Get Dataset

We will use a dataset of GoodReads' "Best Books Ever". I will extract a list of all genres that appear more than 500 times (out of the ~40k books)

Note

Before running the entire notebook, you must download the `glove.6B.100d.txt` dataset. Simply run `./get_glove.sh` .

In [ ]:
```
!bash get_glove.sh
```

```
--2023-04-22 15:40:33--  https://github.com/allenai/spv2/raw/master/model/g
love.6B.100d.txt.gz
Resolving github.com (github.com)... 140.82.112.3
Connecting to github.com (github.com)|140.82.112.3|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://media.githubusercontent.com/media/allenai/spv2/master/mod
el/glove.6B.100d.txt.gz [following]
--2023-04-22 15:40:33--  https://media.githubusercontent.com/media/allenai/
spv2/master/model/glove.6B.100d.txt.gz
Resolving media.githubusercontent.com (media.githubusercontent.com)... 185.
199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to media.githubusercontent.com (media.githubusercontent.com)|18
5.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 134409071 (128M) [application/octet-stream]
Saving to: ‘glove.6B.100d.txt.gz’

glove.6B.100d.txt.g 100%[===================>] 128.18M   299MB/s    in 0.4s

2023-04-22 15:40:35 (299 MB/s) - ‘glove.6B.100d.txt.gz’ saved [134409071/13
4409071]

glove.6B.100d.txt.gz:    61.3% -- replaced with glove.6B.100d.txt
```

In [ ]:
```
import pandas as pd

# Load csv
df = pd.read_csv('books.csv')

# Remove all rows with language not English
eng_df = df[df['language'] == 'English']

# Remove all rows with description or genres as NaN
eng_df = eng_df.dropna(subset=['description', 'genres'])

# Remove all duplicate descriptions
eng_df = eng_df.drop_duplicates(subset=['description'])

# Reset index
eng_df = eng_df.reset_index(drop=True)

eng_df
```

Out[ ]:

	title	series	author	rating	description	language	isbn
0	The Hunger Games	The Hunger Games #1	Suzanne Collins	4.33	WINNING MEANS FAME AND FORTUNE.LOSING MEANS CE...	English	9.78044E+12
1	Harry Potter and the Order of the Phoenix	Harry Potter #5	J.K. Rowling, Mary GrandPré (Illustrator)	4.50	There is a door at the end of a silent corrido...	English	9.78044E+12
2	To Kill a Mockingbird	To Kill a Mockingbird	Harper Lee	4.28	The unforgettable novel of a childhood in a sl...	English	1E+13
3	Pride and Prejudice	NaN	Jane Austen, Anna Quindlen (Introduction)	4.26	Alternate cover edition of ISBN 9780679783268S...	English	1E+13
4	Twilight	The Twilight Saga #1	Stephenie Meyer	3.60	About three things I was absolutely positive.\...	English	9.78032E+12
...	...	...	...	...	...	...	...
42028	Fractured	Fateful #2	Cheri Schmidt (Goodreads Author)	4.00	The Fateful Trilogy continues with Fractured. ...	English	2.94001E+12
42029	Anasazi	Sense of Truth #2	Emma Michaels	4.19	'Anasazi', sequel to 'The Thirteenth Chime' by...	English	1E+13
42030	Marked	Soul Guardians #1	Kim Richardson (Goodreads Author)	3.70	--READERS FAVORITE AWARDS WINNER 2011--Sixteen...	English	9.78146E+12
42031	Wayward Son	NaN	Tom Pollack (Goodreads Author), John Loftus (G...	3.85	A POWERFUL TREMOR UNEARTHS AN ANCIENT SECRETBu...	English	9.78145E+12
42032	Daughter of Helaman	Stripling Warrior #1	Misty Moncur (Goodreads Author)	4.02	Fighting in Helaman's army is Keturah's deepes...	English	9.7816E+12

42033 rows × 23 columns

In [ ]:
```
# Extract the title, description, and genres columns
cut_df = eng_df[['title', 'description', 'genres']]

# Print the description of the 2nd row
print(cut_df['description'][1])
```

```
There is a door at the end of a silent corridor. And it’s haunting Harry Po
ttter’s dreams. Why else would he be waking in the middle of the night, scr
eaming in terror?Harry has a lot on his mind for this, his fifth year at Ho
gwarts: a Defense Against the Dark Arts teacher with a personality like poi
soned honey; a big surprise on the Gryffindor Quidditch team; and the loomi
ng terror of the Ordinary Wizarding Level exams. But all these things pale
next to the growing threat of He-Who-Must-Not-Be-Named - a threat that neit
her the magical government nor the authorities at Hogwarts can stop.As the
grasp of darkness tightens, Harry must discover the true depth and strength
of his friends, the importance of boundless loyalty, and the shocking price
of unbearable sacrifice.His fate depends on them all.
```

In [ ]:
```
# Iterate through the genres column and add them to the list
genres = []
for genre in cut_df['genres']:
    genres.extend(genre.strip('][').split(', '))

# Remove extra set of single quotes
genres = [genre.replace("'", "") for genre in genres if genre != '']

# Sort genres alphabetically
genres.sort()

# Get unique genres
unique_genres = list(set(genres))

# REMOVE "Fiction"
unique_genres.remove('Fiction')

# Count number of each unique genre
# WARNING: This takes like 20 seconds TT
genre_counts = {genre: genres.count(genre) for genre in unique_genres}
```

In [ ]:
```
# Remove all genres that appear less than 500 times
filtered_genre_counts = {genre: count for genre, count in genre_counts.items

# Total count of books
total = df.shape[0]

# Sort genres by count
filtered_genre_counts = {k: v/total for k, v in sorted(filtered_genre_counts
filtered_genre_counts
```

Out[ ]:

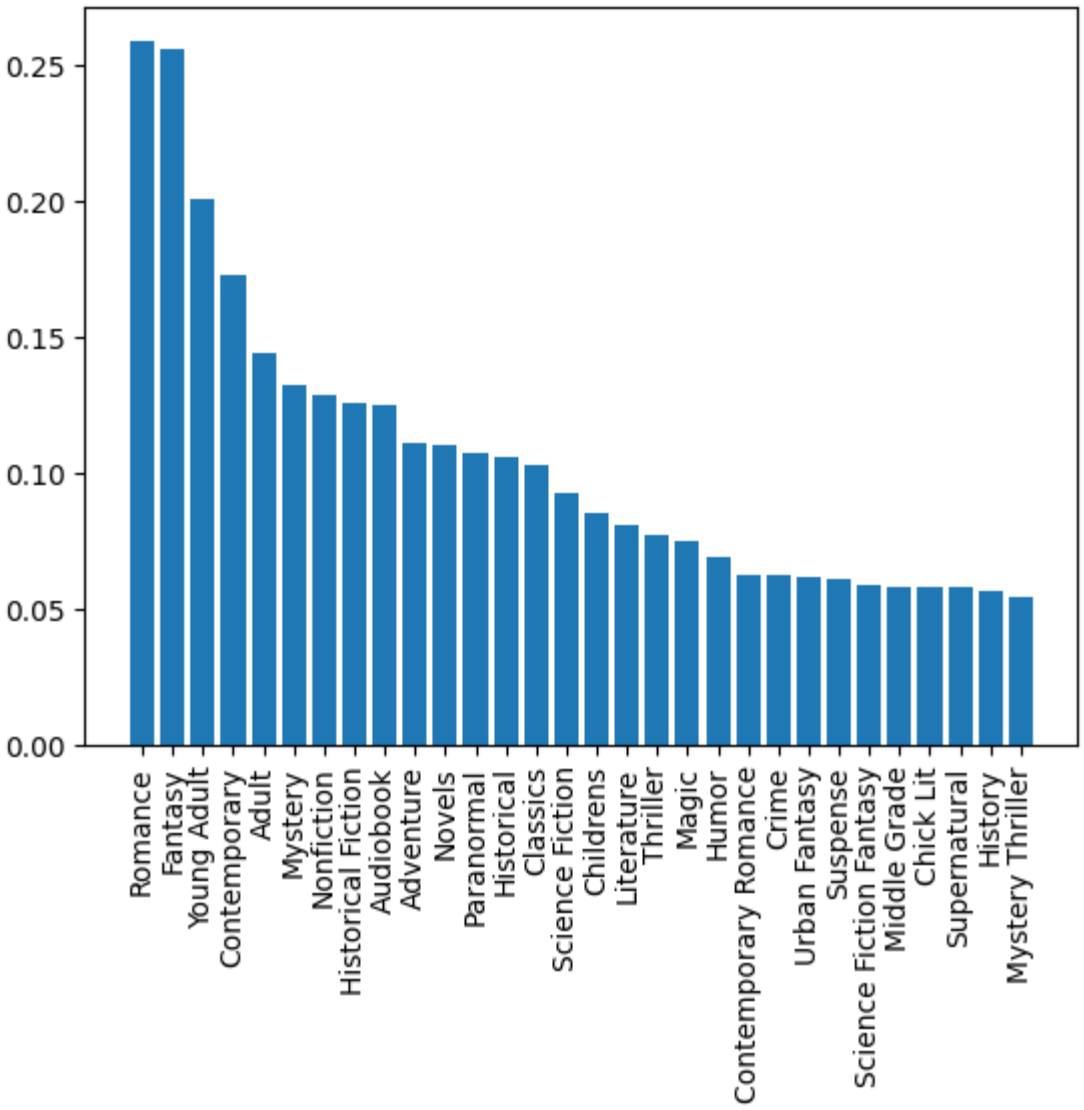
```
{'Romance': 0.2583939936735394,
 'Fantasy': 0.25568809786958346,
 'Young Adult': 0.20042684553527193,
 'Contemporary': 0.172510385304318,
 'Adult': 0.1437173672777164,
 'Mystery': 0.13247456076832195,
 'Nonfiction': 0.12824421662410915,
 'Historical Fiction': 0.12555737642440642,
 'Audiobook': 0.12473798544151835,
 'Adventure': 0.11077022752391479,
 'Novels': 0.11006517016654598,
 'Paranormal': 0.10732116315408362,
 'Historical': 0.10615877129463776,
 'Classics': 0.10312893021837723,
 'Science Fiction': 0.09293418194290941,
 'Childrens': 0.08535005145013148,
 'Literature': 0.08060520599108198,
 'Thriller': 0.07723236403826365,
 'Magic': 0.07530774800868936,
 'Humor': 0.06928617706467471,
 'Contemporary Romance': 0.06286443843134266,
 'Crime': 0.06265482678455733,
 'Urban Fantasy': 0.06210221426121422,
 'Suspense': 0.060996989214527994,
 'Science Fiction Fantasy': 0.05878653912115553,
 'Middle Grade': 0.05817675978505278,
 'Chick Lit': 0.057795647699988566,
 'Supernatural': 0.05777659209573536,
 'History': 0.05661420023628949,
 'Mystery Thriller': 0.054518083768436296,
 'Paranormal Romance': 0.052669690155874846,
 'Biography': 0.050954685773085866,
 'Teen': 0.04981134951789321,
 'Horror': 0.04941118182857578,
 'Adult Fiction': 0.0485727352414345,
 'British Literature': 0.043561111322840046,
 'Realistic Fiction': 0.04310377682076299,
 'Literary Fiction': 0.04274172033995198,
 'Philosophy': 0.04001676893174282,
 'Short Stories': 0.03866382102976485,
 'New Adult': 0.0385685430084988,
 'Memoir': 0.038435153778726326,
 'Erotica': 0.03550059072373185,
 'Vampires': 0.03485270017912268,
 'Drama': 0.03483364457486947,
 'Religion': 0.033766530736689664,
 'Christian': 0.03309958458782728,
 'War': 0.03254697206448416,
 'American': 0.03130835778802546,
 'Juvenile': 0.029688631426502535,
 'Graphic Novels': 0.029498075383970427,
 'Dystopia': 0.029231296924425474,
 '20th Century': 0.028640573192575937,
 'Family': 0.028164183086245666,
 'Comics': 0.027859293418194292,
 'Biography Memoir': 0.027440070124623652,
```

'Politics': 0.02654445672472274,
'High Fantasy': 0.025953732992873204,
'Psychology': 0.025439231678036512,
'LGBT': 0.02473417432066771,
'Historical Romance': 0.024010061359045695,
'Action': 0.023609893669728266,
'School': 0.023133503563397995,
'Spirituality': 0.02273333587408057,
'Autobiography': 0.021856778078432868,
'Animals': 0.021189831929570486,
'Science': 0.021151720721064065,
'Christian Fiction': 0.020656275010480583,
'Young Adult Fantasy': 0.020484774572201686,
'Poetry': 0.020446663363695262,
'Self Help': 0.020179884904150312,
'Military Fiction': 0.019188993482983346,
'Comedy': 0.01907465985746408,
'Mythology': 0.018998437440451238,
'Detective': 0.01749304470444758,
'Epic Fantasy': 0.01667365372155951,
'Coming Of Age': 0.01667365372155951,
'Erotic Romance': 0.016406875262014557,
'Graphic Novels Comics': 0.016101985593963183,
'Speculative Fiction': 0.016044818781203552,
'Abuse': 0.015358817028087961,
'Reference': 0.015187316589809062,
'Inspirational': 0.015053927360036587,
'Romantic Suspense': 0.01467281527497237,
'High School': 0.014653759670719158,
'France': 0.013891535500590723,
'Dark': 0.013529479019779717,
'Shapeshifters': 0.013434200998513663,
'Book Club': 0.013338922977247609,
'Christianity': 0.012976866496436602,
'Amazon': 0.012748199245398072,
'Novella': 0.012633865619878806,
'19th Century': 0.012614810015625595,
'Fairy Tales': 0.012557643202865962,
'Queer': 0.012557643202865962,
'World War II': 0.012538587598612752,
'Art': 0.012481420785853119,
'Essays': 0.012252753534814588,
'Travel': 0.012233697930561378,
'Post Apocalyptic': 0.012214642326308167,
'Time Travel': 0.01206219749228248,
'Witches': 0.012024086283776058,
'Demons': 0.011776363428484317,
'Young Adult Contemporary': 0.011776363428484317,
'Business': 0.011585807385952208,
'Comic Book': 0.011528640573192576,
'Sports': 0.011528640573192576,
'Music': 0.011452418156179733,
'Picture Books': 0.0113952513434201,
'Werewolves': 0.011357140134913677,
'Manga': 0.011261862113647624,
'American History': 0.010880750028583406,

```
 'Womens': 0.010709249590304509,
 'Asia': 0.010709249590304509,
 'Dragons': 0.010461526735012766,
 'Space': 0.010442471130759556,
 'Feminism': 0.010347193109493502,
 'Love': 0.010156637066961393,
 'Anthologies': 0.010118525858454972,
 'Faith': 0.010023247837188918,
 'Westerns': 0.009966081024429285,
 'Ghosts': 0.009947025420176074,
 'Magical Realism': 0.009775524981897175,
 'Theology': 0.009756469377643965,
 'Space Opera': 0.009718358169137544,
 'College': 0.009565913335111857,
 'Epic': 0.009546857730858645}
```

Distribution of top 30 genres

In [ ]:
```
import matplotlib.pyplot as plt

# Extract first 20 genres
filtered_genre_counts_top = dict(list(filtered_genre_counts.items())[:30])

# Plot the genres as a bar chart
plt.bar(filtered_genre_counts_top.keys(), filtered_genre_counts_top.values()
plt.xticks(rotation=90)
plt.show()
```



In [ ]:
```
len(filtered_genre_counts)
```

Out[ ]: 127

Create training data

In [ ]:
```
# This will be used to map genres to a list of 0s and 1s
genre_set = list(filtered_genre_counts)

def get_genre_arr(field):
    outlist = [0] * len(genre_set)
    for i, genre in enumerate(genre_set):
        if genre in field:
            outlist[i] = 1
    return outlist

# These are the lists that will be used to train the model
# Title list is just used for human debugging
genre_count_list = cut_df['genres'].apply(get_genre_arr)
title_list = cut_df['title']
description_list = cut_df['description']
```

In [ ]:
```
genre_df = pd.DataFrame(genre_count_list.tolist(), columns=genre_set)
```

In [ ]:
```
genre_df
```

Out[ ]:

	Romance	Fantasy	Young Adult	Contemporary	Adult	Mystery	Nonfiction	Historical Fiction	Audiobo
0	1	1	1	0	1	0	0	0	
1	0	1	1	0	1	0	0	0	
2	0	0	1	0	1	0	0	1	
3	1	0	0	0	1	0	0	1	
4	1	1	1	0	1	0	0	0	
...	...	...	...	...	...	...	...	...	
42028	1	1	1	0	1	0	0	0	
42029	0	0	1	0	1	1	0	0	
42030	1	1	1	0	1	0	0	0	
42031	0	0	0	0	0	1	0	1	
42032	1	1	1	0	1	0	0	1	

42033 rows × 127 columns

In [ ]:
```
import re
import unicodedata

pattern = re.compile(r'[^a-zA-Z\s]')

# Clean description
def clean_desc(desc: str):
    # Replace non alphabetic characters with spaces using regex
    desc = pattern.sub(' ', desc)

    # Replace all extra spaces with single spaces
    desc = re.sub('\W+', ' ', desc)

    # Remove leading and trailing spaces
    desc = desc.strip()

    # Convert to lowercase
    desc = desc.lower()

    # Normalize unicode characters
    desc = unicodedata.normalize('NFKD', desc).encode('ascii', 'ignore').dec

    return desc

description_list = description_list.apply(clean_desc)
```

In [ ]:
```
from sklearn.model_selection import train_test_split
import numpy as np

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(description_list, genre_
```

In [ ]:
```
# Get the unique words in the descriptions
vocab = set()
description_list.apply(lambda x: vocab.update(x.split(" ")))
vocab.remove('')
vocab = list(vocab)
```

In [ ]:
```
vocab.sort()
```

In [ ]:
```
from keras.preprocessing.text import Tokenizer
from keras.utils import pad_sequences

tokenizer = Tokenizer(num_words=5000)
tokenizer.fit_on_texts(X_train)


X_train = tokenizer.texts_to_sequences(X_train)
X_test = tokenizer.texts_to_sequences(X_test)

vocab_size = len(tokenizer.word_index) + 1
maxlen = 1000

X_train = pad_sequences(X_train, padding='post', maxlen=maxlen)
X_test = pad_sequences(X_test, padding='post', maxlen=maxlen)
```

In [ ]:
```
from numpy import array
from numpy import asarray
from numpy import zeros

embeddings_dictionary = dict()

glove_file = open('glove.6B.100d.txt', encoding="utf8")

for line in glove_file:
    records = line.split()
    word = records[0]
    vector_dimensions = asarray(records[1:], dtype='float32')
    embeddings_dictionary[word] = vector_dimensions
glove_file.close()

embedding_matrix = zeros((vocab_size, 100))
for word, index in tokenizer.word_index.items():
    embedding_vector = embeddings_dictionary.get(word)
    if embedding_vector is not None:
        embedding_matrix[index] = embedding_vector
```

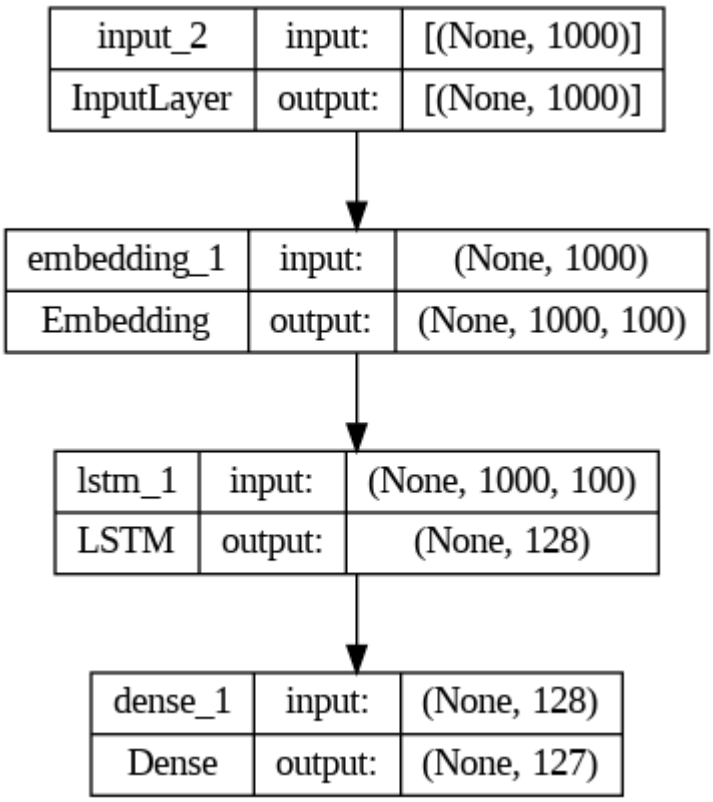
In [ ]:
```
from keras.layers import LSTM, Embedding
from keras.models import Model
from keras.layers.core import Dense
from keras.layers import Input

deep_inputs = Input(shape=(maxlen,))
embedding_layer = Embedding(vocab_size, 100, weights=[embedding_matrix], tra
LSTM_Layer_1 = LSTM(128)(embedding_layer)
dense_layer_1 = Dense(len(genre_set), activation='sigmoid')(LSTM_Layer_1)
model = Model(inputs=deep_inputs, outputs=dense_layer_1)

model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['acc'])
```

In [ ]:
```
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 1000)]            0

 embedding_1 (Embedding)     (None, 1000, 100)         10385700

 lstm_1 (LSTM)               (None, 128)               117248

 dense_1 (Dense)             (None, 127)               16383

=================================================================
Total params: 10,519,331
Trainable params: 133,631
Non-trainable params: 10,385,700
_________________________________________________________________
```

In [ ]:
```
from keras.utils import plot_model
plot_model(model, show_shapes=True, show_layer_names=True)
```

Out[ ]:



In [ ]:
```
history = model.fit(X_train, y_train, batch_size=128, epochs=2, verbose=1, v
```

```
Epoch 1/2
237/237 [==============================] - 713s 3s/step - loss: 0.2212 - ac
c: 0.0336 - val_loss: 0.1881 - val_acc: 0.0321
Epoch 2/2
237/237 [==============================] - 710s 3s/step - loss: 0.1887 - ac
c: 0.0323 - val_loss: 0.1885 - val_acc: 0.0321
```

In [ ]:
```
score = model.evaluate(X_test, y_test, verbose=1)

print("Test Score:", score[0])
print("Test Accuracy:", score[1])
```

```
132/132 [==============================] - 61s 460ms/step - loss: 0.1902 -
acc: 0.0362
Test Score: 0.19024476408958435
Test Accuracy: 0.03615604341030121
```

In [ ]:
```
# Convert the predictions to a list of genres
def get_genres_from_prediction(prediction):
    genres = []
    for i, genre in enumerate(genre_set):
        if prediction[i] > 0.4:
            genres.append(genre)
    return genres

# Predict
TEXT = ''
P = model.predict(pad_sequences(tokenizer.texts_to_sequences([clean_desc(TEX
print(get_genres_from_prediction(P[0]))
print(P[0])

# Get the predictions for the first 10 books in the test set
predictions = model.predict(X_test[0:10])
for i, prediction in enumerate(predictions):
    print(title_list.iloc[i])
    print(get_genres_from_prediction(prediction))
    print()
```

```
1/1 [==============================] - 0s 135ms/step
['Adult']
[0.33605823 0.30191395 0.22866361 0.21360056 0.41926804 0.16353963
 0.1766652  0.14330363 0.18137546 0.11371192 0.19966763 0.12950827
 0.17013028 0.15624234 0.12138409 0.08820471 0.21497695 0.10950684
 0.09495632 0.10867362 0.07386114 0.08365641 0.07535788 0.09380054
 0.0566878  0.05640694 0.06773544 0.0835561  0.07361025 0.06997751
 0.05792454 0.06330445 0.06428464 0.06968126 0.06927243 0.06554246
 0.0625001  0.06793436 0.0548686  0.04270452 0.04045228 0.05761433
 0.04142811 0.03914176 0.06459928 0.0456055  0.04904626 0.04195905
 0.07444394 0.03532544 0.04611309 0.03013543 0.045244   0.03667369
 0.04688472 0.03975899 0.03227377 0.031859   0.0401502  0.0262626
 0.03389919 0.02789578 0.0565532  0.02773294 0.0305691  0.02870414
 0.14736068 0.02627006 0.026818   0.02736424 0.02460751 0.02134088
 0.02656917 0.02541051 0.02317808 0.0176956  0.02413111 0.01718615
 0.0211896  0.01754444 0.01987125 0.01583225 0.02115366 0.01871144
 0.02016718 0.02795686 0.02129927 0.01611014 0.01659668 0.01796553
 0.01341135 0.01423026 0.01548746 0.01521358 0.01506739 0.01733457
 0.01989722 0.01853883 0.02758331 0.01007296 0.0131412  0.01579426
 0.01439769 0.01557694 0.0157341  0.01537544 0.01250444 0.0135258
 0.01208161 0.01475715 0.0156063  0.01220054 0.02346283 0.01915411
 0.01421334 0.01455502 0.01567236 0.01612229 0.01053297 0.01300236
 0.01268159 0.01317593 0.0126197  0.01287231 0.01002509 0.0107242
 0.01871071]
1/1 [==============================] - 0s 468ms/step
The Hunger Games
['Adult']

Harry Potter and the Order of the Phoenix
['Adult']

To Kill a Mockingbird
['Adult']

Pride and Prejudice
['Adult']

Twilight
['Adult']

The Book Thief
['Adult']

Animal Farm
['Adult']

The Chronicles of Narnia
['Adult']

J.R.R. Tolkien 4-Book Boxed Set: The Hobbit and The Lord of the Rings
['Adult']

Gone with the Wind
['Adult']
```

I have decided to start over

The previous genres and descriptions did not have enough correlation to train a good enough model. I am switching to a database of book reviews and their ratings to try to predict ratings through the reviews. It will use similar techniques as above, but on a different dataset. The new dataset is from Amazon Book Reviews.

I am also downloading the data using the Kaggle API because the dataset is humongous (yikes). But you will need to follow these instructions to get an API key.

In [ ]:
```
import json
import os

# Load credentials from kaggle.json
config = {}
with open('kaggle.json', 'r') as f:
    config = json.load(f)

# Set env
os.environ['KAGGLE_USERNAME'] = config['username']
os.environ['KAGGLE_KEY'] = config['key']
```

In [ ]:
```
!pip install kaggle
!kaggle datasets download -d mohamedbakhet/amazon-books-reviews
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: kaggle in /usr/local/lib/python3.9/dist-packages (1.5.13)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.9/dist-packages (from kaggle) (8.0.1)
Requirement already satisfied: tqdm in /usr/local/lib/python3.9/dist-packages (from kaggle) (4.65.0)
Requirement already satisfied: requests in /usr/local/lib/python3.9/dist-packages (from kaggle) (2.27.1)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.9/dist-packages (from kaggle) (2.8.2)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.9/dist-packages (from kaggle) (1.26.15)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.9/dist-packages (from kaggle) (1.16.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.9/dist-packages (from kaggle) (2022.12.7)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.9/dist-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-packages (from requests->kaggle) (3.4)
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dist-packages (from requests->kaggle) (2.0.12)
Downloading amazon-books-reviews.zip to /content
 99% 1.06G/1.06G [00:14<00:00, 103MB/s]
100% 1.06G/1.06G [00:14<00:00, 79.7MB/s]
```

In [ ]:
```
!unzip -u amazon-books-reviews.zip
```

```
Archive:  amazon-books-reviews.zip
  inflating: Books_rating.csv
  inflating: books_data.csv
```

In [ ]:
```
import pandas as pd

# Load data
df = pd.read_csv('Books_rating.csv')
df
```

Out[ ]:

	Id	Title	Price	User_id	profileName	review/helpfulness
0	1882931173	Its Only Art If Its Well Hung!	NaN	AVCGYZL8FQQTD	Jim of Oz "jim-of-oz"	7/7
1	0826414346	Dr. Seuss: American Icon	NaN	A30TK6U7DNS82R	Kevin Killian	10/10
2	0826414346	Dr. Seuss: American Icon	NaN	A3UH4UZ4RSVO82	John Granger	10/11
3	0826414346	Dr. Seuss: American Icon	NaN	A2MVUWT453QH61	Roy E. Perry "amateur philosopher"	7/7
4	0826414346	Dr. Seuss: American Icon	NaN	A22X4XUPKF66MR	D. H. Richards "ninthwavestore"	3/3
...	...	...	...	...	...	...
2999995	B000NSLVCU	The Idea of History	NaN	NaN	NaN	14/19
2999996	B000NSLVCU	The Idea of History	NaN	A1SMUB9ASL5L9Y	jafrank	1/1
2999997	B000NSLVCU	The Idea of History	NaN	A2AQMEKZKK5EE4	L. L. Poulos "Muslim Mom"	0/0
2999998	B000NSLVCU	The Idea of History	NaN	A18SQGYBKS852K	Julia A. Klein "knitting rat"	1/11
2999999	B000NSLVCU	The Idea of History	NaN	NaN	NaN	7/49

3000000 rows × 10 columns

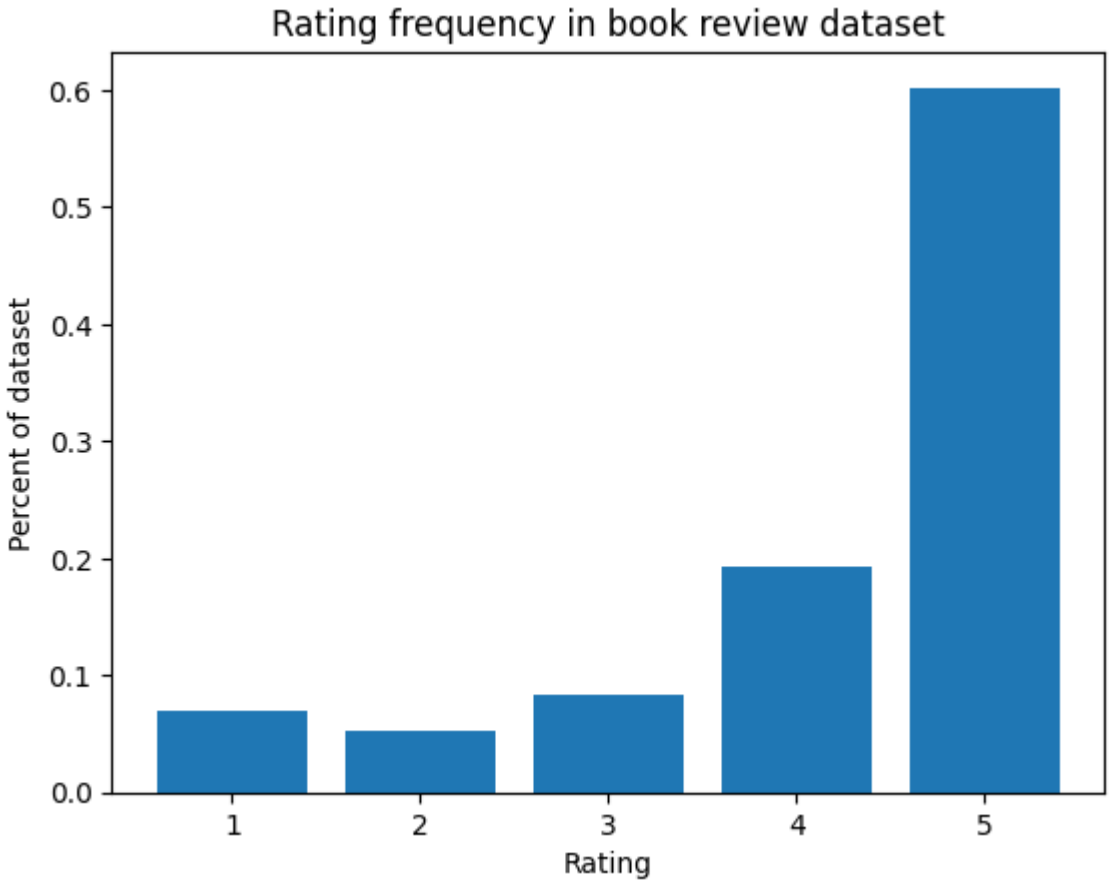
In [ ]:
```
# Cut dataframe; can change later when finished
# We will use 100000 entries for this example
smol_df = df.iloc[:100000]
smol_df
```

Out[ ]:

	Id	Title	Price	User_id	profileName	review/helpfulness	r
0	1882931173	Its Only Art If Its Well Hung!	NaN	AVCGYZL8FQQTD	Jim of Oz "jim-of-oz"	7/7	
1	0826414346	Dr. Seuss: American Icon	NaN	A30TK6U7DNS82R	Kevin Killian	10/10	
2	0826414346	Dr. Seuss: American Icon	NaN	A3UH4UZ4RSVO82	John Granger	10/11	
3	0826414346	Dr. Seuss: American Icon	NaN	A2MVUWT453QH61	Roy E. Perry "amateur philosopher"	7/7	
4	0826414346	Dr. Seuss: American Icon	NaN	A22X4XUPKF66MR	D. H. Richards "ninthwavestore"	3/3	
...	...	...	...	...	...	...	
99995	B000KEPCVS	April MOrning	NaN	NaN	NaN	1/1	
99996	B000KEPCVS	April MOrning	NaN	NaN	NaN	1/1	
99997	B000KEPCVS	April MOrning	NaN	NaN	NaN	1/1	
99998	B000KEPCVS	April MOrning	NaN	A3GW18RTWRWGZZ	Errika	1/1	
99999	B000KEPCVS	April MOrning	NaN	NaN	NaN	3/4	

100000 rows × 10 columns

In [ ]:
```
# Plot reviews on bar chart
import matplotlib.pyplot as plt

# Get count of each review score
val_counts = smol_df['review/score'].value_counts()

# Get total # of entries
count = smol_df.shape[0]

val_counts = val_counts.apply(lambda x : x / count)
val_counts = val_counts.sort_index()
# Plot the genres as a bar chart
plt.bar(val_counts.keys(), val_counts)
plt.xlabel('Rating')
plt.ylabel('Percent of dataset')
plt.title('Rating frequency in book review dataset')
plt.show()
```



The dataset consists of book reviews and the ratings that those reviews correspond to. The model should be able to predict the user's review score (1-5) based on the review text.

In [ ]:
```
# Extract columns that we want and rename columns
in_df = smol_df[['review/score', 'review/text']]
in_df.columns = ['score', 'review']
in_df
```

Out[ ]:

	score	review
0	4.0	This is only for Julie Strain fans. It's a col...
1	5.0	I don't care much for Dr. Seuss but after read...
2	5.0	If people become the books they read and if "t...
3	4.0	Theodore Seuss Geisel (1904-1991), aka "D...
4	4.0	Philip Nel - Dr. Seuss: American IconThis is b...
...	...	...
99995	3.0	I somewhat liked april morning. It was a quick...
99996	3.0	I somewhat liked april morning. It was a quick...
99997	4.0	I enjoyed this book very much. Although it was...
99998	3.0	I have read the novel, April Morning, and i fo...
99999	4.0	If you want to read an outstanding book about ...

100000 rows × 2 columns

In [ ]:
```
# Count average # of words (approx)
def count_words(text):
    return

vocab_counts = in_df['review'].apply(lambda text: len(text.split(' ')))
vocab_counts.describe()
```

Out[ ]:
```
count    100000.000000
mean        146.859390
std         165.493393
min           1.000000
25%          49.000000
50%          95.000000
75%         181.000000
max        4928.000000
Name: review, dtype: float64
```

In [ ]:
```
# Split score array into vectorized array
label_arr = [1.0, 2.0, 3.0, 4.0, 5.0]

score_arr = []
for row in in_df['score']:
    curr_row = [0] * len(label_arr)
    for i, score in enumerate(label_arr):
        if row == score:
            curr_row[i] = 1
    score_arr.append(curr_row)

out_df = pd.DataFrame(score_arr, columns=label_arr)
```

In [ ]:
```
out_df
```

Out[ ]:

	1.0	2.0	3.0	4.0	5.0
0	0	0	0	1	0
1	0	0	0	0	1
2	0	0	0	0	1
3	0	0	0	1	0
4	0	0	0	1	0
...	...	...	...	...	...
99995	0	0	1	0	0
99996	0	0	1	0	0
99997	0	0	0	1	0
99998	0	0	1	0	0
99999	0	0	0	1	0

100000 rows × 5 columns

In [ ]:
```
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(in_df['review'], out_df,
```

In [ ]:
```
from keras.layers import TextVectorization

MAX_LEN = 200
MAX_FEATURES = 5000

# Create text vectorization layer
text_vec = TextVectorization(
    output_sequence_length=MAX_LEN,
    pad_to_max_tokens=True,
    max_tokens=MAX_FEATURES,
    standardize='lower_and_strip_punctuation',
    split='whitespace',
    output_mode='int',
)
```

In [ ]:
```
# Adapt vectorizer
text_vec.adapt(X_train)
```

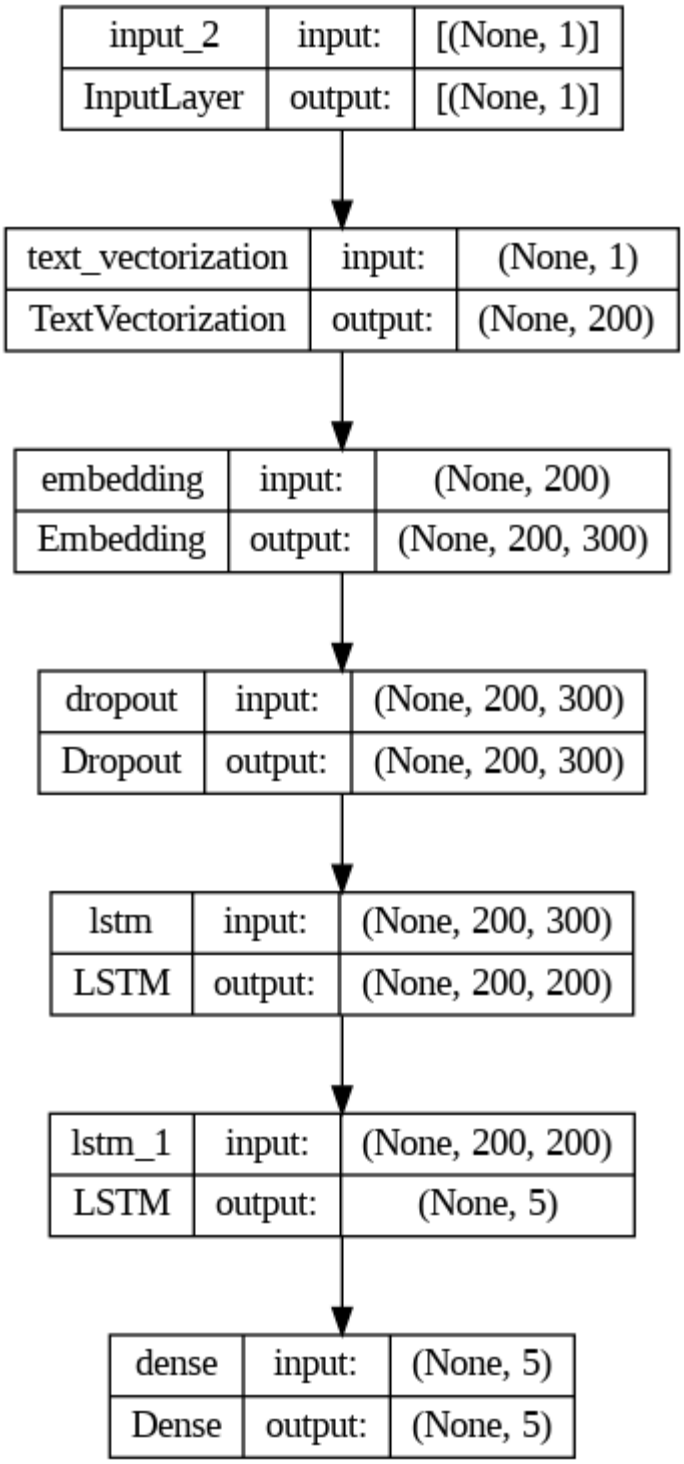
In [ ]:
```
from keras.models import Sequential
from keras.layers import Dense, Dropout, LSTM, Embedding
from keras import Input
import tensorflow as tf

EMBEDDING_OUT = 300

# Create the model
model = Sequential()
model.add(Input(shape=(1,), dtype=tf.string))
model.add(text_vec)
model.add(
    Embedding(
        input_dim=MAX_FEATURES,
        input_length=MAX_LEN,
        output_dim=EMBEDDING_OUT
    )
)
model.add(Dropout(0.6))
model.add(LSTM(MAX_LEN,return_sequences=True))
model.add(LSTM(5))
model.add(Dense(5,activation='softmax'))
model.compile(optimizer='adam',loss='categorical_crossentropy', metrics=['ac
```

In [ ]:
```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 text_vectorization (TextVec  (None, 200)              0
 torization)

 embedding (Embedding)       (None, 200, 300)          1500000

 dropout (Dropout)           (None, 200, 300)          0

 lstm (LSTM)                 (None, 200, 200)          400800

 lstm_1 (LSTM)               (None, 5)                 4120

 dense (Dense)               (None, 5)                 30

=================================================================
Total params: 1,904,950
Trainable params: 1,904,950
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:
```
from keras.utils import plot_model
plot_model(model, show_shapes=True, show_layer_names=True)
```

Out[ ]:



In [ ]:
```
history = model.fit(X_train, y_train, batch_size=128, epochs=2, verbose=1, v
```

```
Epoch 1/2
563/563 [==============================] - 1221s 2s/step - loss: 1.1809 - a
ccuracy: 0.5993 - val_loss: 1.1863 - val_accuracy: 0.6027
Epoch 2/2
563/563 [==============================] - 1172s 2s/step - loss: 1.1672 - a
ccuracy: 0.6020 - val_loss: 1.1640 - val_accuracy: 0.6027
```

In [ ]:
```
# Save model
model.save('review_class')
```

```
WARNING:absl:Found untraced functions such as _update_step_xla, lstm_cell_l
ayer_call_fn, lstm_cell_layer_call_and_return_conditional_losses, lstm_cell
_1_layer_call_fn, lstm_cell_1_layer_call_and_return_conditional_losses whil
e saving (showing 5 of 5). These functions will not be directly callable af
ter loading.
```

In [ ]:
```
!zip -r review_class.zip review_class
```

```
  adding: review_class/ (stored 0%)
  adding: review_class/keras_metadata.pb (deflated 89%)
  adding: review_class/variables/ (stored 0%)
  adding: review_class/variables/variables.index (deflated 59%)
  adding: review_class/variables/variables.data-00000-of-00001 (deflated
6%)
  adding: review_class/saved_model.pb (deflated 88%)
  adding: review_class/assets/ (stored 0%)
  adding: review_class/fingerprint.pb (stored 0%)
```

In [ ]:
```
from keras.models import load_model

# Load model
model = load_model('review_class')
```

In [ ]:
```
# Test model
score = model.evaluate(X_test, y_test, verbose=1)

print("Test Score:", score[0])
print("Test Accuracy:", score[1])
```

```
313/313 [==============================] - 75s 238ms/step - loss: 1.1659 -
accuracy: 0.6022
Test Score: 1.1658990383148193
Test Accuracy: 0.6021999716758728
```

In [ ]:
```
# Test random review
TEST_INPUT = "The \"Dragon\" book makes any bookshelf look more beautiful, a
model.predict([TEST_INPUT])
```

```
1/1 [==============================] - 0s 136ms/step
```

Out[ ]:
```
array([[0.06691363, 0.04487224, 0.08195179, 0.18375634, 0.622506  ]],
      dtype=float32)
```

Write up your analysis of the performance of various approaches

The first attempt to build a model resulted in complete failure! I used the "GoodReads Best Books" dataset, which contained a list of genres and descriptions of the books. My first attempt at making a bot was bad. I used the GoodReads Best Book dataset and tried to use the description to do multiclass classification of genres. However, the correlation of the description and genres was not high enough, so the model always gave me the highest frequency genre. I initially had a model that performed decently, but I realized that my accuracy measurement was wrong! After that, I used the Glove dataset to create embeddings, but it was huge and slowed down the process. My second attempt went much better. I used the Amazon Book Reviews dataset and created a model to predict the rating (classify into 1-5) that the user gave based on their review body. At first, I used only a sequential model but quickly realized that I needed a RNN to be more accurate. I added a Dropout layer and 2 LSTM layers which fed into a Dense output layer.

The use of the Amazon Book Reviews dataset was a better choice since it resulted in a higher correlation between the review body and the rating given by the user. Additionally, the use of an RNN with 2 LSTM layers and a Dense output layer with a Dropout layer is a more sophisticated approach than the simple sequential model used initially. This indicates that the use of a more complex model can lead to better results, but this can come at a cost of increased computation time.

The use of the Glove dataset to create embeddings in the first attempt was not ideal, as it was too large and slowed down the process. It's important to use appropriate datasets that are both relevant to the task at hand and manageable in size. In the second attempt, the Amazon Book Reviews dataset was a better choice, as it was more focused on the task of predicting ratings.

The success of the second attempt indicates that using a more complex model and an appropriate dataset can lead to better results. However, it's also important to balance complexity with efficiency, as overly complex models can be computationally expensive and time-consuming to train. I faced a lot of issues in both memory and time. I started running out of memory even in Google Colab, and I started running out of TIME as the models took more than 30 minutes to train.