

# Bidirectional LSTM for Shakespeare Text Generation

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## Abstract

This paper explores generating Shakespeare text using Bidirectional LSTMs. I trained multiple models with variable dropout rate, hidden size, and activation function. The results show that higher hidden size and lower dropout rate results in lower cross-entropy loss and more coherent text generation. Comparing RELU and Tanh activation functions shows that the RELU results in higher loss but more coherent text generation.

## Introduction

Vanilla Recurrent Neural Network (RNN) architectures have shown great success in generating short text, however, are poor at generating longer text due to the vanishing gradient problem. The output of the current hidden state is affected by all of the previous hidden states, so the neural network has to backpropagate through all of the hidden states in order to update. As the RNN iterates through the previous states, the gradient slowly vanishes, which stops the network from updating and converging. An improved model should have a long term memory so that the current hidden states are heavily affected by the older hidden states. The Long Short Term Memory (LSTM) architecture fixes the vanishing gradient problem by replacing the RNN cells with LSTM cells that contain additional gates to provide the model with a short and long term memory. Using LSTM will improve the model's ability to produce long text that

coherently connects the end of the text to the beginning.

Bidirectional RNNs are also known to increase a model's ability to generate long coherent sentences as the model gains more context from the sentence by reading it from beginning to end and reverse. Certain words in english sentences only make sense in the context of future words, thus bidirectional RNNs fix this issue by reading the text in reverse to give more context to the hidden state, then by just reading the text from beginning to end.

## Architecture

The architecture used is from this source [1], a Bidirectional LSTM with a size of 256 and a RELU activation function, then a .6 dropout layer, and a softmax activation. The batch size is 32, the training sequence length is 30, and the model ran for 50 epochs with a learning rate of .001. The model uses early stopping so none of the models reach the 50th epoch. The data is a collection of Shakespeare plays and the training and validation dataset is a 90% and 10% split. I also trained models with a size of 128 and 512, dropout of .2 and .4, and a model with a tanh activation function.

## Experiment

I ran the model with 6 different sets of hyperparameters with variable hidden size, activation function, and dropout. The model parameters of the experiments are (256, RELU, .2), (256, RELU, .4), (128, RELU, .6), (256, RELU, .6), (512, RELU, .6), and (256, Tanh, .6) where the arguments are hidden size, activation function, dropout rate. The results from the experiment are in the appendix.

## Results

The final loss value of the 128, 256, and 512 hidden size models are 5.3362, 5.1236, and 4.5733 respectively. This shows a strong inverse correlation between hidden size and loss. Comparing the first 10 words from the generated text of each model shows that there is a weak correlation of text comprehension and model size

128: “on forfeit god life henry surely first , pains then were”

256: “shrinks come hear i mortal flowers have good come froth”

512: “the hath such, and than thee. you and I go“

The final loss value of .2, .4, and .6 dropout rates are 4.4860, 5.1418, 5.1236, showing that higher dropout increases loss.

Comparing the first 10 words from the generated text of each model shows that there might be correlation of text comprehension and dropout rate.

.2: “the trust from ? with man and and to a 's a”

.4: “the pride of ' , to on the name : and that not”

.6: “shrinks come hear i mortal flowers have good come froth”

Tanh activation function has a final loss value of 4.8955 which is significantly smaller than RELU’s loss of 5.1236.

However, looking at a sample text from the Tanh activation function shows that the model is very poor at generating text “a . , the , , with is ; , , , , , . is ; ; the to and”.

## Conclusion

The Bidirectional LSTM architecture shows promising results that improve on traditional RNN architectures. After training the same architecture with different hyperparameters, I found that lower dropout rate, larger hidden size, and the RELU activation function increase the model’s performance. Future research could involve looking into different batch sizes, other loss functions, and variable learning rates.

## References

1. <https://github.com/campdav/Text-Generation-using-Bidirectional-LSTM-and-Doc2Vec-models/blob/master/1%20-%20generate%20sentence.ipynb>
2. *The Unreasonable Effectiveness of Recurrent Neural Networks*, karpathy.github.io/2015/05/21/rnn-effectiveness/.
3. Campion, David. “Text Generation Using Bidirectional LSTM and Doc2Vec Models 1/3.” *Medium*, Medium, 14 Feb. 2018, medium.com/@david.campion/text-generation-using-bidirectional-lstm-and-doc2vec-models-1-3-8979eb65cb3a.

## Appendix

### Model:

rnn\_size = 256, RELU activation, .6 dropout

Layer (type)	Output Shape	Param #
<hr/>		
bidirectional_1 (Bidirection (None, 512)		25794560
<hr/>		
dropout_1 (Dropout)	(None, 512)	0
<hr/>		
dense_1 (Dense)	(None, 12338)	6329394
<hr/>		
activation_1 (Activation)	(None, 12338)	0
<hr/>		
Total params: 32,123,954		
Trainable params: 32,123,954		
Non-trainable params: 0		

### Error Values:

Train on 25241 samples, validate on 255 samples

Epoch 1/50  
25241/25241 [=====] - 126s  
5ms/step - loss: 7.0484 - categorical\_accuracy: 0.0534 - val\_loss:  
6.3338 - val\_categorical\_accuracy: 0.0667  
Epoch 2/50  
25241/25241 [=====] - 125s  
5ms/step - loss: 6.0867 - categorical\_accuracy: 0.0826 - val\_loss:  
6.3197 - val\_categorical\_accuracy: 0.0667  
Epoch 3/50  
25241/25241 [=====] - 127s  
5ms/step - loss: 5.8142 - categorical\_accuracy: 0.0981 - val\_loss:  
6.3442 - val\_categorical\_accuracy: 0.0784  
Epoch 4/50  
25241/25241 [=====] - 126s  
5ms/step - loss: 5.5986 - categorical\_accuracy: 0.1019 - val\_loss:  
6.4520 - val\_categorical\_accuracy: 0.0784  
Epoch 5/50  
25241/25241 [=====] - 126s  
5ms/step - loss: 5.3912 - categorical\_accuracy: 0.1075 - val\_loss:  
6.5142 - val\_categorical\_accuracy: 0.0824  
Epoch 6/50  
25241/25241 [=====] - 125s  
5ms/step - loss: 5.1236 - categorical\_accuracy: 0.1227 - val\_loss:  
6.7283 - val\_categorical\_accuracy: 0.0824

### Example Output:

“shrinks come hear i mortal flowers have good come froth cunning  
the be redress my blister'd seeming said afterward hands they your  
loath or for love that betide god grace , honour ; than o policy the  
now thoughts hast 'll that porch what the broken escalus their very  
or stormy ill give man good foes care , times little george fortune  
'll thy sworest o'erwhelm with come king were with grumio this  
virtues but , my julietta are for happy honourable doit and she ?  
lowest richard liking you nor proclaim'd is sun him brother i  
expedition the thou”

### Model:

rnn\_size = 128, RELU activation, .6 dropout

Layer (type)	Output Shape	Param #
<hr/>		
bidirectional_2 (Bidirection (None, 256)		12766208
<hr/>		
dropout_2 (Dropout)	(None, 256)	0
<hr/>		
dense_2 (Dense)	(None, 12338)	3170866
<hr/>		
activation_2 (Activation)	(None, 12338)	0
<hr/>		
Total params: 15,937,074		
Trainable params: 15,937,074		
Non-trainable params: 0		

### Error Values:

Train on 25241 samples, validate on 255 samples

Epoch 1/50  
25241/25241 [=====] - 112s  
4ms/step - loss: 7.0334 - categorical\_accuracy: 0.0677 - val\_loss:  
6.3794 - val\_categorical\_accuracy: 0.0667  
Epoch 2/50  
25241/25241 [=====] - 111s  
4ms/step - loss: 6.1264 - categorical\_accuracy: 0.0781 - val\_loss:  
6.3369 - val\_categorical\_accuracy: 0.0667  
Epoch 3/50  
25241/25241 [=====] - 112s  
4ms/step - loss: 5.8790 - categorical\_accuracy: 0.0889 - val\_loss:  
6.4091 - val\_categorical\_accuracy: 0.0706  
Epoch 4/50  
25241/25241 [=====] - 110s  
4ms/step - loss: 5.6903 - categorical\_accuracy: 0.0998 - val\_loss:  
6.4763 - val\_categorical\_accuracy: 0.0706  
Epoch 5/50  
25241/25241 [=====] - 111s  
4ms/step - loss: 5.5043 - categorical\_accuracy: 0.1067 - val\_loss:  
6.6198 - val\_categorical\_accuracy: 0.0824  
Epoch 6/50  
25241/25241 [=====] - 110s  
4ms/step - loss: 5.3362 - categorical\_accuracy: 0.1138 - val\_loss:  
6.7898 - val\_categorical\_accuracy: 0.0745

### Example Output:

“on forfeit god life henry surely first , pains then were night should  
nurse well inforced ! coriolanus richard yourself ? well john limed  
she noise dead day follow'd the a glorious make him - memory lies  
bed long have pair i while name thy crown dare we hope must how  
my sweet shalt you frame shall face be good gone enfoldings  
blessed with know court put current bed lend provost that i long  
the his bloody holy name long a servants thee long morrow the  
inforced reason wife there senator one nine day blasphemy thanks  
this which feasting learned”

Model:

rnn\_size = 512, RELU activation, .6 dropout

Layer (type)	Output Shape	Param #
bidirectional_3 (Bidirection (None, 1024)		52637696
dropout_3 (Dropout)	(None, 1024)	0
dense_3 (Dense)	(None, 12338)	12646450
activation_3 (Activation)	(None, 12338)	0

Total params: 65,284,146  
Trainable params: 65,284,146  
Non-trainable params: 0

Error Values:

Train on 25241 samples, validate on 255 samples  
Epoch 1/50  
25241/25241 [=====] - 157s  
6ms/step - loss: 6.8248 - categorical\_accuracy: 0.0739 - val\_loss: 6.2513 - val\_categorical\_accuracy: 0.0667  
Epoch 2/50  
25241/25241 [=====] - 154s  
6ms/step - loss: 5.9686 - categorical\_accuracy: 0.0943 - val\_loss: 6.1998 - val\_categorical\_accuracy: 0.0784  
Epoch 3/50  
25241/25241 [=====] - 160s  
6ms/step - loss: 6.3813 - categorical\_accuracy: 0.1049 - val\_loss: 6.1286 - val\_categorical\_accuracy: 0.0863  
Epoch 4/50  
25241/25241 [=====] - 157s  
6ms/step - loss: 5.4501 - categorical\_accuracy: 0.1193 - val\_loss: 6.2030 - val\_categorical\_accuracy: 0.1098  
Epoch 5/50  
25241/25241 [=====] - 160s  
6ms/step - loss: 5.1778 - categorical\_accuracy: 0.1313 - val\_loss: 6.2785 - val\_categorical\_accuracy: 0.1020  
Epoch 6/50  
25241/25241 [=====] - 157s  
6ms/step - loss: 4.9190 - categorical\_accuracy: 0.1430 - val\_loss: 6.4267 - val\_categorical\_accuracy: 0.1020  
Epoch 7/50  
25241/25241 [=====] - 159s  
6ms/step - loss: 4.5733 - categorical\_accuracy: 0.1655 - val\_loss: 6.5168 - val\_categorical\_accuracy: 0.1137

Example Output:

“the hath such, and than thee. you and I go . : then , the tricks :  
hastings : you , to you and you . do : then you , you , you you you ,  
for ? , : you , you you , you have you you you . i : you , i it , you it  
it . me : you , you ? is : you you you , you you you you , it it it it  
is it is . it is . then you you you you”

Model:

rnn\_size = 256, RELU activation, .4 dropout

Error Values:

Train on 25241 samples, validate on 255 samples  
Epoch 1/50  
25241/25241 [=====] - 259s  
10ms/step - loss: 6.6443 - categorical\_accuracy: 0.0702 - val\_loss: 6.3150 - val\_categorical\_accuracy: 0.0667  
Epoch 2/50  
25241/25241 [=====] - 257s  
10ms/step - loss: 6.0555 - categorical\_accuracy: 0.0782 - val\_loss: 6.3392 - val\_categorical\_accuracy: 0.0667  
Epoch 3/50  
25241/25241 [=====] - 259s  
10ms/step - loss: 5.8083 - categorical\_accuracy: 0.0935 - val\_loss: 6.3411 - val\_categorical\_accuracy: 0.0902  
Epoch 4/50  
25241/25241 [=====] - 258s  
10ms/step - loss: 5.4849 - categorical\_accuracy: 0.1032 - val\_loss: 6.4657 - val\_categorical\_accuracy: 0.0980  
Epoch 5/50  
25241/25241 [=====] - 261s  
10ms/step - loss: 5.1418 - categorical\_accuracy: 0.1208 - val\_loss: 6.5093 - val\_categorical\_accuracy: 0.1098

Example Output:

“the pride of ' , to on the name : and that not of most . we : : i , and  
you , and , to to my , my my , on , and to by king as . : richard , ,  
tell , , you me . gloucester : thou 's stand , , and , and time which  
that . no . : : my , a there , i as ? love : so 's he , i your , go than , i ,  
for him and to day , it to the true”

Model:

rnn\_size = 256, RELU activation, .2 dropout

Error Values:

Train on 25241 samples, validate on 255 samples

Epoch 1/50

25241/25241 [=====] - 261s

10ms/step - loss: 7.5039 - categorical\_accuracy: 0.0531 - val\_loss: 6.3358 - val\_categorical\_accuracy: 0.0667

Epoch 2/50

25241/25241 [=====] - 257s

10ms/step - loss: 6.0489 - categorical\_accuracy: 0.0778 - val\_loss: 6.3177 - val\_categorical\_accuracy: 0.0667

Epoch 3/50

25241/25241 [=====] - 258s

10ms/step - loss: 5.7801 - categorical\_accuracy: 0.0806 - val\_loss: 6.3718 - val\_categorical\_accuracy: 0.0706

Epoch 4/50

25241/25241 [=====] - 256s

10ms/step - loss: 5.4316 - categorical\_accuracy: 0.0949 - val\_loss: 6.4877 - val\_categorical\_accuracy: 0.0824

Epoch 5/50

25241/25241 [=====] - 259s

10ms/step - loss: 4.9879 - categorical\_accuracy: 0.1214 - val\_loss: 6.5580 - val\_categorical\_accuracy: 0.0863

Epoch 6/50

25241/25241 [=====] - 258s

10ms/step - loss: 4.4860 - categorical\_accuracy: 0.1580 - val\_loss: 7.0239 - val\_categorical\_accuracy: 0.0941

Example Output:

“the trust from ? with man and and to a 's a of a ; of the into of the , the of ; the a that , you , the that of not of and , the , . the : , a , the the , a and the with of and , and , , and me , and , you , you , in , and the that , . : he is in to . ; , for the - of , , the you , , you you , and you of , , and”

Model:

rnn\_size = 256, Tanh activation, .6 dropout

Error Values:

Train on 25241 samples, validate on 255 samples

Epoch 1/50

25241/25241 [=====] - 124s

5ms/step - loss: 6.5579 - categorical\_accuracy: 0.0765 - val\_loss: 6.3471 - val\_categorical\_accuracy: 0.0667

Epoch 2/50

25241/25241 [=====] - 122s

5ms/step - loss: 6.1628 - categorical\_accuracy: 0.0782 - val\_loss: 6.3199 - val\_categorical\_accuracy: 0.0667

Epoch 3/50

25241/25241 [=====] - 126s

5ms/step - loss: 5.9554 - categorical\_accuracy: 0.0784 - val\_loss: 6.3524 - val\_categorical\_accuracy: 0.0667

Epoch 4/50

25241/25241 [=====] - 126s

5ms/step - loss: 5.6815 - categorical\_accuracy: 0.0930 - val\_loss: 6.3361 - val\_categorical\_accuracy: 0.0902

Epoch 5/50

25241/25241 [=====] - 128s

5ms/step - loss: 5.3288 - categorical\_accuracy: 0.1115 - val\_loss: 6.4966 - val\_categorical\_accuracy: 0.0980

Epoch 6/50

25241/25241 [=====] - 125s

5ms/step - loss: 4.8955 - categorical\_accuracy: 0.1461 - val\_loss: 6.7565 - val\_categorical\_accuracy: 0.1059

Example Output:

“a , the , , with is ; , , , , , , . is ; ; the to and , , . on the is ; , . . ; , . . ; life ; , , , . . ; is , ! , ; is , , , ; , , , , , , , , , , ! , , , the , of the we , , , , ; , ; as , ”