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Deep Learning

Assignment 3

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Introduction

The assignment's goal was to create a Recurrent Neural Network that could learn song lyrics and their melodies and then generate new lyrics given a starting melody and a few words. The model was trained using L1-loss since the model output was embedding the predicted word, with the melody files and lyrics for each song provided as input. We did not split our training set into a validation set either because we preferred to train the model on as much information as possible. The LSTM network architecture was chosen for this task because of its ability to remember previous data, which is important for generating coherent lyrics that depend on the words and melody that came before it. The input sequence length, consisting of a series of lyrics, greatly affected the model's ability to make accurate predictions. Different sequence lengths were experimented with to determine the optimal length for the task. After training the model, it could be used to generate the lyrics for a whole song by starting with an initial "seed" of a few words, predicting the next word in the sequence, and then using that prediction to advance the sequence like a moving window.

Dataset Analysis

- 600 song lyrics for the training
- 5 songs for the test set
- Midi files for each song containing just the song's melody.
- Song lyrics features-
    - The length of a song is the number of words in the lyrics that are also present in word2vec data.

Word2Vec

We utilized the gensim library to obtain vector representations of the words in the lyrics, allowing us to use the most similar function to the most similar vector representation of the input word. The similarity function used to compare the vectors is cosine similarity, which measures the cosine of the angle between two vectors in a multi-dimensional space. This helped us generate the lyrics for a song by identifying the words that are semantically like the input word, thus making the generated lyrics coherent.

The model we used was pre-trained on a large dataset of 840 billion tokens, meaning it has seen vast text data. For each word in the dataset, the model has learned a vector representation of length 300. This vector captures the meaning and context of the word within the dataset and allows the model to understand the relationship between words and their similarity.

```
word2vec.most_similar(word2vec['happy'],topn=10)
```

```
[('happy', 1.0000001192092896),
 ("'m", 0.7080122232437134),
 ('glad', 0.6905032396316528),
 ('pleased', 0.6712467074394226),
 ('really', 0.657589852809906),
 ('always', 0.6494665145874023),
 ('everyone', 0.6449035406112671),
 ('everybody', 0.6344363689422607),
 ('feel', 0.6336807608604431),
 ('i', 0.6298314929008484)]
```

An example of a vector representation of the word "**happy**" and finding the 5 words closest to it semantically:

It can happen that the similarity between the vector and itself is 1. The word glad also received a high similarity score in relation to the word.

Code Design

1. **Main.ipynb** - The script automates the entire process of building the model from start to finish, including data preprocessing, running experiments to select the best parameters, and evaluating the model's performance on the test set. It streamlines all the necessary steps required to train, test, and evaluate the model in one place.

2. **Preprocessing.Ipynb** - The script includes all the functions required for the initial stages of preparing the data, such as creating features using melodies, converting text into tokens, and functions for working with the word2vec model. These functions are necessary to preprocess the information and make it suitable for the model to learn from.

3. **DataLoader_class.ipynb** - The notebook includes the SongDataSet class, which is responsible for specifying the structure of the data that will hold the input and output of each example, for the purpose of training the model. This class defines how the data will be organized and stored, so that the model can easily access and use it during the training phase.

4. **RNN.ipynb** - The notebook holds the implementation of the class of the LSTM network, and the loss function that we implemented ourselves for the purpose of the task.

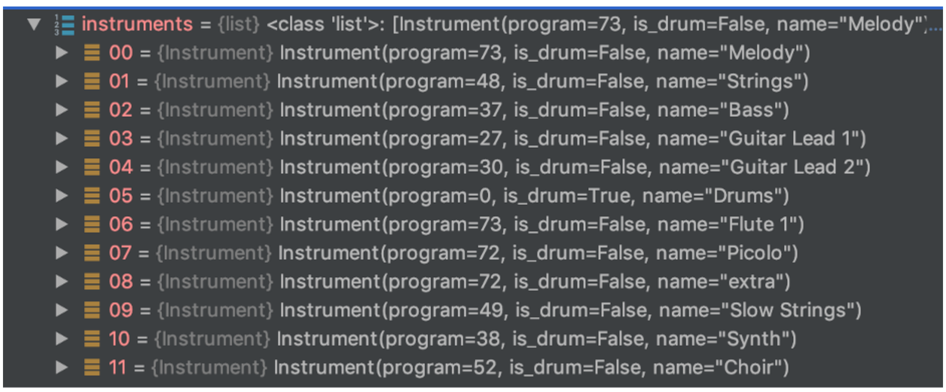
Melody Feature Integration

We formulated two approaches for incorporating the melody in the training step -

Method 1:

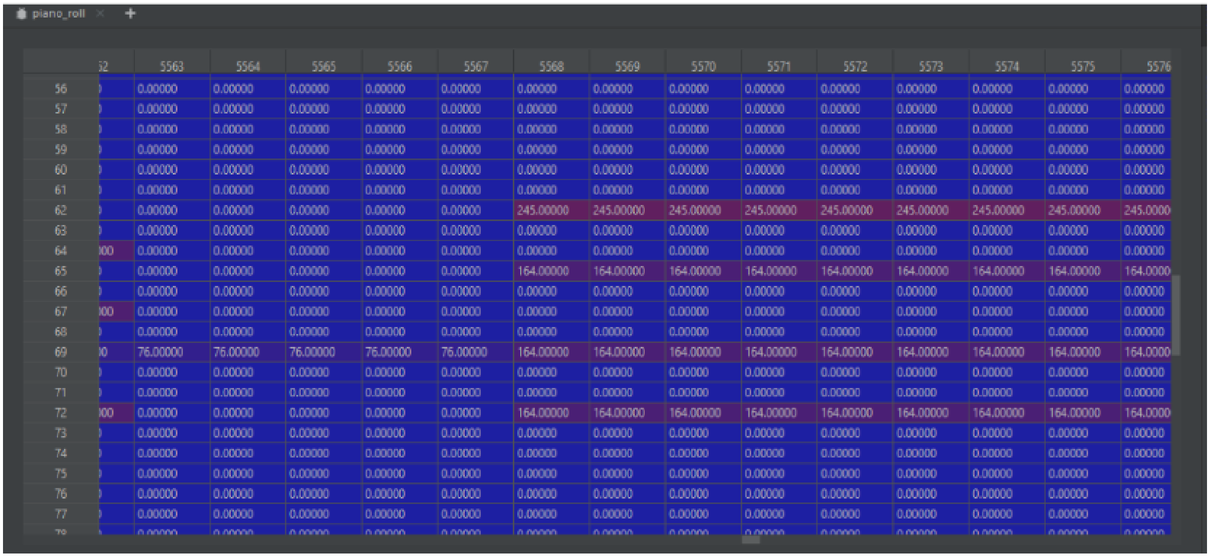
In this approach, we extracted features related to the instruments and changing beats of each song. To define the time range of each word, we divide the length of the melody by the number of words in each song. We analyze the instruments used and count the number used for each word.

We also use the pretty_midi's get_beats() function to find all beat changes in the song and their times, counting the number of beat changes during the word's time frame as an additional attribute to the grid.



Method 2:

Each pretty midi object has a getPianoRoll(fs) function that returns a matrix representing the notes used in the midi file in time scale (Figure 1). This function returns a matrix of size 128*(the length of the song) multiplied by how many times a sample is taken every second, denoted by the fs parameter. For example, for fs=5 every 1/5 second a sample will be made, that is 5 samples per second so for a 50 second song we will have 250 samples. With this method, we can control the granularity of the data. Each column in this matrix represents the notes played in this sample, with the help of this information we can extract the number of notes per word (with the help of the number of words in each song), and insert them as an additional feature in the network.


piano_roll

	52	5563	5564	5565	5566	5567	5568	5569	5570	5571	5572	5573	5574	5575	5576
56	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
57	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
58	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
59	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
60	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
61	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
62	)	0.00000	0.00000	0.00000	0.00000	0.00000	245.00000	245.00000	245.00000	245.00000	245.00000	245.00000	245.00000	245.00000	245.0000
63	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
64	00	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
65	)	0.00000	0.00000	0.00000	0.00000	0.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.0000
66	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
67	00	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
68	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
69	0	76.00000	76.00000	76.00000	76.00000	76.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.0000
70	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
71	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
72	00	0.00000	0.00000	0.00000	0.00000	0.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.00000	164.0000
73	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
74	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
75	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
76	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
77	)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

<u>Combining the features of the word with the features of the melody</u> -

When constructing a model, the vector representation of each word is augmented by incorporating additional features. For example, if the size of the vector for a word is 300, and the size of the additional features is 2, the resulting vector passed to the LSTM network would have a size of 302. This augmented vector contains both the original word embedding and the added features.

Architecture

We used an LSTM network, which is a type of recurrent neural network, to predict the next word in a sequence. The input to the network included both an embedding vector, which represents the meaning of a word, and melody features, which captures the musical information. The output of the network was a 300-dimensional vector that represented the predicted vector representation of the next word in the sequence.

Layers -

Input: A sequence of words, where each word is represented by its index.

1. Embedding layer: Converts each index of a word into its vector representation by using a database of words in the songs and their vector representation using Word2Vec dictionary.
2. One-way LSTM layer: Receives as input the vector representation of the words, and the feature vector created from the melody of the song for each word. The layer performs an iterative process and at the end produces an output that contains for each word in the sequence its hidden layer.
3. Dense layer: The layer receives the output of the LSTM layer which contains for each word a vector with the size of the units parameter. The output of the layer for each word is a vector of size 300 that represents the vector of the next word in the sequence.

Loss -

The problem we'll describe is known as the "common word problem" in natural language processing, where the model tends to predict common words more often because they are more likely to be correct. To address this issue, we proposed modifying the loss function used in training the model by adding a term frequency component.

The L1 loss function compares two vectors and calculates the absolute difference between them, then takes the average of those differences to represent the overall error. By dividing this error by the log of the term frequency of the real word, words that are more common will have a lower error, which would help reduce the model's tendency to predict common words. This modification would encourage the model to predict less common words with higher accuracy.

The implementation of the custom L1 loss:

```
class Custom_L1_Loss(nn.Module):
    def __init__(self):
        super(Custom_L1_Loss, self).__init__();
        self.loss = nn.L1Loss(reduction='none')
    def forward(self, predictions, targets, tf):
        loss_value = self.loss(predictions,targets)
        mean_loss = loss_value.mean(dim=-1)
        weighted_loss = torch.mean(mean_loss/tf)
        return weighted_loss
```

experiments

Experiment parameters -

1. seq_length: Different sequence lengths, 1, 5 and 9, to see how much the length of the sequence affects the results.
2. num_layers: The number of layers in the LSTM network, two options - 1 and 2.
3. units: The number of neurons in the hidden layer of the LSTM layer, two options - 256 and 512.
4. Learning_rate: We tried 2 values, 0.01 and 0.001.
5. Batch_size: We tried 32 and 64.

Calculation of the cosine similarity -

The cosine similarity was calculated by taking the predicted 50 words for each song, comparing the vector representation of the predicted word to the representation of the corresponding word in the original song, averaging all the values for each song, and then averaging the results across all songs.

	batch_size	learning_rate	num_layers	seq_length	units	time (sec)	loss	cosine_similarity
0	32	0.001	1	1	256	927.680	0.035895	3.749
1	32	0.001	1	1	512	972.886	0.035730	3.773
2	32	0.001	1	5	256	197.841	0.032205	3.559
3	32	0.001	1	5	512	211.579	0.030003	3.661
4	32	0.001	1	9	256	121.680	0.031660	3.793
5	32	0.001	1	9	512	125.070	0.029067	3.835
6	32	0.001	2	1	256	1075.188	0.036023	3.582
7	32	0.001	2	1	512	1166.587	0.035649	3.643
8	32	0.001	2	5	256	243.835	0.029330	3.844
9	32	0.001	2	5	512	275.931	0.025605	3.507
10	32	0.001	2	9	256	150.908	0.028387	3.608
11	32	0.001	2	9	512	170.181	0.024005	0.393
12	32	0.010	1	1	256	920.539	0.039227	0.351
13	32	0.010	1	1	512	979.629	0.039184	3.530
14	32	0.010	1	5	256	193.854	0.038254	3.751
15	32	0.010	1	5	512	210.563	0.038130	3.702
16	32	0.010	1	9	256	122.061	0.037062	3.676
17	32	0.010	1	9	512	125.324	0.036378	3.840
18	32	0.010	2	1	256	1079.946	0.038677	3.867
19	32	0.010	2	1	512	1172.743	0.038931	3.514
20	32	0.010	2	5	256	237.129	0.036409	3.890
21	32	0.010	2	5	512	275.878	0.035962	3.581
22	32	0.010	2	9	256	142.436	0.034973	3.893
23	32	0.010	2	9	512	174.846	0.034294	3.551
24	64	0.001	1	1	256	564.534	0.035699	3.593

25	64	0.001	1	1	512	576.943	0.035531	3.704
26	64	0.001	1	5	256	117.776	0.032461	3.601
27	64	0.001	1	5	512	129.242	0.030279	3.736
28	64	0.001	1	9	256	76.341	0.032066	3.622
29	64	0.001	1	9	512	77.856	0.029511	3.560
30	64	0.001	2	1	256	644.030	0.035845	3.662
31	64	0.001	2	1	512	685.409	0.035488	3.535
32	64	0.001	2	5	256	141.931	0.029586	3.613
33	64	0.001	2	5	512	164.396	0.025796	3.711
34	64	0.001	2	9	256	82.980	0.028825	3.560
35	64	0.001	2	9	512	110.684	0.024355	3.759
36	64	0.010	1	1	256	567.936	0.038946	3.768
37	64	0.010	1	1	512	583.696	0.038969	3.534
38	64	0.010	1	5	256	119.604	0.036917	3.794
39	64	0.010	1	5	512	129.117	0.036378	3.759
40	64	0.010	1	9	256	76.557	0.034784	3.531
41	64	0.010	1	9	512	77.649	0.033713	3.867
42	64	0.010	2	1	256	644.721	0.038191	3.781
43	64	0.010	2	1	512	686.123	0.038203	3.711
44	64	0.010	2	5	256	142.247	0.035147	3.618
45	64	0.010	2	5	512	164.558	0.034377	3.884
46	64	0.010	2	9	256	83.145	0.033173	3.540
47	64	0.010	2	9	512	110.614	0.032024	3.712

best parameters(based on loss and cosine similarity) -

batch size = 32

learning rate = 0.001

num layers = 2

sequence length = 9

units = 512

run time explanation - It was observed that shorter sequences resulted in longer training times, and that longer sequences yielded better results in terms of both model quality (as

measured by loss and similarity) and running time.
Therefore, it is recommended to train the model on longer sequences.

Experiment various options of features-

Once the optimal parameters for the model have been determined, all three networks will be trained using these parameters. The first network will receive both the vector representation of the words and features of the instruments, the second network will receive the vector representation of the words and the features of the piano, and the third network will only accept the vector representation of the words.

	Model used	seq length	time	loss	cosine similarity
0	LSTM with insturments features	9	200.087	0.022	0.390
1	LSTM with piano features	9	500.027	0.023	0.387
2	LSTM without features	9	170.181	0.024	0.393

It appears that incorporating additional features into the model did not greatly impact its performance, as evidenced by similar results in terms of loss and similarity between predicted words. The model that included features of instruments had the lowest loss, but the model without these features showed the highest level of similarity. Therefore, we will conduct a manual analysis of the words produced by each model to further evaluate their performance.

Results Evaluation

In this assignment, we were tasked with generating lyrics for five songs in the test set. One way to evaluate the results is by counting how many times our model correctly predicted the actual word used in the song. However, this method is not an accurate measure of the model's performance, as it does not take into account the possibility of the model generating a word that is similar to the actual word but not an exact match. To properly evaluate the model's lyrical abilities, we have devised several other methods, taking into account that the model's predictions should have the same number of words as the original song:

Cosine Similarity:
This is a general method to compare the similarity of two vectors. So if our model predicted "happy", and the original lyrics had the word "smile", we take the vector of each word from the embedding matrix and calculate the cosine similarity, 1 being the best and 0 the worst.

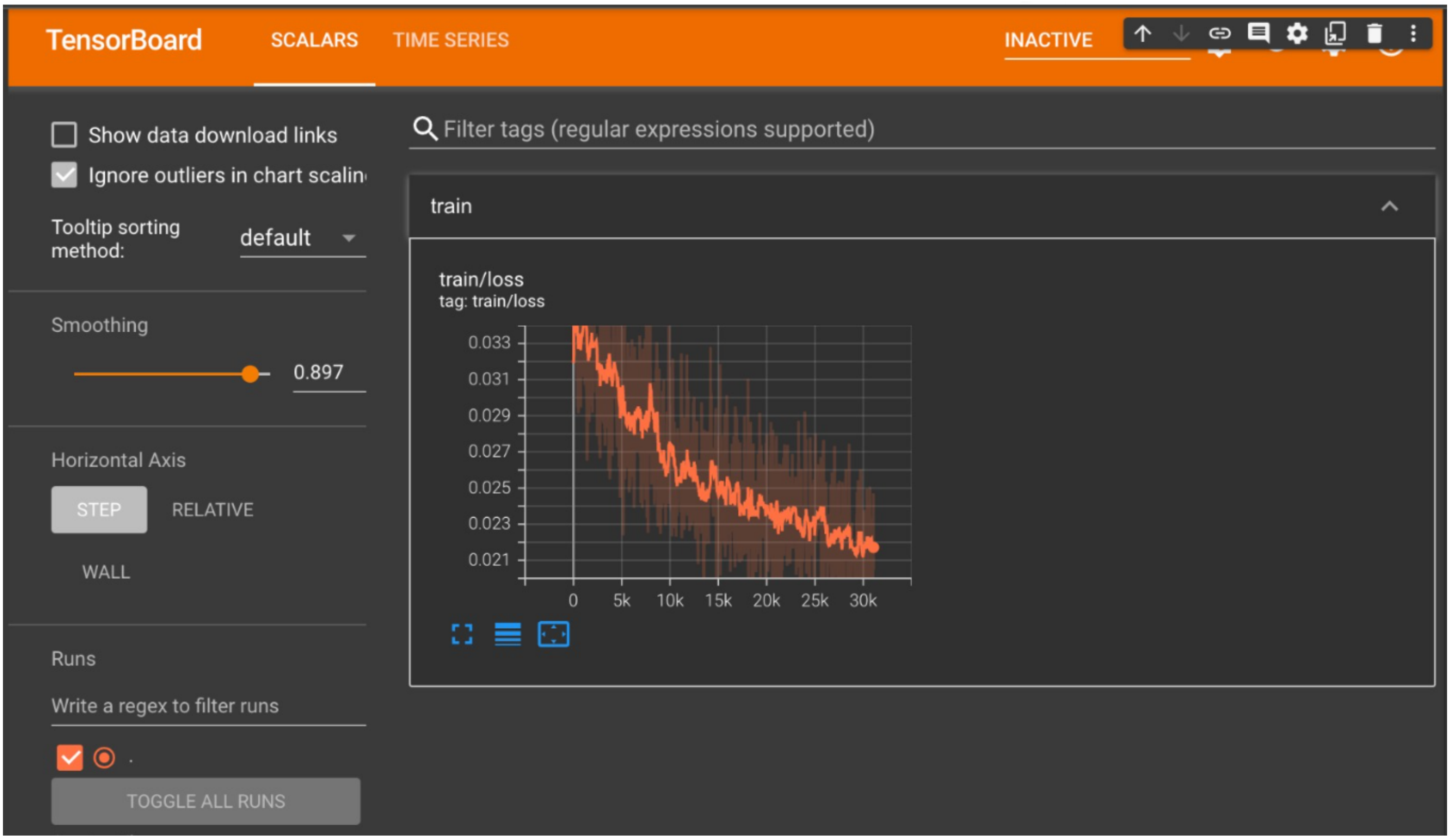
Choose the next word

During testing, it was observed that the model repeatedly used the same word twice in a row. Additionally, we found that relying on the word with the highest similarity as the output of the network resulted in the repetition of specific words. To address these issues, two solutions were proposed:

1. Selecting the 10 most similar words and selecting a word using the softmax function according to the probability that it corresponds to the image.
2. Enforcing the model to produce a different word than the one it previously generated.

Model with simple instruments features - sequence length 1:

A screenshot from the TensorBoard framework:



Lyrics for the bangles - eternal flame(55 words) input: **close**

close but time when think 10. because well come my to take going really this want like we what if way sure. so others, me think well what though if want just now even do it even though like they only even only just why all what. will, never but not

input: **your**

your but what ? as what really could go get , it but really get thinks what but so you do should however we it we sure can only what not my would something what if me we get not but again anything however in it same . because even of something about it they also

input: **eyes**

eyes however know not can take go so only even because so , way going just off not what so come why others both only would what can just let we because think when because but though although just you go sure even time if both do should take get just get out even both but

Lyrics for billy joel - honesty(95 words)

input: **if**

if going down time they going if even sure think all come so way . even while now really never hear honestly one also . honestly others although going but way that even want takes could same way in although even and why so what nothing that come even all same but now this way only even while not although forgotten one just time while it alright but it but really want why allow even . both same down it also . though but if way i when never think know they but would it come

input: **you**

you not but really think when did going would up take , this more it these if just because how though much if really though anybody would want even because they while going really on really something that as we never go you both well going , down come same those . out same only , going what them know really same come , just although going know them maybe even in not . so both going want to so should they come they also we things but this then same come this time just but input: **search**

search even what not but they know sure well way be what both you would get do so did come now only but know same when just going ? put it come it going so all if just know up because also so get younger only not well feel even so you thing if make really me thing think but so though this think . , though not going you to think ? but however think things when well not way as although your go feelings you because what well i so think come well but

Lyrics for cardigans - lovefool(77 words)

input: **dear**

dear all me even just ask tell i somebody give something me way , although same know not it you well . others although why what can that come they so think more while well because so even way just to when know me way time while but that nothing we think so well only also although kind always this funky beautiful well just get let get it this while . because same the even crazy kinda so

input: **i**
i would if do even when just we really come laughin well one as we the did rule although . way even come one going same come although so which they because you even i but come really even anyway get it things both only really you able others going out but this want a will just but could this because just what when even you does because that not me think though just might so because know

input: **fear**

fear even think its if going i instead need it but others if so things so could but been so because one in only one something get everyone going when then if what when just so everyone those if so will everyone be same know others come everyone back well not just what ought know able well them just even it should come even going even before up although . now they when looked maybe now they time

Lyrics for aqua - barbie girl(93 words)

input: **hiya**

hiya let tell we this soulful frightful we but you okay remember in well so even too did they others again maybe . well both want say decided same would and know to would even could ? but well think actually sure nothing however sure although it before we now you but things thing what way not this do even well come only on one something well that . thing also but decisions thing well though but ? nothin . but while come playin to while tenderness although think while because things though them

input: **barbie**

barbie in the streets one woman one they , come time same because not way get in well same also although ugh did anything however what . even however only however just it do we however we and come should and been want both help all as way me both i know i same because even same going this you part i as want going what it know going same back now well when just when know i know get while so only get always when shouting want after to because it but just

input: **hi**

hi ! our they want not give come only in so ? even well anything this maybe which all way same also this everybody even it but just this does but its why not even what should things so that just really that wanted if but ? husband when know really why do others they ? nothing also so say kinda we bit what it what think take even get if they if might want . try but only guess yells anything they we do i and what go think because time in all

<u>Lyrics for blink 182 - all the small things(58 words)</u>

input: **all**

all time not same although but because myself they think they , why we not have why want . out when time never this they mind just . know as get of get think get while very because really but not gonna pretend yet however when what i so sure it even but not ? you also ? because

input: **the**

the they not does when going i here sure even so because way now but if because when while even yourself will so if actually you so what everyone could do think , . we but well good because without well they so i those things and not . what however so not way but it though so could

input: **small**

small now this but going just again something it one get well just same take . only but go somebody this know everybody as what make really they want why what as my ? know . know same know come we not if you what even you sure something we though we same even both one even only it

Model with piano features - sequence length 1:

Lyrics for the bangles - eternal flame

input: **close**

close feelin dreams baby that cause like friends im have day cool let be their would your wit oblivion such forgiven oh may doll nothing down i now around suddenly ball have empty that lovely how you lonely no goes gone you are called of for wanted me life of stress apart say i all way.

input: **your**

your gentle i were remember how swear she neither too girl out through with more love me me eyes said have i used heartache hmm anymore desire battling she when stay be part lights spend by bite again say try ruining slide lover i eyes get always honey of maybe to it hope its white i.

input: **eyes**

eyes and walk the night woah not live you his world more when just wakes you you fans me to it son napping you up i that it da we me let the i longing my do maybe warm fought a believe guys the hear blind dont your through this a down what tell gonna oh.

Lyrics for billy joel - honesty

input: **if**

if do hell your as you hard so the be of mable we love do fat give around em with if show you me its of some can top tell if like over baby an the out that a right get as their leaves are oh come happy joy fight me thief give i goodbye sharing like hey all it later you open right i to tonight wake be shift i sister no i on got years wear to make show dont learn be you the live from outer jump pain the myself face shes raps.

input: **you**

you sherry really but take my girl you and its kick knew so or the a tuya love no how love have of the me there the like its if i winter see reason baa i have would want im high him dancin ever but performed wanna the i mean the you when ill say get well leave up just actor that shit now do the chaka over dead got better to no my the imitating me and my can here and itself footsteps to like leave looked are phone for will will keep my mind.

input: **search**

search it so class und any you and that friends cried day whoa fine the i three the in the you lovin its a and said hall way others let night hey beautiful plans dishes save beer store evil back summer yeah forget when well both strong said you me way your the reproduction jolly im what told the really to love huh the you baby go river get id and uranus what around with the down and you would always i heart dont with once go land mind come still so to them one else.

<u>Lyrics for cardigans - lovefool</u>

input: **dear**

dear to pick tears slide low live such ill yourself me deep out crazy never kick i the belongs get others shelter before her it i wasnt survive ring off baby im to want life ho hanging if i each high you out mine you won rang woman i the do you we you certain guy the jesus my my much flame to you just you world pretty me to dont fault to ear know see love guide.

input: **i**

i dumb look me kit i ive and clothes type meet all of didnt love baby the to you i the baby heart these and up look i out just family the what baby theyre all my love down sittin money be from something stars out no while now your got guide and time some was my you off would you is na man he and reflect down hes best in hand be shotgun to leaves the that.

input: **fear**

fear at ive no i your be friend kill thats you years im so right your hurts a if love ill night ever feel what his like ride behind love but man a going can good and gone do see if have name all turn the is start the about you down breaking you at the lady did hard call you the about endangering ass thing together in fall love i they its a up drop youre out.

Lyrics for aqua - barbie girl

input: **hiya**

hiya put there to copa out kick when sad when it my cars girl the with in i me the some a around eyes stay cause be clock we never still cant missed anytime motion quiet ive go hot it on the a you had and sign live tennessee no fools got so i father hope for never for you the just it there me my believe other oh red your dont dream the drives the they chorus the happy crosses they to i i because if won this i want didnt ask the.

input: **barbie**

barbie me go to country smiling all now from love she my is this world not that in to though i beat your be bad new hard cant pretty to wont to round do things without try it walking of ill things in man love a hands were for well you to no chuckie gonna i wish done arms tell lets it beat waiting found we good man write i nigga at do never you it ooh try are attention yeah oh hurt that too without roll yourself with the you feeling switch dont.

input: **hi**

hi this feeling gotta that alone im do she sweet and you ever you the in had the the raise up skies it youre do me its illuminated song with what that feel other mine time the easily what when you and three cause beat and its gets christmas your you sad a behind nothing a i number back or never and who your move beat you driving you i love and of do other like on go when oh yea heart plane after her that mine never soul like one you made you.

Lyrics for blink 182 - all the small things

input: **all**

all live ive fire love did my right so truck reading it life its sin heal well two home we confused mony its song you tried could mask know find for amadeus where sailor you and the to wo insane yeah skin wind ride song me heart up bite a a new a i let money world didnt on.

input: **the**

the love want risk whoa breakin take need cebu me amadeus control weve lose and try cryin away know hopes away what theres makes in you right drunk live ever ever one bop your lovely on steal bet i say somebody say gonna sad stay frosty a grease scene his hangin your dry touch mind i you you your.

input: **small**

small lost with sun find when casbah you time huh to pleasure for you see make the life dont you me to she the waitin honey weed all fill fired wish on alone thats like im the to and yeah long sure the broadway the need someone always achy dont well i as seen my that boy your that.

Analysis of how the Seed and Melody Effects the Generated Lyrics

The generated lyrics were found to be mostly nonsensical and containing many common words from the dataset. The advanced melody features did not seem to improve the overall quality of the lyrics, as indicated by both quantitative and subjective evaluations. A peculiar pattern was observed where once a word appeared, it frequently reappeared or variations of it also appeared. This is likely due to the model's ability to maintain a cell state and predict words based on their embeddings. It was also noticed that the choice of seed had a significant impact on the generated lyrics. This suggests that the melody plays a relatively small role in predicting lyrics compared to the seed, as observed in the evaluation table, the results are slightly better with the melody attached but not by much, meaning that the first word plays a much more important role than the melody in predicting the lyrics.