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Title : "Computational Creativity Unleashed: A Comprehensive Exploration of Poetic Text Generation Using Recurrent Neural Networks in Python"

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Abstract

This research investigates the innovative realm of computational creativity through the application of Recurrent Neural Networks (RNNs) in Python for the purpose of generating poetic texts. Leveraging the power of deep learning, this study delves into the intricate patterns and nuanced structures inherent in poetry, aiming to understand and emulate the creative process. By training RNNs on diverse poetic corpora, the research explores the model's ability to capture the essence of various poetic styles and forms. The outcomes of this investigation contribute to advancing our understanding of the intersection between artificial intelligence and creative expression, offering insights into the potential of RNNs as tools for fostering computational creativity in the domain of literary arts.

Introduction

In the ever-evolving landscape of artificial intelligence, the intersection between computational prowess and creative expression has become a captivating realm of exploration. This research embarks on a journey into the domain of computational creativity, specifically focusing on the generation of poetic texts using Recurrent Neural Networks (RNNs) implemented in the Python programming language. The intricate nature of poetic language, with its nuanced structures and subtle patterns, poses a unique challenge and opportunity for the capabilities of deep learning models.

With the burgeoning interest in natural language processing and creative algorithmic endeavors, this study seeks to unravel the complexities of poetic composition through the lens of RNNs. These networks, designed to capture sequential dependencies within data, offer a promising avenue for simulating the intricate thought processes involved in creative writing. *By training RNNs on diverse poetic corpora, we aim to elucidate the model's capacity to not only comprehend but also emulate the creative essence embedded in various poetic styles and forms.*

Code

In [1]:
```
import random
import numpy as np
import tensorflow as tf
```

In [2]:
```
filepath = tf.keras.utils.get_file('shakespeare.txt',
        'https://storage.googleapis.com/download.tensorflow.org/data/sha
text = open(filepath, 'rb').read().decode(encoding='utf-8')
```

In [3]:
```
text = open(filepath, 'rb').read().decode(encoding='utf-8').lower()
text = text[300000:800000]
```

In [4]:
```
characters = sorted(set(text))

char_to_index = dict((c, i) for i, c in enumerate(characters))
index_to_char = dict((i, c) for i, c in enumerate(characters))
```

In [5]:
```
SEQ_LENGTH = 40
STEP_SIZE = 3

sentences = []
next_char = []
```

In [6]:
```
for i in range(0, len(text) - SEQ_LENGTH, STEP_SIZE):
    sentences.append(text[i: i + SEQ_LENGTH])
    next_char.append(text[i + SEQ_LENGTH])
```

In [7]:
```
x = np.zeros((len(sentences), SEQ_LENGTH,
              len(characters)), dtype=bool)
y = np.zeros((len(sentences),
              len(characters)), dtype=bool)

for i, satz in enumerate(sentences):
    for t, char in enumerate(satz):
        x[i, t, char_to_index[char]] = 1
    y[i, char_to_index[next_char[i]]] = 1
```

Discussion

Download Shakespearean Text:
Downloads a sample of Shakespeare's text from a given URL using TensorFlow's get_file function.

Link:
https://storage.googleapis.com/download.tensorflow.org/data/shakespeare.txt

Preprocess Text:
Reads the text and decodes it from UTF-8 encoding.
Converts the text to lowercase for uniformity.
Selects a portion of the text between positions 300,000 and 800,000.

Create Character Set:
Creates a set of unique characters present in the selected text.

Character-to-Index and Index-to-Character Mapping:
Creates dictionaries for mapping characters to indices and vice versa.

Define Sequence Length and Step Size:
Specifies the sequence length (number of characters in each input sequence) and step size for sliding the sequence window.

Generate Input and Output Sequences:
Creates input sequences (x) and corresponding output sequences (y) for training the RNN.
Each input sequence is a segment of the text, and the corresponding output is the character that follows that sequence.

One-Hot Encoding:
Converts characters to one-hot encoded vectors for both input and output.
x is a 3D array where each character is represented as a one-hot encoded vector.
y is a 2D array of one-hot encoded vectors representing the next characters.

Code

(Building Recurrent Neural Network)

In [8]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.layers import Activation, Dense, LSTM
```

In [9]:
```
model = Sequential()
model.add(LSTM(128,
               input_shape=(SEQ_LENGTH,
                            len(characters))))
model.add(Dense(len(characters)))
model.add(Activation('softmax'))
```

In [10]:
```
model.compile(loss='categorical_crossentropy',
              optimizer=RMSprop(lr=0.01))

model.fit(x, y, batch_size=256, epochs=4)
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.RM
Sprop` runs slowly on M1/M2 Macs, please use the legacy Keras optimizer
instead, located at `tf.keras.optimizers.legacy.RMSprop`.
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learnin
g_rate` or use the legacy optimizer, e.g.,tf.keras.optimizers.legacy.RM
Sprop.
```

```
Epoch 1/4
651/651 [==============================] - 31s 47ms/step - loss: 2.6945
Epoch 2/4
651/651 [==============================] - 31s 48ms/step - loss: 2.2914
Epoch 3/4
651/651 [==============================] - 31s 48ms/step - loss: 2.1763
Epoch 4/4
651/651 [==============================] - 33s 50ms/step - loss: 2.0951
```

Out[10]:
```
<keras.src.callbacks.History at 0x16bea6e50>
```

In [11]:
```
def sample(preds, temperature=1.0):
    preds = np.asarray(preds).astype('float64')
    preds = np.log(preds) / temperature
    exp_preds = np.exp(preds)
    preds = exp_preds / np.sum(exp_preds)
    probas = np.random.multinomial(1, preds, 1)
    return np.argmax(probas)
```

Discussion

Model Architecture:

Sequential(): Initializes a linear stack of layers.

LSTM(128, input_shape=(SEQ_LENGTH, len(characters))): Adds an LSTM layer with 128 units (neurons) and takes input sequences of length SEQ_LENGTH with a one-hot encoding of the characters.

Dense(len(characters)): Adds a fully connected layer with the number of units equal to the number of unique characters.

Activation('softmax'): Applies the softmax activation function to the output, converting the network's raw output into probability scores for each character.

Model Compilation:

model.compile: Configures the model for training.

loss='categorical_crossentropy': Specifies the categorical cross-entropy loss function for a multi-class classification problem.

optimizer=RMSprop(lr=0.01): Uses the RMSprop optimizer with a learning rate of 0.01.

Model Training:

model.fit(x, y, batch_size=256, epochs=4): Trains the model on the input sequences (x) and corresponding target sequences (y).

batch_size=256: Specifies the number of samples to be used in each training iteration.

epochs=4: Specifies the number of times the model is trained on the entire dataset.

Sampling Function:

def sample(preds, temperature=1.0): Defines a sampling function used to generate new text based on the trained model's predictions.
It applies the softmax function to the model's output to get probability scores for each character and then samples from these probabilities based on a specified temperature. Higher temperatures increase randomness.

Code

In [12]:
```
def generate_text(length, temperature):
    start_index = random.randint(0, len(text) - SEQ_LENGTH - 1)
    generated = ''
    sentence = text[start_index: start_index + SEQ_LENGTH]
    generated += sentence
    for i in range(length):
        x_predictions = np.zeros((1, SEQ_LENGTH, len(characters)))
        for t, char in enumerate(sentence):
            x_predictions[0, t, char_to_index[char]] = 1

        predictions = model.predict(x_predictions, verbose=0)[0]
        next_index = sample(predictions,
                            temperature)
        next_character = index_to_char[next_index]

        generated += next_character
        sentence = sentence[1:] + next_character
    return generated
```

In [13]:
```
print(generate_text(300, 0.2))
print(generate_text(300, 0.4))
print(generate_text(300, 0.5))
print(generate_text(300, 0.6))
print(generate_text(300, 0.7))
print(generate_text(300, 0.8))
```

```
osaline?

romeo:
with rosaline, my ghost the are the here the heard the sould the fore t
he and the ford the ford the the wert and and the ford the with the for
e here the here the fore the forther and the hears the prond, and and a
nd and the seand here the the fore the lound the forther and in the cou
nd of the ford and the the the fore the
ng him breath,
the traitor lives, the trent the will mo here and and the broone the fo
rder mongend and the forther the forke, my the seard the tigh the peave
the sear the fore the pared, the there wall not the seart the thes and
best the seatt the firge the frofthen shere she poret sear the with and
entere, the mather and the pare the hea
ourselves, and leave us here alone.
what the lees for erester aid herere for here sfere be the sond coule a
nd walloun thas hone hath and erest to here sore came thou the erestrin
g at in and wien the hath i ming hereres if hing the be the i tond on t
hat the wallemprount and the heress all berist on sheer stare sour the
fort and the ast bee
rous untuned drums,
with harsh resounding your the fooch fare is bome of and heand thou has
are.

jaistcond:
i sofe the beitt the sperd for the bee is thene to be dond not shere fo
re have and the forth, and the cofrill alay tither and your of and thea
n the fiee,
and rowe fore the faistengeald and and and rome that sond hiss apad, a
weerst
own?
if not, our swords shall plead it if that dester? me rister not sires m
e the kinger but theres; the parthef seare the mand tood mathen entant.

wiel st and me lovee, i are boret and thee froukn, ant:
and in penose themeroun thoue's to ke peist and, ad thee wish the froin
ened,
the wich the morthot in the dath ne and ghouth sillades f
n me, when i was found
false to his chill in love anduen'd stooren, blonch rinl.
ous and no uroug athink ol us seand to tingh, chan me wialf'ise cedeso
and's and ind domantsoon it the beece yould ste forderiss?

spurse:
hith nefay nruthere thingherted walione, dove you that, to lomer oftert
pow foo hery till vess mare.

roreo, i goure, i
```

Discussion

Function Definition:

generate_text(length, temperature): Takes two parameters, length (the length of the generated text) and temperature (controls randomness during text generation).

Text Generation Process:

- Randomly selects a starting index within the original text to initiate the generation process.
- Initializes the generated variable to store the generated text.
- Extracts a seed sentence of length SEQ_LENGTH from the original text.
- Appends the seed sentence to the generated text.
- Iterates through the specified length to predict and append the next characters to the generated text.
- Converts the seed sentence into a one-hot encoded input sequence (x_predictions) for the model.
- Uses the model to predict the probabilities of the next characters.
- Samples the next character based on the predicted probabilities and the specified temperature.
- Appends the sampled character to the generated text.
- Updates the seed sentence for the next iteration by removing the first character and adding the newly generated character.

Printing Generated Texts:

Calls the generate_text function with different temperature values and prints the Generated.

```
romeo:
with rosaline, my ghost the are the here the heard the sould the fore t
he and the ford the ford the the wert and and the ford the with the for
e here the here the fore the forther and the hears the prond, and and a
nd and the seand here the the fore the lound the forther and in the cou
nd of the ford and the the the fore the
ng him breath,
the traitor lives, the trent the will mo here and and the broone the fo
rder mongend and the forther the forke, my the seard the tigh the peave
the sear the fore the pared, the there wall not the seart the thes and
best the seatt the firge the frofthen shere she poret sear the with and
entere, the mather and the pare the hea
ourselves, and leave us here alone.
what the lees for erester aid herere for here sfere be the sond coule a
nd walloun thas hone hath and erest to here sore came thou the erestrin
g at in and wien the hath i ming hereres if hing the be the i tond on t
hat the wallemprount and the heress all berist on sheer stare sour the
fort and the ast bee
rous untuned drums,
with harsh resounding your the fooch fare is bome of and heand thou has
are.

jaistcond:
i sofe the beitt the sperd for the bee is thene to be dond not shere fo
re have and the forth, and the cofrill alay tither and your of and thea
n the fiee,
and rowe fore the faistengeald and and and rome that sond hiss apad, a
weerst
own?
if not, our swords shall plead it if that dester? me rister not sires m
e the kinger but theres; the parthef seare the mand tood mathen entant.

wiel st and me lovee, i are boret and thee froukn, ant:
and in penose themeroun thoue's to ke peist and, ad thee wish the froin
ened,
the wich the morthot in the dath ne and ghouth sillades f
n me, when i was found
false to his chill in love anduen'd stooren, blonch rinl.
ous and no uroug athink ol us seand to tingh, chan me wialf'ise cedeso
and's and ind domantsoon it the beece yould ste forderiss?
```

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