Lyrics Generation Using LSTM and RNN

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Lyrics Generation using LSTM and RNN

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ABSTRACT:

For years, both the music and AI groups have been interested in automatic lyric creation. Early rule-based techniques have mostly been supplanted by deep-learning-based systems as computer power and data-driven models have evolved. This paper explores the capability of deep learning to generate lyrics for a designated musical genre. Previous lyric generation research in the field of computational linguistics has been restricted to Recurrent Neural Networks (RNN) or Gated Recurrent Units (GRU). Instead, we have used an LSTM network to generate lyrics for a certain genre from a sample lyric as input. We also look at how modern deep learning techniques may be used to improve the songwriting process by learning from artists and their significant works. We find our LSTM model to generate both rap and pop lyrics well, capturing average line length, and in-song and across-genre word variation very closely to the text it was trained upon.

By adjusting the model's parameters, the neural network was pre-trained on the lyrics of certain composers and musicians. A multilayer LSTM-based training model with bidirectional neurons and BERT integration is used in this research. To generate a comprehensive set of lyrics, the lyrics supplied as input are divided down into a word and rhyme index. This model is generative, therefore each trial yielded a unique set of lyrics. The model produces a loss of less than 0.06 when the parameters are set correctly. The differences in the results of permutations of different dropout positions were analyzed. Some of the model's lyrics were determined to be of suitable quality. Overall, our findings suggest that deep learning techniques may be utilized to support the creative process of songwriting.

***Keywords*:** Lyric generation, Long Short Term Memory (LSTM), Recurrent Neural Network (RNN), Deep Neural Network (DNN), Dropout.

I. INTRODUCTION

One of the oldest, if not the oldest art that ever existed – Music - has been there since the very dawn of humankind. Starting with the caveman's music which consisted mainly of grunts and the sound of banged objects to the Renaissance, Baroque, classical, and finally to the pop culture in the 21st century. Music has existed in almost every known culture around the world. [1] It has grown with us over time by becoming a universal language that everyone understands irrespective of our race, religion, nationality, age, gender, language, or skin color.

Lyrics writing is a crucial part of the process of songwriting, and good lyrics contribute to expressiveness and influence the emotional valence of the music. [2] Writing lyrics from scratch, however, does not come easily to everybody. The task is comparable in its complexity to poetry writing with similar demands on expressiveness, conciseness, and form. Additional constraints due

to melodic properties require basic music understanding and complicate the task even more. Thus, automatic lyrics generation is a useful and important task that aims at inspiring musicians to songwriting

The study focuses on creating a lyrics generator using LSTM at both the character and word levels (Long short-term memory).
A generative model was used to assist the songwriting process, which included a recurrent neural network (RNN) and transfer learning. Artists spend their entire careers perfecting their ability to write songs that are emotive, relevant, and innovative. This was a job that artificial intelligence might help with. Instead of having struggling artists sift through hours of viable material, what if we could automate the process by having a neural network creates line after line of decent content that the artist may then choose from as inspiration? The issue was significant since it is difficult to write appropriate lyrics that follow a strong rhyme scheme, but artificial intelligence may not only speed up but also make the process easier for artists. The outcomes were promising, and at times were indistinguishable from popular songwriting approaches.

II. LITERATURE REVIEW

A. *Rhythm-based Lyrics Generation*. Tra-la-la lyric is a system that generates lyrics based on pre-made tunes. Oliveira, Cardoso, and Pereira investigated the link between words, the musical rhythm of melodies, and rhymes. They created many algorithms that could do syllabus separation and identify the "syllable stress" of a given word. They also established a separate database to record terms and grammatical kinds. Unfortunately, the end output was of poor quality. [3]

B. *Rap Lyrics Generation*. Nguyen and Sa created a rap lyric generator. This application provides a database of over 40,000 existing rap lyrics. The words and verses from the current lyrics are then combined to form a new lyric. The lyrics were created using a linear interpolation technique. However, the outcomes were judged to be insufficiently fluent. As a result, they adopt the four-gram form. They also offered a database of rhyming terms from two separate phrases. They were able to compose phrases that rhymed with each other in this manner. Finally, all of the phrases were recreated to fit the song's structure and arrangement. The generator works alright, however, the lyrics don't make sense and aren't related to a certain issue. [4]

C. *Automated Poem Generation WASP* (Automated Spanish Poet) is the first poem production tool that blends natural language generating techniques with artificial intelligence. It is a system that uses human input as a seed. The system is based on the forward inference rule. The outcomes were regarded as poor and unsuccessful. [5]

D. *Semantic similarity in lyrics*. Logan, Kositsky, and Moreno investigated the use of lyrics to automatically identify and categorize music, as well as to detect artist similarities. The song lyrics were gathered from several websites. To analyze the content and semantics of the lyrics, techniques such as PLSA (Probabilistic Latent Semantic Analysis) and the k-means clustering approach were applied. The system's similarity is determined by mixing it with another sound system. There are pros and downsides to both approaches utilized. As a result, a combination of

the two strategies would almost certainly be far superior, but that is something for future research. [6]

E. *Titular and LyriCloud*. Titular and LyriCloud are two software programs created to produce intelligent and interactive lyrics composition tools for artists. Titular is a semi-automatic song title generating method, whereas LyriCloud recommends comparable word clouds depending on the supplied seed. We adopted a model-based approach. Profanity and disparaging terms were filtered away, and the words that occurred most frequently in the database were the ones most likely to feature in the created song's final title. They obtain good results, but occasionally the title has no semantic value and is confusing to the reader. [7]

F. *Natural Language Processing and Lyrics Generation*. The lyrics were analyzed by Mahedero, Martinez, and Cano using simple natural language processing technologies. Experiments were carried out on the text to recognize the language, classify it according to different topics, extract structures, and hunt for commonalities. The 500 lyrics were chosen from a variety of websites. The total number of curates obtained was 92. The Naive-Bayes classifier was employed. To determine similarity, the Inverse Document Frequency (IDF) and Cosine distance were utilized. Language identification proved to be a simpler assignment than the others. [8]

G. *Classification of lyrics based on rhyme and style*. Rudolf Mayer and colleagues are versed in rhyming and stylistic aspects for grading and processing lyrics. To analyze the lyrics, they employed a word group, lyrics tags, and other statistical aspects. A rhyme is two words that sound the same when spelled together. Words near the conclusion of a stanza are frequently utilized for this characteristic. The proposed method's effectiveness was not properly assessed. [9]

H. *Automated Sega lyrics generation*. Bhaukauraly, Didorally, and Pudaruth collaborated to create a tool allowing lyricists to produce Sega lyrics in Mauritian Creole. Sixty-six respondents were asked to judge ten songs as either man-made or machine-generated. Five of these ten tracks were written by myself. The created lyrics appear to be of high quality since around half of the respondents were unsure if the lyrics previously existed or were generated by a computer program. The fundamental shortcoming of this study is a lack of information in the implementation of how sentences are generated or produced. [10]

III. Background Details

Recurrent Neural Networks (RNN)

RNNs are a form of Neural Network that allows for the use of previous outputs as inputs. They employ the abstract idea of Sequential Memory, which states that a sequence of items provides greater information and efficiency in obtaining a model's output (think the Alphabet). Sequences have an intrinsic property of structure and information. RNNs can recognize patterns and sequences and utilize them to create predictions. They do this by establishing a feedback loop in the network that uses prior data to guide the next iteration of inputs. The hidden state is a vector representation of prior inputs in this feedback loop. This permits information to remain across the model, which is impossible with standard feed-forward networks. [11]

RNNs have several advantages, including the ability to analyze any length of input sequence since the model's size does not scale with the amount of the input, and the ability to take into account previous historical data while operating. RNNs help identifies patterns in data sequences such as text, audio, or numerical time series data because of their benefits. Our method has a narrower domain using RNNs, however, the ***Vanishing Gradient Problem*** might impair text (lyric) production. [12]

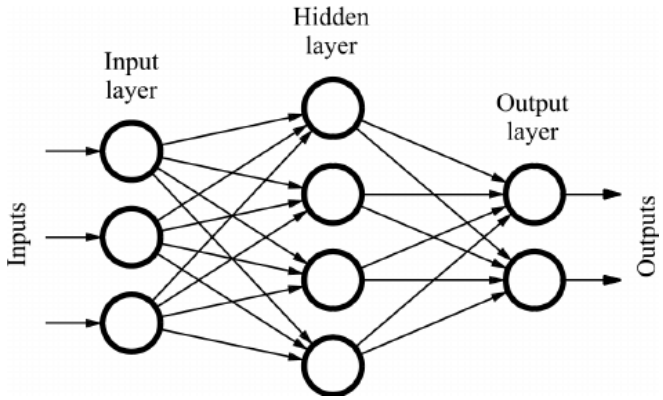


Figure 1: Conventional Feed-Forward NN[13]

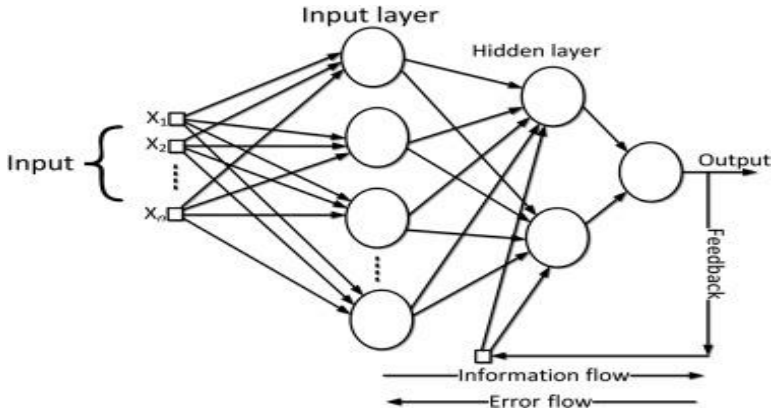
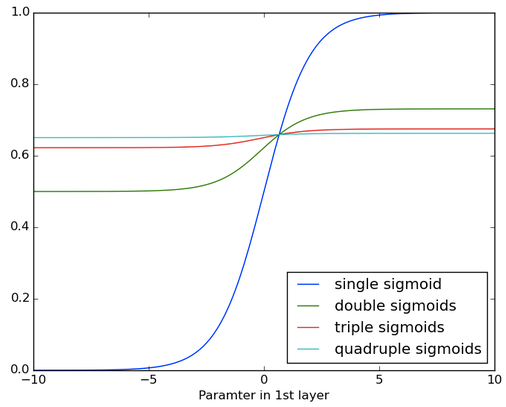
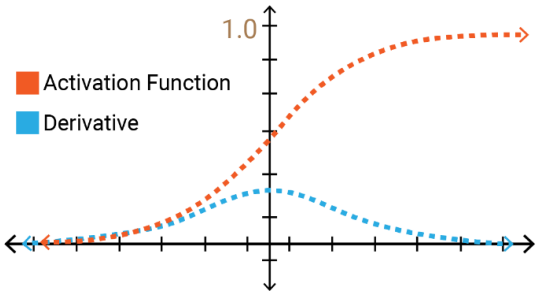


Figure 2: Recurrent Neural Network [14]

Long Short-Term Memory (LSTM)

As previously stated, RNNs have difficulties learning long-term dependencies across time steps. RNNs have a short-term memory and can't access information from the past. The Vanishing Gradient Problem occurs when the gradient of the loss function (values used to update weights) diminishes rapidly during back-propagation and eventually disappears. A gradient that gets too thin (and finally zero) doesn't help you learn much. Because of the microscopic adjustments of the weights by exceedingly small gradients, the neural network's earlier layers are unable to learn. [15]





Figures 3 and 4: Vanishing Gradient Problem [16] [17]

One can utilize LSTMs to fix this issue. An LSTM is a form of RNN that can learn long-term dependencies. LSTMs are capable of preserving errors that can be transmitted backward in time and layers. They improve RNNs by allowing them to learn across multiple time steps by keeping the error value constant.

LSTMs can do this by employing gates, which are tensor operations that can figure out what information to add or remove from the hidden state. The LSTM network has an input gate, a "forget" gate, and an output gate in each unit. The input gate can evaluate the worth of provided data. The "forget gate" can select whether information should be discarded or saved for later use. The output gate is responsible for determining whether or not the information is relevant at a given phase. The gates take inputs as sigmoid function parameters throughout each phase. The sigmoid returns a number between 0 (allow nothing through the gate) and 1 (permit everything through the gate) (let everything through the gate). This idea is used in back-propagation (updating layer values).

LSTMs may pick which information to take forward and which information to drop by employing these gates. These gates assist govern information flow inside the network and allow the error value to remain throughout the network, giving them a significant benefit over RNNs. We concluded that adopting LSTMs would be the best line of action for our lyric generation model. LSTM units were used to form a network because we're trying to produce lyrics based on an initial input sequence. [18]

Most linear algebra operations may be parallelized to enhance the speed with GPU support, and vector operations like matrix multiplication and gradient descent can be applied to huge matrices that are processed in parallel. The Compute Unified Device Architecture (CUDA) interface enables vector operations to make use of GPU parallelism. CuDNN LSTM uses CUDA to implement large-matrix kernels on the GPU. [19]

CuDNNLSTM is optimized for CUDA parallel processing and will not run without a GPU. LSTM, on the other hand, is intended for regular CPUs. Parallelism allows for faster execution times.

As a result, CuDNNLSTMs were used in the model instead of ordinary LSTMs. We were able to obtain a total training duration almost 5 times faster than conventional LSTM execution with this simple adjustment.

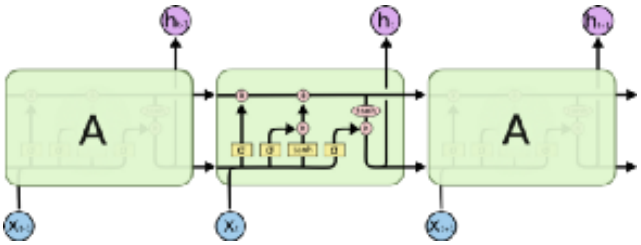


Figure 5: LSTM Network Diagram [20]

Input Lyrics Data

Finding a dataset to feed into the LSTM network was the first step in creating our lyric generator. Fortunately, I was able to find a somewhat robust dataset on *Kaggle* [21]. Lyrics from prominent musicians such as Taylor Swift, Coldplay, Linkin Park, Eminem, The Chain Smokers, and others were included in the dataset.

Our goal was to create a lyrics generator that closely matched a certain artist's songwriting style. Because we ran into memory difficulties numerous times while creating our lyric generator, the difficulty with the dataset was extracting a portion of it that was sufficient but not too huge. To train our models using this information, we built unique CSV files for each artist.

Pre-processing: The Lyrics of a particular artist were joined to form a single file, and standardized, by making all characters lowercase and removing any non-alphanumeric characters. The sting was then broken into a word and rhyme index.

Model Building

The Neural Network has four 256-node bi-directional LSTM layers, one input layer with the 100 character sequences formed during data pre-processing, a flattened, dense, dropout, and lastly an activation layer with a 'soft-max' activation function. A call-back function is used to determine which character is most likely to appear given the preceding character. In our example, the *'checkpoint call-back'*, a call-back is a function that is invoked after each epoch. A checkpoint call-back saves the model's weights each time the model improves

Dropout is a regularization strategy that excludes input and recurrent connections to LSTM units from activation and weight updates when training a network. This reduces overfitting while also boosting model performance. [22]

The training parameters include 30 epochs, a batch size of 128, and a validation split of 20% (4:1). Once the models were trained and fit to the data given, we were able to input a 100 or more-character sequence and watch the model output as many song lines as specified by the user.

The model predicts output one character at a time since it is character-based. To facilitate this operation, a tensor was generated by mapping unique characters to their frequency in the data. This was performed using Keras' *Tokenizer* function, which allowed us to compress and vectorize

characters effectively based on their input frequency. Every character that appears in an artist's total song lyrics is assigned to two different dictionaries. The data is divided into samples and labels. After that, the data is reshaped, the size is normalized, and one-hot encoding is applied. The generated tensor is then converted into the corresponding character and concatenated to the 'key' string. This new 'key' string is then inputted back into the model to generate the tensor of the subsequent character.

The loss function used is *'Categorical Cross Entropy'* because several articles before this study had also used the same loss function. The optimizer we used is *'Adam'* because it is computationally efficient and doesn't have too many memory requirements.

BERT Integration

BERT (Bidirectional Encoder Representations from Transformers) is a new NLP approach developed by Google researchers. BERT works on a high level by employing transformers (an NLP approach that uses Attention) to analyze and learn the relationship between words. It is a bidirectional approach that can comprehend the context or relationship of a word to its surrounding words in a corpus. The BERT model's major benefit is that it allows for transfer learning, which substantially speeds up the training process while preserving accuracy.

Consequently, *'Bidirectional CuDNNLSTM layers'* were introduced into the neural network. [23] This integration allowed the network to generate more nuanced, human-like lyrics. Also, as mentioned in the previous sections, a shift was done from LSTM to CuDNNLSTM, because the former uses the CPU and the latter uses the GPU, that's why CuDNNLSTM is much faster than LSTM. Results were generated almost 15 times faster.

Batch Sizes

Initially, a default batch size of four was used, however, this resulted in an extremely noisy stochastic gradient descent of the loss function. It was found that raising the batch size to 64 or 128 units resulted in a steady gradient descent and greatly reduced training time.

Unidirectional vs Bidirectional Neurons

An LSTM's hidden state preserves information from earlier inputs. The information stored by the unidirectional LSTM is restricted to the past since the only inputs it has seen are from the past. Bidirectional processing sends your inputs in two directions: one from the past to the future and one from the future to the past. This differs from unidirectional processing in that the LSTM running backward maintains information from the future, whereas the two hidden states together preserve information from both the past and the future at any point in time. Although establishing their optimum application is tough, bi-directional LSTMs offer outstanding results since they are better at comprehending context. Let's say we try to predict the next word in a sentence, on a high level what a unidirectional LSTM will see is, [24]

The boys went to...

And will try to predict the next word only by this context, with bidirectional LSTM you will be able to see information further down the road for example

Forward LSTM: *The boys went to ...*

Backward LSTM: *... and then they got out of the pool*

You can see that using the information from the future it could be easier for the network to understand what the next word is.

IV. RESULTS AND DISCUSSIONS

Generated Lyrics

With dropout layer:

The use of a dropout layer in the model was able to affect the overall overfitting of the testing results only very slightly. However, its implementation brought out an interesting feature in the result. As evident from the attached results, oftentimes it was seen to generate a set of words/phrases several times in succession. Although this effect in no way affected the overall appeal of the generated lyrics, it did add a slight poetic edge to the lyrics. Such use of phrases in literature is a poetic device called *'Repetition'*, which is employed to make a phrase/text more noticeable.

```
Seed :
" takeaway, yeah, yeah, yeah-yeah
your heart for takeaway
your heart for takeaway, yeah-yeah, yeah-yea "

h
your heart for takeaway, yeah, yeah, yeah-yeah
bafore i love you, na, na, na
i'm gonna leave you, na, na, na
before i'm someone you leave behind
i'll break your heart so you don't break mine
before i love you, na, na, na
i'm gonna leave you, na, na, na
even if i'm not here to stay
i still want your heart
your heart for takeaway, yeah, yeah, yeah-yeah
your heart for takeaway, yeah, yeah, yeah-yea
Done
```

OBSN: Since the given *seed/key* phrase, has a repetitive phrase, the model can pin on nuance and use the same phrase and device to give the lyric a more poetic edge.

```
Seed :
" m okay when thinkin' 'bout you
you were right when you said it, keep my cards to my chest
and i neve "

r let no one know me, i pushed you out
now i get that you needed just a little more love
and to just see me wide open and breaking down
when no one's there to listen, i will hear your pain
i know that i was less than, but you know people change
so tell me, what's the difference if we still feel the same?
it takes a little distance to make you see the way
i go from okay, i'm okay to i'm not okay
fr
Done
```

OBSN: Here the given *seed/key* phrase, has no repetitive phrase, yet the model can use the phrase "I'm okay" and use the *'repetitive'* device to

Without dropout layer

As compared to the former implementation with the dropout layers, here the 'repetitive' element only appears about 25% of the time, whereas in the former it was around 66.67%. The lyrics generated are otherwise indistinguishable from the former implementation, even with a higher overfitting and validation loss. Furthermore, on performing an opening poll with peers, this set of results proved to be far more acceptable as song lyrics, with an edge of over 80%.

```
Seed :
" ause
he's the reason for the teardrops on my guitar
the only thing that keeps me wishing on a wishin "

g star
he's the song in the car
i keep singing, don't know why i do...
drew walks by me
can't he tell that i can't breathe?
and there he goes, so perfectly
the kind of flawless i wish i could be
she'd better hood him tight, give him all her love
look in those beautiful eyes and know she's lucky 'cau
Done
```

```
Seed :
" ause
he's the reason for the teardrops on my guitar
the only thing that keeps me wishing on a wishin "

g star
he's the song in the car
i keep singing, don't know why i do...
drew walks by me
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and there he goes, so perfectly
the kind of flawless i wish i could be
she'd better hood him tight, give him all her love
look in those beautiful eyes and know she's lucky 'cau
Done
```

```
Seed :
" to me
i can't help but wish you took me with you
and this is when the feeling sinks in
i don't wanna "

 miss you like this
come back be here, come back be here
i guess you're in london today
i don't wanna need you this way
come back be here, come back be here
this is falling in love in the cruelest way
this is falling for you and you are worlds away
nawhh you're aooadu and thating inte me she break
t
Done
```

```
Seed :
"
and you said, "i never regretted the day that i called you mine"
can i call you mine? ooh, ah, ooh
 "


can i call you mine? ooh, ah, ooh
can i call you mine?
ooh, ah, ooh
can i call you mine?

do you mean, do you mean what you say?
what you said, now you can't take away
you're my gospel, but i'm losing faith, losing faith
do you mean, do you mean what you say?
take a minute, do you need to stop and think?
what we have, no, we can't throw away, throw away
show me that you mean it, ayy
show me that you mean it
do you really mean it?
everything happens for a reason
show me that you mean it do you, d
Done
```

Inclusion/Exclusion of the Dropout layer(s)

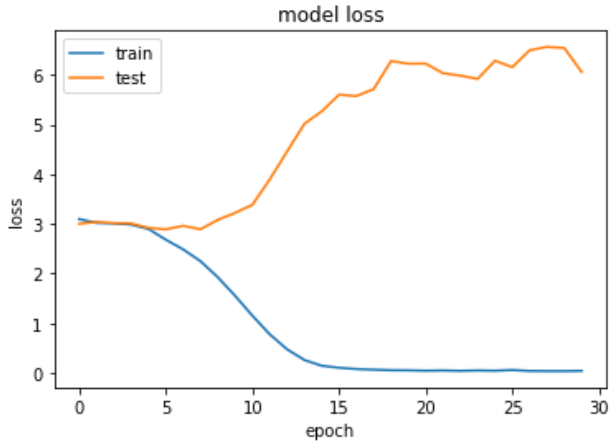
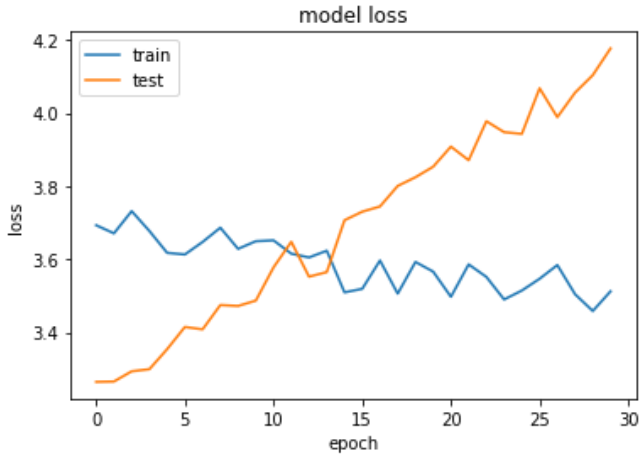


Figure 6: Comparison of validation loss vs testing loss in bidirectional LSTM implementation

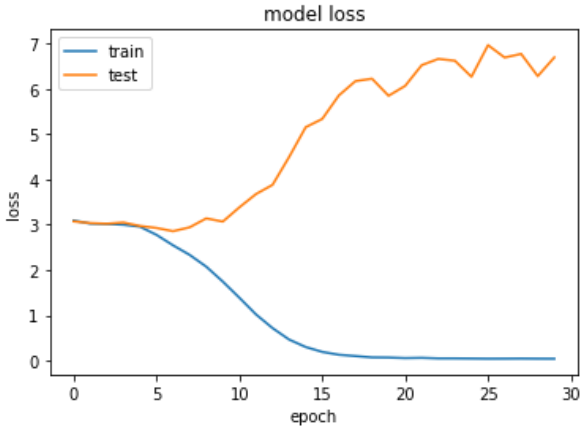
Loss - 0.0420 valalidation loss - 6.0612 (Control)



Ex1.

Comparison of validation loss vs testing loss in 1st dropout implementation (just after Dense layer) This served as a control for the experiments with the dropouts.

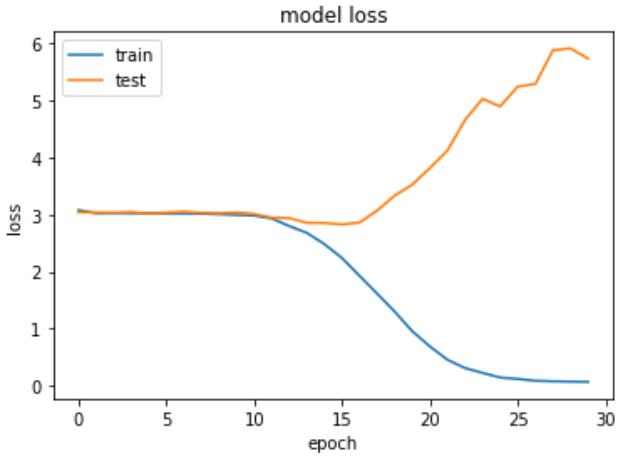
Loss - 3.5126 validation-loss - 4.1771



Ex2.

Comparison of validation loss vs testing loss in 2nd dropout implementation, after every hidden layer.

Loss - loss0.0655 validation-loss - 5.7330



Ex3.

Comparison of validation loss vs testing loss in 3rd dropout implementation, after hidden layers, just before the output Dense layer.

Loss - 0.0427 validation-loss - 6.6893

As evident from the training vs testing loss values, our model appears to be overfitting the data. The conventional response is to try to mitigate this by the addition of dropout layers. A model trained

with zero dropout layers served as the control for this test. Three possible configurations of the dropout layer(s) were tested:

- 1st dropout implementation (just after Dense layer) – *general implementation*
- 2nd dropout implementation, after every hidden layer.
- 3rd dropout implementation, after hidden layers, just before the output Dense layer.

Through multiple runs, it was found that although the 3rd implementation did successfully reduce the overfitting to a certain extent, the difference between the testing and training loss was still worthwhile. But the difference arises in the lyrics generated.

The model with a dropout layer often got caught in endless loops of certain words and phrases. The final lyrics generated were also not of sufficiently high quality. Whereas the model, without any dropout layer, having a more distinct difference between training and testing loss, was able to generate higher quality lyrics at every iteration.

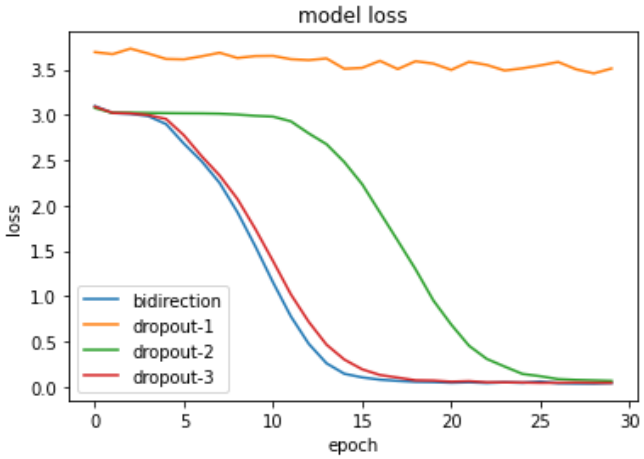
Further Comparisons

The traditional implementation of the dropout layers in a Neural Network places it just after the Dense Layer. As seen in the following graphs, this becomes quite evident even with this system. Over subsequent changes in the number of epochs spent in training the model, the graphs of training and validation loss show fairly constant values for the traditional implementation. (*dropout 1*)

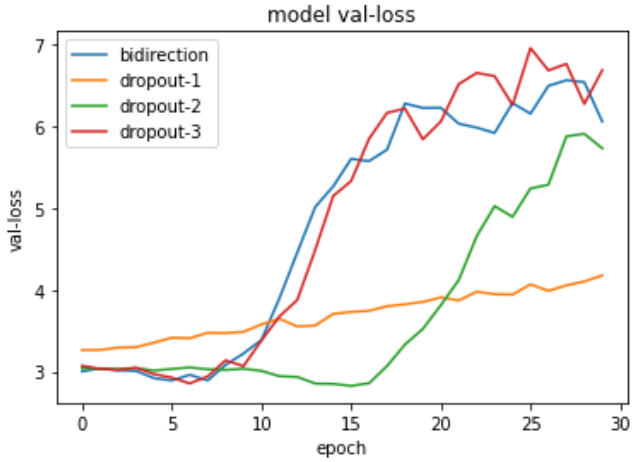
The dropout layer positioned just before the Dense layer (*dropout-3*), produces training and validation loss closely resembling that of the control (*bidirectional*) curve. This shows that having the dropout layer at this position contributes next to nothing towards the goal of countering the overfitting issue.

When the dropout layer is positioned after every hidden layer (*dropout-2*), the approach worked best particularly for the lower values of epochs, up to around 12. Till this point, it was not only providing stable loss values for both training and validation sets but lower loss values. However, after the critical point of 12 epochs, the values showed a drastic change assuming a sigmoid structure just like the control (*bidirectional*) curve but heavily skewed towards the right, i.e. higher epoch values, and finally merging with the control and dropout-3 curves at around epoch 25.

Thus it was evident that for an overall controlled state, the traditional approach proved to be the best, however at lower epoch values, positioning similar dropout layers between hidden layers, also serves as a viable alternative.



Comparison of loss in bidirectional, 1st, 2nd, and 3rd dropout implementation



Comparison of validation loss in bidirectional, 1st 2nd, and 3rd dropout implementation

V. OBSERVATIONS AND INFERENCES

The phenomenon of overfitting (inferring bias), draws close parallels to human creativity. As social-being, we all have some likes or dislikes, and we always tend to be a bias toward the things we admire. This is reflected in the artist's songwriting as well, where the degree of bias is shown towards certain emotions. The overfitting, in theory, is somewhat able to simulate that creative bias, resulting in far more 'human-like' lyrics being generated.

According to the over-fitted brain theory, organisms' brains face the same difficulty of overfitting to their daily stimulus distribution, resulting in poor generalization and overfitting. The brain may recover the generalizability of its perceptual and cognitive capacities and improve task performance by imagining out-of-distribution sensory stimuli every night. [25]

Similarly, it is possible that the overfitting problem faced by our model can be generalized using intermittent and finely tuned '*noise-injections'*, in the form of noisy or corrupted, or faulty data. This is a common method implemented in handing overfitting in the case of DNNs.

VI. CONCLUSION AND FUTURE WORK

We can now create our mixtapes! The lyric generator we created is significant and interesting to us because we were able to dive deeper into NLP and neural networks to see what kind of abstract applications they have. In this day and age, when everything is becoming automated and enhanced due to machine learning, our study seems to align with the idea that the applications of NLP and data science can extend to any field imaginable. It's fascinating to see how interdisciplinary data science truly is and how it can bridge the gap between STEM and other distinct fields (in this case, music).

There are a plethora of ways we might enhance and build on this concept in the future. First and foremost, several of the difficulties highlighted in the preceding sections, such as the overfitting problem, may certainly be addressed, by noise injections. Despite the usage of GPU-accelerated neurons, the training time was fairly long, and this has to be addressed in the future too. Fine-tuning parameters is one course of action that may be taken to see if model performance can be improved, both from the LSTM and BERT sides of the application.

This concept might be extended to different literary styles and mediums, such as poetry, and with the correct dataset, the lyrics generator may evolve into a poetry generator. Adding further layers or establishing a concurrent LSTM to add pitch and rhythm to the lyrics is one avenue that can also be considered. As a result of which, we may be able to create a more comprehensive, healthy music-generating engine.

VII. REFERENCES

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