Automatic Text Generation using Deep NLP on Machinelearninggeek.com Data

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Generating text to write articles using `Tensorflow`, `Keras` and `Long Short Term Memory(LSTM)`. The dataset for the assignment was fetched using `requests` library from [Machine Learning Geek]

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- Batch : MSc 3rd Sem (Data Science and Analytics)
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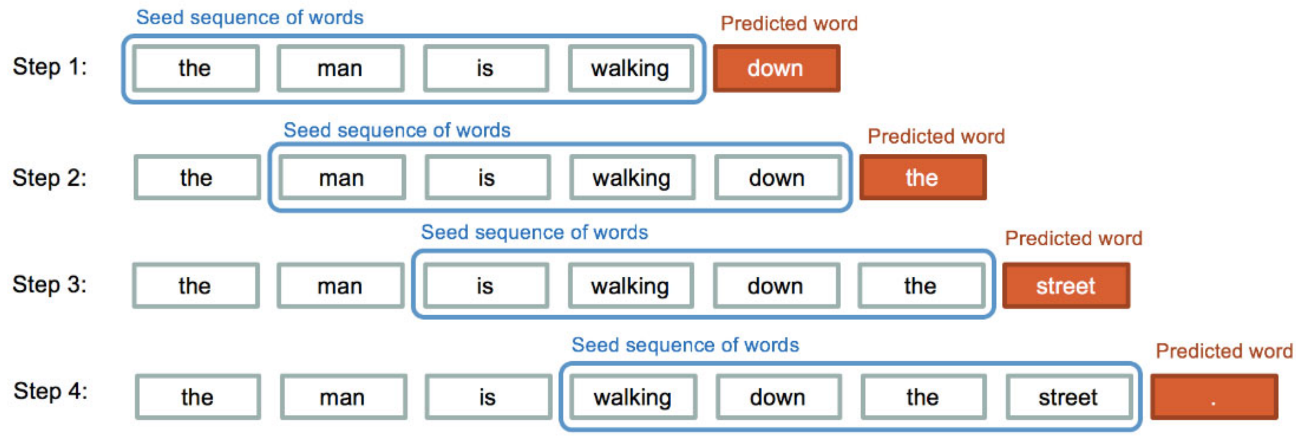
Automatic Text Generation

Automatic text generation is the generation of natural language texts by computer. It has applications in automatic documentation systems, automatic letter writing, automatic report generation, etc. In this , we are going to generate words given a set of input words.

LSTM

- Long Short-Term Memory (LSTM) networks are a modified version of recurrent neural networks, which makes it easier to remember past data in memory.
- Generally LSTM is composed of a cell (the memory part of the LSTM unit) and three “regulators”, usually called gates, of the flow of information inside the LSTM unit: an input gate, an output gate and a forget gate.
- Intuitively, the cell is responsible for keeping track of the dependencies between the elements in the input sequence.
- The input gate controls the extent to which a new value flows into the cell, the forget gate controls the extent to which a value remains in the cell and the output gate controls the extent to which the value in the cell is used to compute the output activation of the LSTM unit.
- The activation function of the LSTM gates is often the logistic sigmoid function.
- There are connections into and out of the LSTM gates, a few of which are recurrent. The weights of these connections, which need to be learned during training, determine how the gates operate.



Building a NLP Pipeline for Text Generation

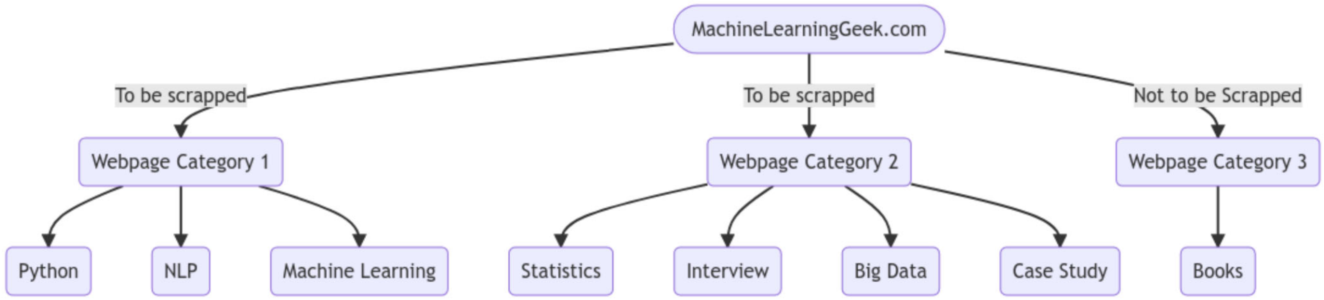
Step 1 : Data Acquisition

- In the first step we will get the data from website https://machinelearninggeek.com/ using the `requests` library and scrap it using the `BeautifulSoup` Library
- Once we are done with this step we will use `pandas` to convert it into a csv file

```
import requests
from bs4 import BeautifulSoup as bs
import re
import pandas as pd
import tensorflow as tf
```

Structure of the website

- In order to scrap the website we first need to understand the Document Object Model (DOM) of the website
- The website is composed of three category of pages which differ in their structure, link syntax and the way information is displayed on them
- The three category are being displayed in the diagram below out of which only two contains text which is to be scrapped



Finding the title and list of pages of various category

```
init_request = requests.get('https://machinelearninggeek.com/')
webpages = []
soup = bs(init_request.content,'html.parser')
header = soup.find('div',class_="menu-primary-container")
nav_bar = header.find('ul')
nav_bar_links = nav_bar.find_all('a')
for link in nav_bar_links:
  webpages.append([link.text,link.get('href')])
webpage_urls = webpages[0:7]
webpage_urls
```

```
[['Machine Learning', 'https://machinelearninggeek.com/machine-learning/'],
 ['NLP', 'https://machinelearninggeek.com/nlp/'],
 ['Statistics', 'https://machinelearninggeek.com/category/statistics/'],
 ['Interview', 'https://machinelearninggeek.com/category/interview/'],
 ['Python', 'https://machinelearninggeek.com/python/'],
 ['Big Data', 'https://machinelearninggeek.com/category/big-data/'],
 ['Case Studies',
  'https://machinelearninggeek.com/category/business-analytics/']]
```

Fetching Articles and Titles

```
def fetch_data(link):
    article = []
    r = requests.get(link)
    soup = bs(r.content,'html.parser')
    # r2 = soup.find('header',class_="entry-header")
    # r2 = re.sub('\n','',r2.text)
    r1 = soup.find('div',class_="entry-content clearfix")
    paras = r1.find_all('p')
    for para in paras:
      article.append(para.text)
    return " ".join(article)

def fetch_header(link):
```

```
  r = requests.get(link)
  soup = bs(r.content,'html.parser')
  r2 = soup.find('header',class_="entry-header")
  r2 = re.sub('\n','',r2.text)
  return r2

lst = []
for webpage in range(len(webpage_urls)):
  r = requests.get(webpage_urls[webpage][1])
  soup = bs(r.content,'html.parser')
  if (webpage==0)or(webpage==1)or(webpage==4):
    s = soup.find('div',class_="entry-content clearfix")
    unor = s.find_all('ul')
    for u in unor:
      links = u.find_all('a')
      for link in links:
        try:
          lst.append([webpage_urls[webpage][0],fetch_header(link.get('href')),fetch_data(link
        except:
          continue
  else:
    s = soup.find_all('div',class_="entry-content clearfix")
    for t in s:
      links = t.find_all('a')
      for link in links:
        try:
          lst.append([webpage_urls[webpage][0],fetch_header(link.get('href')),fetch_data(link
        except:
          continue
```

```
len(lst)
```

```
105
```

Exporting the Dataset

```
lst[1]
```

```
['Machine Learning',
 'Activation Functions ',
 'The activation function defines the output of a neuron in terms of the induced
local field. Activation functions are a single line of code that gives the neural
networks non-linearity and expressiveness.\xa0There are many activation functions
such as Identity function, Step function, Sigmoid function, Tanh, ReLU, Leaky ReLU,
Parametric ReLU, and Softmax function. We can see some of them in the following
table: In this tutorial, we are going to cover the following topics: The identity
function is a function that maps input to the same output value. It is a linear
operator in vector space. Also, a known straight-line function where activation is
proportional to the input. The simplest example of a linear activation function is a
linear equation. \xa0f(x) = a * x,where a ∈ R The major problem with such kind of
```

```
linear function it cannot handle complex scenarios.\xa0 In Binary Step Function, if
the value of Y is above a certain value known as the threshold, the output is True(or
activated) and if it’s less than the threshold then the output is false (or not
activated). It is very useful in the classifier. The main problem with the binary
step function is zero gradients or it is not differentiable at zero. It cannot update
the gradient in backpropagation. It only works with binary class problems because it
maps to only two categories 0 and 1. In the Bipolar Step Function, if the value of Y
is above a certain value known as the threshold, the output is +1and if it’s less
than the threshold then the output is -1. It has bipolar outputs (+1 to -1). It can
be utilized in single-layer networks.\xa0 It is also called S-shaped functions.
Logistic and hyperbolic tangent functions are commonly used in sigmoid functions.
There are two types of sigmoid functions. Binary Sigmoid Function or Sigmoid function
is a logistic function where the output values are either binary or vary from 0 to 1.
It is differentiable, non-linear, and produces non-binary activations But the problem
with Sigmoid is the vanishing gradients. Also, sigmoid activation is not a zero-
centric function. Hyperbolic Tangent Function or Tanh is a logistic function where
the output value varies from -1 to 1. Also known as Bipolar Sigmoid Function. The
output of Tanh centers around 0 and sigmoid’s around 0.5. Tanh Convergence is usually
faster if the average of each input variable over the training set is close to zero.
When you struggle to quickly find the local or global minimum, in such case Tanh can
be helpful in faster convergence. The derivatives of Tanh are larger than Sigmoid
that causes faster optimization of the cost function. Tanh suffered from vanishing
gradient problems. ReLu stands for the rectified linear unit (ReLU). It is the most
used activation function in the world. It output 0 for negative values of x. This is
also known as a ramp function. The name of the ramp function is derived from the
appearance of its graph. ReLu(Rectified Linear Unit) is like a linearity switch. If
you don’t need it, you “switch” it off. If you need it, you “switch” it on. ReLu
avoids the problem of vanishing gradient. ReLu also provides the benefit of sparsity
and sigmoids result in dense representations. Sparse representations are more useful
than dense representations.  The main problem with ReLU is, it is not differentiable
at 0 and may result in exploding gradients.\xa0 The main problem of ReLU is, it is
not differentiable at 0 and may result in exploding gradients. To resolve this
problem Leaky ReLu was introduced that is differentiable at 0. It provides small
negative values when input is less than 0. The main problem with Leaky ReLu is not
offering consistent predictions in terms of negative data. PReLU (Parametric ReLU)
overcome the dying ReLU problem and Leaky ReLU inconsistent predictions for negative
input values. The core idea behind the Parametric ReLU is to make the coefficient of
leakage into a parameter that gets learned. \xa0 The softmax function is typically
used on the output layer for multi-class classification problems. It provides the
probability distribution of possible outcomes of the network. In conclusion, we can
say in deep learning problems, ReLu is used on hidden layers and sigmoid/softmax on
the output layer. Sigmoid is used for\xa0binary classification, and Softmax is used
for\xa0multi-class classification problems. In this tutorial, we have discussed
various activation functions, types of activation functions such as Identity
function, Step function, Sigmoid function, Tanh, ReLU, Leaky ReLU, Parametric ReLU,
```

```python
import pandas as pd
dataset = pd.DataFrame(lst,columns=['Category','Title','Article'])
dataset.head()
```

	Category	Title	Article
0	Machine Learning	Introduction to Artificial Neural Network	This is an introductory article for the artifi...
1	Machine	Activation Functions	The activation function defines the output

```
dataset.to_csv('21_Automatic_Text_Generation_LSTM_Piyush_Joshi') # Dataset saved to Google Co
```

Step 2 : Data Exploration and Pre-Processing

Data Exploration

```
dataset.groupby(['Category'])['Category'].count()
```

```
Category
Big Data             9
Case Studies         7
Interview           10
Machine Learning    30
NLP                 16
Python              29
Statistics           4
Name: Category, dtype: int64
```

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 105 entries, 0 to 104
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   Category  105 non-null    object
 1   Title     105 non-null    object
 2   Article   105 non-null    object
dtypes: object(3)
memory usage: 2.6+ KB
```

```
flat_list = [num for sublist in lst for num in sublist]
data = ' '.join(flat_list[2::3])
data
```

```
'This is an introductory article for the artificial neural network. It is one of the ma
chine learning techniques that is inspired by the biological neural system and used to
solve pattern recognition problems. An artificial neural network (ANN) is an informatio
n processing element that is similar to the biological neural network. It is a combinat
ion of multiple interconnected neurons that execute information in parallel mode. It ha
s the capability to learn by example. ANN is flexible in nature, it has the capability
to change the weights of the network. ANN is like a black box trained to solve complex
problems. Neural network algorithms are inherently parallel in nature and this parallel
```

Corpus Analysis

A corpus is the compilation of all the text under consideration. In this case its the aggregation of all the text in the column **'Article'**

```
data.split('.')[1]
data[:100]
```

```
'This is an introductory article for the artificial neural network. It is one of the ma
chine learning'
```

```
len(data)
```

```
473880
```

```
import string
```

```
def clean_text(doc):
  tokens = doc.split()
  table = str.maketrans('','',string.punctuation)
  tokens = [w.translate(table) for w in tokens]
  tokens = [word for word in tokens if word.isalpha()]
  tokens = [word.lower() for word in tokens]
  return tokens

tokens = clean_text(data)
print(tokens[:50])
```

```
['this', 'is', 'an', 'introductory', 'article', 'for', 'the', 'artificial', 'neural', 'r
```

```
len(tokens)
```

```
73026
```

```
len(set(tokens))
```

```
5011
```

```
length = 50 + 1
lines = []

for i in range(length,len(tokens)):
  seq = tokens[i-length:i]
  line = ' '.join(seq)
  lines.append(line)
  # if i > 200000:
```

```
  #   break

print(len(lines))
```

```
72975
```

```
tokens[50]
```

```
'network'
```

```
lines[1]
```

```
'is an introductory article for the artificial neural network it is one of the machine
learning techniques that is inspired by the biological neural system and used to solve
pattern recognition problems an artificial neural network ann is an information process
ing element that is similar to the biological neural network it'
```

Step 3: Modelling

Build LSTM Model and Prepare X and y

A Sequential model is appropriate for a plain stack of layers where each layer has exactly one input tensor and one output tensor.

Embedding layer

The Embedding layer is initialized with random weights and will learn an embedding for all of the words in the training dataset. It requires 3 arguments:

`input_dim`: This is the size of the vocabulary in the text data which is vocab_size in this case.

`output_dim`: This is the size of the vector space in which words will be embedded. It defines the size of the output vectors from this layer for each word.

`input_length`: Length of input sequences which is seq_length.

LSTM layer

This is the main layer of the model. It learns long-term dependencies between time steps in time series and sequence data. return_sequence when set to True returns the full sequence as the output.

Dense layer

Dense layer is the regular deeply connected neural network layer. It is the most common and frequently used layer. The rectified linear activation function or relu for short is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero.

```
import numpy as np
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,LSTM,Embedding
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(lines)
sequences = tokenizer.texts_to_sequences(lines)
```

```
sequences = np.array(sequences)
X, y = sequences[:,:-1],sequences[:,-1]
X[0]
```

```
array([  12,    5,   33, 3244,   48,    9,    1,  970,  178,  165,   11,
          5,   76,    2,    1,   93,   58,  419,   19,    5, 1555,   25,
          1, 3243,  178,   87,    3,   35,    6,  207,  567,  408,   74,
         33,  970,  178,  165, 1046,    5,   33,   88,  143, 1738,   19,
          5,  177,    6,    1, 3243,  178])
```

```
vocab_size = len(tokenizer.word_index) + 1
```

```
y = to_categorical(y,num_classes = vocab_size)
```

```
seq_length = X.shape[1]
seq_length
```

```
50
```

```
model = Sequential()
model.add(Embedding(vocab_size,50,input_length=seq_length))
model.add(LSTM(100,return_sequences=True))
model.add(LSTM(100))
model.add(Dense(100,activation='relu'))
model.add(Dense(vocab_size,activation='softmax'))
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 50, 50)            250600

 lstm (LSTM)                 (None, 50, 100)           60400

 lstm_1 (LSTM)               (None, 100)               80400
```

```
 dense (Dense)               (None, 100)               10100

 dense_1 (Dense)             (None, 5012)              506212

=================================================================
Total params: 907,712
Trainable params: 907,712
Non-trainable params: 0
_________________________________________________________________
```

Training and Evaluation

```
model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])
```

```
model.fit(X,y,batch_size=256,epochs=350)
```

```
Epoch 323/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0239 - accuracy: 0.9
Epoch 324/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0190 - accuracy: 0.9
Epoch 325/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0157 - accuracy: 0.9
Epoch 326/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0162 - accuracy: 0.9
Epoch 327/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0179 - accuracy: 0.9
Epoch 328/350
286/286 [==============================] - 4s 14ms/step - loss: 0.0151 - accuracy: 0.9
Epoch 329/350
286/286 [==============================] - 4s 14ms/step - loss: 0.1461 - accuracy: 0.9
Epoch 330/350
286/286 [==============================] - 4s 14ms/step - loss: 0.5042 - accuracy: 0.
Epoch 331/350
286/286 [==============================] - 4s 14ms/step - loss: 0.1637 - accuracy: 0.9
Epoch 332/350
286/286 [==============================] - 4s 14ms/step - loss: 0.0622 - accuracy: 0.9
Epoch 333/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0286 - accuracy: 0.9
Epoch 334/350
286/286 [==============================] - 4s 14ms/step - loss: 0.0185 - accuracy: 0.9
Epoch 335/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0144 - accuracy: 0.9
Epoch 336/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0133 - accuracy: 0.9
Epoch 337/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0125 - accuracy: 0.9
Epoch 338/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0124 - accuracy: 0.9
Epoch 339/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0136 - accuracy: 0.9
Epoch 340/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0477 - accuracy: 0.9
```

```
Epoch 341/350
286/286 [==============================] - 4s 13ms/step - loss: 0.5816 - accuracy: 0.
Epoch 342/350
286/286 [==============================] - 4s 13ms/step - loss: 0.2362 - accuracy: 0.9
Epoch 343/350
286/286 [==============================] - 4s 14ms/step - loss: 0.0752 - accuracy: 0.9
Epoch 344/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0318 - accuracy: 0.9
Epoch 345/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0179 - accuracy: 0.9
Epoch 346/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0140 - accuracy: 0.9
Epoch 347/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0125 - accuracy: 0.9
Epoch 348/350
286/286 [==============================] - 4s 14ms/step - loss: 0.0117 - accuracy: 0.9
Epoch 349/350
286/286 [==============================] - 4s 13ms/step - loss: 0.0109 - accuracy: 0.9
Epoch 350/350
286/286 [==============================] - 4s 14ms/step - loss: 0.0123 - accuracy: 0.9
<keras.callbacks.History at 0x7f7b793efa10>
```

Step 4: Text Generation

```
seed_text = lines[140]
```

```
seed_text
```

```
'idea of ann algorithms is stimulated from the human brain ann learn things by processi
ng input information and adjusting weights to forecast the exact output label we can de
fine a neural network as is an interconnected set of neurons input and output units eac
h connection in this interconnected network assigned with'
```

```
def generate_text_seq(model,tokenizer,text_seq_length,seed_text,n_words):
  text = []
  for _ in range(n_words):
    encoded = tokenizer.texts_to_sequences([seed_text])[0]
    encoded = pad_sequences([encoded],maxlen = text_seq_length,truncating='pre')
    y_predict = np.argmax(model.predict(encoded),axis=-1)
    predicted_word = ''
    for word,index in tokenizer.word_index.items():
      if index == y_predict:
        predicted_word = word
        break
    seed_text = seed_text + ' ' + predicted_word
    text.append(predicted_word)
  return ' '.join(text)
```

```
generate_text_seq(model,tokenizer,seq_length,seed_text,100)
```

```
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 18ms/step
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1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 27ms/step
```

Result

Input Text

idea of ann algorithms is stimulated from the human brain ann learn things by processing input information and adjusting weights to forecast the exact output label we can define a neural network as is an interconnected set of neurons input and output units each connection in this interconnected network assigned with

Generated Text

weight these weights are adjusted as per output label in an adaptive here xn are input variables are weights for the respective inputs and b is the bias y is the output and that is the summation of weighted inputs and bias after learning and adjusting the weights we apply the activation function to map output to a certain range the main purpose of the activation function is to introduce nonlinearity in the network an artificial neural network has a set of neurons with input and output units multiple neurons were arranged in a layered manner each layer is a

```
1/1 [==============================] - 0s 17ms/step
```

```
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 17ms/step
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1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 19ms/step
'weight these weights are adjusted as per output label in an adaptive here xn are input
variables are weights for the respective inputs and b is the bias y is the output and t
hat is the summation of weighted inputs and bias after learning and adjusting the weigh
ts we apply the activation function to map output to a certain range the main purpose o
f the activation function is to introduce nonlinearity in the network an artificial neu
```

✓ 4s completed at 12:16 PM