., 3.6150074e-04,
        7.4739906e-04, 3.7474945e-04],
       [2.0375948e-01, 1.6397835e-03, 7.0628870e-01, ..., 1.4244825e-04,
        1.7959144e-04, 1.2577826e-04],
       [1.8157947e-01, 1.6210200e-02, 1.6569085e-02, ..., 5.1898777e-04,
        1.1707705e-03, 1.2495691e-02],
       ...,
       [8.0192661e-01, 1.2963085e-02, 8.2697436e-02, ..., 7.6436772e-05,
        2.2458947e-04, 4.7921287e-04],
       [4.0676102e-01, 3.1376043e-01, 1.9505654e-02, ..., 5.1931111e-04,
        2.9907925e-03, 6.8307188e-03],
       [1.0215156e-02, 4.2801864e-02, 9.6039724e-04, ..., 3.1199839e-03,
        6.9920416e-03, 2.2620447e-01]], dtype=float32)
```

In [47]:
```python
y_pred_labels = [np.argmax(y_pred[i]) for i in range(0,len(y_pred))]
```

In [48]:
```python
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
accuracy_score(y_test,y_pred_labels)
```

Out[48]:
```
0.5791755049340589
```

In [49]:
```python
conf_mat = confusion_matrix(y_test, y_pred_labels)
fig, ax = plt.subplots(figsize=(8,8))
sns.heatmap(conf_mat, annot=True, cmap="Blues", fmt='d',
            xticklabels=category_id_df.Genre.values,
            yticklabels=category_id_df.Genre.values)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title("CONFUSION MATRIX ", size=16);
```


CONFUSION MATRIX
Actual
drama
documentary
comedy
short
horror
thriller
action
western
reality-tv
family
adventure
music
romance
sci-fi
adult
crime
animation
sport
talk-show
mystery
fantasy
musical
biography
history
game-show
news
war
2000
1750
1500
1250
1000
750
500
250
0

In [50]:

```python
from sklearn import metrics
print(metrics.classification_report(y_test, y_pred_labels,target_names= test_df['Genre'].unique()))
```

```
              precision    recall  f1-score   support

   adventure       0.55      0.78      0.64      2674
      comedy       0.71      0.82      0.76      2629
     western       0.55      0.59      0.57      1469
       drama       0.48      0.30      0.37      1004
   talk-show       0.63      0.62      0.62       472
      horror       0.33      0.09      0.15       308
      family       0.36      0.41      0.38       285
       short       0.84      0.78      0.81       204
     romance       0.23      0.10      0.14       186
 documentary       0.29      0.05      0.09       153
       sport       0.17      0.01      0.02       166
       crime       0.46      0.56      0.50       162
      sci-fi       0.00      0.00      0.00       137
     history       0.36      0.31      0.33       126
    thriller       0.45      0.22      0.29       120
     mystery       0.00      0.00      0.00       100
  reality-tv       0.20      0.10      0.13        94
       music       0.50      0.52      0.51        86
      action       0.17      0.21      0.19        75
     fantasy       0.00      0.00      0.00        68
       adult       0.00      0.00      0.00        72
   biography       0.50      0.02      0.04        55
        news       0.00      0.00      0.00        46
   animation       0.00      0.00      0.00        47
   game-show       0.81      0.33      0.47        39
         war       0.00      0.00      0.00        36
     musical       0.00      0.00      0.00        30

    accuracy                           0.58     10843
   macro avg       0.32      0.25      0.26     10843
weighted avg       0.53      0.58      0.54     10843
```

In [ ]:

```

```