How to create a poet / writer using Deep Learning (Text Generation using Python)

# What are text generators?

Nowadays, there is a huge amount of data that can be categorized as sequential. It is present in the form of audio, video, text, time series, sensor data, etc. A special thing about this type of data is that if two events are occurring in a particular time frame, the occurrence of event A before event B is an entirely different scenario as compared to the occurrence of event A after event B.

However, in conventional machine learning problems, it hardly matters whether a particular data point was recorded before the other. This consideration requires us to use a different approach to our sequence prediction problem.

Text, a stream of characters lined up one after another, is a difficult thing to crack. This is because when handling text, a model may be trained to make very accurate predictions using the sequences that have occurred previously, but one wrong prediction has the potential to make the entire sentence meaningless. However, in case of a numerical sequence prediction problem, even if a prediction goes entirely south, it could still be considered a valid prediction (maybe with a high bias), but it would not be easily readable!

This is what makes text generators tricky!

## Different Steps of Text Generation

Text generation usually involves the following steps:

* Importing Dependencies
* Loading of Data
* Creating Character/Word mappings
* Data Preprocessing
* Modelling
* Generating text

Let’s look at each one in detail.

**Importing Dependencies**

import numpy as np

import pandas as pd

from keras.models import Sequential

from keras.layers import Dense

from keras.layers import Dropout

from keras.layers import LSTM

from keras.utils import np\_utils

**Loading the Data**

text=(open("sonnets.txt").read())

text=text.lower()

Here, we are loading a combined collection of all Shakespearean sonnets that can be downloaded from here. I cleaned up this file to remove the start and end credits, but the original can be downloaded from Moodle. (The Project Gutenberg eBook of Shakespeares Sonnets.txt)

The text file is opened and saved in text. This content is then converted into lowercase, to reduce the number of possible words (more on this later).

**Creating character/word mappings**

Mapping is a step in which we assign an arbitrary number to a character/word in the text. In this way, all unique characters/words are mapped to a number. This is important, because machines understand numbers far better than text, and this subsequently makes the training process easier.

characters = sorted(list(set(text)))

n\_to\_char = {n:char for n, char in enumerate(characters)}

char\_to\_n = {char:n for n, char in enumerate(characters)}

I have created a dictionary with a number assigned to each unique character present in the text. All unique characters are first stored as a list of characters and are then enumerated by assigning a number to each character. Eg.

{'\n': 0, ' ': 1, '!': 2, "'": 3, '(': 4, ')': 5, ',': 6, '-': 7, '.': 8, ':': 9, ';': 10, '?': 11, 'a': 12, 'b': 13,…..}

I’ve also created a number to character list, so that I can easily decode the numbers, inorder to read the text.

It must also be noted here that I have used character level mappings and not word mappings. However, when compared with each other, a word-based model shows much higher accuracy as compared to a character-based model. This is because the latter model requires a much larger network to learn long-term dependencies as it not only has to remember the sequences of words, but also has to learn to predict a grammatically correct word. However, in case of a word-based model, the latter has already been taken care of.

But since this is a small dataset (with 17,670 words), and the number of unique words (4,605 in number) constitute around one-fourth of the data, it would not be a wise decision to train on such a mapping. This is because if we assume that all unique words occurred equally in number (which is not true), we could have a word only occurring roughly four times in the entire training dataset, which is just not sufficient to build a text generator.

**Data preprocessing**

This is the trickiest part when it comes to building LSTM models. Transforming the data at hand into a relatable format is a difficult task.

**Python Code:**

X = []

Y = []

length = len(text)

seq\_length = 100

for i in range(0, length-seq\_length, 1):

sequence = text[i:i + seq\_length]

label =text[i + seq\_length]

X.append([char\_to\_n[char] for char in sequence])

Y.append(char\_to\_n[label])

Here, X is our train array, and Y is our target array.

seq\_length is the length of the sequence of characters that we want to consider before predicting a particular character.

The for loop is used to iterate over the entire length of the text and create such sequences (stored in X) and their dependent values (stored in Y). Now, it’s difficult to visualize the concept of dependent values here. Let’s understand this with an example:

For a sequence length of 4 and the text “hello ireland”, we would have our X and Y (not encoded as numbers for ease of understanding) as below:

X Y

[h, e, l, l] [o]

[e, l, l, o] [ ]

[l, l, o, ] [i]

[l, o, , i] [r]

…. ….

Now, LSTMs accept input in the form of (number\_of\_sequences, length\_of\_sequence, number\_of\_features) which is not the current format of the arrays. Also, we need to transform the array Y into a one-hot encoded format.

X\_modified = np.reshape(X, (len(X), seq\_length, 1))

X\_modified = X\_modified / float(len(characters))

Y\_modified = np\_utils.to\_categorical(Y)

We first reshape the array X into our required dimensions. Then, we scale the values of our X\_modified (by dividing by the length of the character list) so that our neural network can train faster and there is a lesser chance of getting stuck in a local minima. Also, our Y\_modified is one-hot encoded to remove any ordinal relationship that may have been introduced in the process of mapping the characters. That is, ‘a’ might be assigned a lower number as compared to ‘z’, but that doesn’t signify any relationship between the two.

Our final arrays will look like:

X\_modified Y\_modified

[[ 0.44444444],

[ 0.33333333],

[ 0.66666667],

[ 0.66666667]] [ 0., 0., 0., 0., 0., 0., 0., 0., 1.]

[[ 0.33333333],

[ 0.66666667],

[ 0.66666667],

[ 0.88888889]] [ 1., 0., 0., 0., 0., 0., 0., 0., 0.]

[[ 0.66666667],

[ 0.66666667],

[ 0.88888889],

[ 0. ]] [ 0., 0., 0., 0., 0., 1., 0., 0., 0.]

[[ 0.66666667],

[ 0.88888889],

[ 0. ] [ 0.55555556]] [ 0., 0., 0., 0., 0., 0., 0., 1., 0.]

**Modelling**

model = Sequential()

model.add(LSTM(400, input\_shape=(X\_modified.shape[1], X\_modified.shape[2]), return\_sequences=True))

model.add(Dropout(0.2))

model.add(LSTM(400))

model.add(Dropout(0.2))

model.add(Dense(Y\_modified.shape[1], activation='softmax'))

model.compile(loss='categorical\_crossentropy', optimizer='adam')

We are building a sequential model with two LSTM layers having 400 units each. The first layer needs to be fed in with the input shape. In order for the next LSTM layer to be able to process the same sequences, we enter the return\_sequences parameter as True.

Also, dropout layers with a 20% dropout have been added to check for over-fitting. The last layer outputs a one hot encoded vector which gives the character output.

**Generating Text**

string\_mapped = X[99]

# generating characters

for i in range(seq\_length):

x = np.reshape(string\_mapped,(1,len(string\_mapped), 1))

x = x / float(len(characters))

pred\_index = np.argmax(model.predict(x, verbose=0))

seq = [n\_to\_char[value] for value in string\_mapped]

string\_mapped.append(pred\_index)

string\_mapped = string\_mapped[1:len(string\_mapped)]

We start off with a random row from the X array, that is an array of 100 characters. After this, we target predicting another 100 characters following X. The input is reshaped and scaled as previously and the next character with maximum probability is predicted.

seq is used to store the decoded format of the string that has been predicted till now. Next, the new string is updated, such that the first character is removed, and the new predicted character is included.

**Experimenting with different models**

The baseline model, when trained for 1 epoch with a batch size of 100, gave the following output:

's the riper should by time decease,

his tender heir might bear his memory:

but thou, contracted toet she the the the the the the the the

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thi the the the the the the the the the the the the the the the the the

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This output doesn’t make much sense. It is nothing but a repetition of the same prediction, as if it’s stuck in a loop. This is because language prediction models are way too complex when compared to the miniature model that we have trained.

Let’s try to train the very same model, but for a longer period of time.

**A more trained model**

This time we trained our model for 100 epochs and a batch size of 50. We at least obtained a non-repetitive sequence of characters, which contains a decent number of legitimate words. Also, the model learnt to produce a sonnet-like word structure.

'The riper should by time decease,

his tender heir might bear his memory:

but thou, contracted to thine own besire,

that in the breath ther doomownd wron to ray,

dorh part nit backn oy steresc douh dxcel;

for that i have beauty lekeng norirness,

for all the foowing of a former sight,

which in the remame douh a foure to his,

that in the very bumees of toue mart detenese;

how ap i am nnw love, he past doth fiamee.

to diserace but in the orsths of are orider,

waie agliemt would have me '

However, this model is still not good enough to produce quality content. So now we’ll do what everyone does when a deep learning model is not producing decent results. Build a deeper architecture!

**A deeper model**

A wise man once said: if the model is not doing a good job, increase the number of layers! I’m going to do the same with my model. Let’s add another LSTM layer with 400 units followed by a dropout layer of 0.2 fraction and see what we get.

"The riper should by time decease,

his tender heir might bear his memory:

but thou, contracted to the world's false sporoe,

with eyes so dond touls be thy domfornds,

which for memorion of the seasons new;

mike own self-love to shou art constant

how can i then be oy love doth give,

the rose looks fair, but fairer bomments age.

now with the seas that i have seen dychl

that mot to teed of you, if h ho bontent,

and all the ress of the heartai thee;

the world will was iis bound and farty "

The result is interesting. The grammar has enhanced itself, keeping the sonnet structure and punctuation intact. However, this still requires a lot of improvement. Let’s try and explore a wider network, one with a greater number of units.

**A wider model**

I increased the number of units to 700 on each of the two LSTM layers. This tweak produced the following poetry:

"The riper should by time decease,

his tender heir might bear his memory:

but thou, contracted to thine own bright eyes,

feed'st thy sigh aare so beuider poise,

oor maty dis surre that gairs mot me love thee;

when i braye the would and lays in the eesire.

than thmu disgrmed stand with my bootr still nsentente;

tell ia to thou art thou wilt woon'thy sook,

and touain then tor, give thy soue semping.

whose whod the better of your befaiss nu sante,

though i, suoll oas, and i lose bouh twa"

This is a little disappointing at first, because the words have lost their meaning. But, what’s interesting to note here is that there is some rhyme that is building up. The model is trying to understand poetry after all! But, we still need to produce real and sensible words.

Let’s put it all together in a one gigantic model.

**A gigantic model**

I increased the number of layers to three, each having 700 units and trained it for 100 epochs. The result produced I not a bad piece of poetry! Take a look:

"The riper should by time decease,

his tender heir might bear his memory:

but thou, contracted to thine own bright eyes,

feed'st thy light's flame with self-substantial fuel,

my beept is she breat oe bath dasehr ill:

tirse do i pine and turfeit day by day,

or gluttoning on all, or all away.

Lxxvi

why is my verse so barren of new pride,

so far from variation or quick change?

why with the time do i not glance aside

to new-found methods, and to compounds strange?

why write i stil"

This not only has sensible words but has also learnt to rhyme!. We could have had a more sensible sonnet had the data that was fed into the network been cleaned properly! But as a starting piece, this model has more than done what it was asked.

## Conclusion

What makes a text generator more efficient is its capability to generate relevant stories. This is being implemented by many models at the output level, to generate actual language-like text, which can be difficult to differentiate from one written by humans.