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Deep Learning

Assignment 3 - lyrics generation using RNNs

This assignment explores the application of automatic sentence generation techniques to the task of lyrics generation based on melodies. Using data of song lyrics and melodies stored as .mid (MIDI) files, the objective is to train a neural network to produce contextually relevant lyrics for given melodies.

The data files we received included:

- MIDI files – the melody of each song stored in MIDI format.
- Two CSV files (train and test) containing the song title, artist, and lyrics.

<u>Data Extraction:</u>

The datasets were extracted in Colab notebook.

<u>Dataset Analysis:</u>

Number of songs in the training set: 600

Number of songs in the test set: 5

```
Size of train dataset: 600 rows
Size of test dataset: 5 rows
```

We checked for missing values in our datasets and confirmed that there are none in either the training or test files.

```
Checking for missing values in train dataset:
Artist       0
Song Name    0
Lyrics       0
dtype: int64

Checking for missing values in test dataset:
Artist       0
Song Name    0
Lyrics       0
dtype: int64
```

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Preprocessing:

1. **Adding Columns**:
   Columns for the song title, artist, and lyrics were added to the CSV files, as they initially lacked column names.
2. **Mapping MIDI Files**:
   To ensure proper mapping between the lyrics and their corresponding MIDI files, we introduced a new column, MIDI_files_name, in both datasets. This column followed a consistent naming convention (Artist_-_SongName), facilitating seamless integration of lyrics and melody data.
3. **Contraction Expansion**:
   Using a predefined dictionary of common English contractions (e.g., "he's" → "he is", "don't" → "do not"), we expanded contractions in the lyrics to ensure consistent and standardized text representation.
4. **Punctuation Removal**:
   A function was applied to remove unnecessary punctuation, retaining only periods and spaces. This preserved sentence structure while cleaning extraneous symbols.
5. **Additional Cleaning**:

- Removed text inside square brackets ([]) and parentheses (()), which often contain metadata like annotations or song credits.
- Replaced special characters like & and handled spacing issues to ensure uniform text formatting.

6. **Tokenization with NLTK**:
   The cleaned lyrics were tokenized into words using the word_tokenize function from NLTK, followed by converting all words to lowercase for normalization.
7. **Regex Tokenization**:
   A simple tokenizer using regex (\b\w+\b) was applied as an additional step to extract and standardize individual words.

Word2vec:

We loaded pre-trained Word2Vec Google News 300 embeddings, which represent words as 300-dimensional vectors trained on a large corpus of Google News data. These embeddings capture semantic and syntactic relationships between words, providing a meaningful representation of lyrics for the model.

```
import gensim.downloader


# Download pre-trained GloVe Word2Vec embeddings (300 dimensions)
print("Downloading Word2Vec embeddings...")
word2vec_model = gensim.downloader.load('word2vec-google-news-300')
print("Word2Vec embeddings loaded.")
```

We created an embedding matrix mapping the dataset vocabulary to 300-dimensional Word2Vec embeddings. Words found in the pre-trained Word2Vec model are assigned their corresponding embeddings, while unknown words are given random vectors. This ensures all unique words (7293) in the dataset have meaningful numeric representations, enabling the model to leverage semantic relationships for better lyric generation.

```
Embedding matrix created with 7293 words.
```

We converted tokenized lyrics into sequences of embedding vectors using the pre-trained Word2Vec embeddings. Each word is replaced by its corresponding vector from the embedding matrix, with unknown words mapped to zero vectors. The resulting embedded sequences are stored in new columns (Lyrics_embeddings) for both train and test datasets, enabling the model to process numerical representations of the lyrics.

```
Example of embedding sequence for a lyric:
[[-0.06396484 -0.02197266 -0.03808594 ... -0.21191406 -0.25
   0.07714844]
 [-0.08105469  0.08642578  0.14160156 ... -0.09375     0.00352478
   0.16894531]
 [-0.20703125 -0.05688477 -0.13574219 ...  0.21582031  0.04150391
   0.33007812]
 ...
 [ 0.38671875  0.20605469 -0.00361633 ... -0.20605469 -0.09179688
  -0.17089844]
 [-0.22558594 -0.0324707   0.0402832  ... -0.06738281 -0.09912109
  -0.1640625 ]
 [ 0.20019531  0.15429688  0.10302734 ... -0.24316406  0.0078125
  -0.14453125]]
```

We created a vocabulary by combining all unique words from the tokenized lyrics in both the train and test datasets. Each word is then assigned a unique index using a word-to-index mapping, where indexing starts from 1 (reserving 0 for padding).

```
Vocabulary size: 7293
Sample word-to-index mapping: {'dessert': 1, 'ninth': 2, 'd': 3, 'stall': 4, 'idol': 5, 'lebte': 6, 'payin': 7, 'doz': 8, 'cd': 9, 'atheist': 10}
```

We convrted tokenized lyrics into sequences of numerical indices using the previously created word-to-index mapping. Each word in the lyrics is replaced with its corresponding index, and words not in the vocabulary are mapped to 0. A new column, Lyrics_word_to_idx, is added to both the train and test datasets to store these indexed sequences.

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```
Sample train dataset with word-to-index sequences:
                                      Lyrics_tokenize  \
0  [goodbye, norma, jean, though, i, never, knew,...
1  [winding, your, way, down, on, baker, street, ...
2  [you, know, i, need, your, love, you, ve, got,...
3  [come, on, check, it, out, ya, ll, check, it, ...
4  [let, the, beat, control, your, body, let, the...

                                   Lyrics_word_to_idx
0  [956, 5820, 1839, 4621, 6169, 5963, 3677, 2763...
1  [4083, 2733, 4813, 3447, 134, 5414, 1633, 1190...
2  [2763, 4663, 6169, 1963, 2733, 2289, 2763, 264...
3  [4563, 134, 948, 4580, 5579, 6408, 3689, 948, ...
4  [5181, 2268, 4336, 5084, 2733, 4195, 5181, 226...
```

This is the structure of our train and test datasets after applying all preprocessing steps described:

	Artist	Song Name	Lyrics	MIDI_files_name	Lyrics_tokenize	Lyrics_embeddings	Lyrics_word_to_idx
0	elton john	candle in the wind	goodbye norma jean though i never knew you at ...	elton john_-_candle in the wind	[goodbye, norma, jean, though, i, never, knew,...	[[-0.06396484375, -0.02197265625, -0.038085937...	[956, 5820, 1839, 4621, 6169, 5963, 3677, 2763...
1	gerry rafferty	baker street	winding your way down on baker street lite in ...	gerry rafferty_-_baker street	[winding, your, way, down, on, baker, street, ...	[[0.0830078125, 0.302734375, 0.072265625, 0.16...	[4083, 2733, 4813, 3447, 134, 5414, 1633, 1190...
2	gerry rafferty	right down the line	you know i need your love you ve got that hold...	gerry rafferty_-_right down the line	[you, know, i, need, your, love, you, ve, got,...	[[0.2041015625, 0.01318359375, 0.07568359375, ...	[2763, 4663, 6169, 1963, 2733, 2289, 2763, 264...
3	2 unlimited	tribal dance	come on check it out ya ll check it out the tr...	2 unlimited_-_tribal dance	[come, on, check, it, out, ya, ll, check, it, ...	[[0.0218505859375, 0.060791015625, 0.045410156...	[4563, 134, 948, 4580, 5579, 6408, 3689, 948, ...
4	2 unlimited	let the beat control your body	let the beat control your body let the beat co...	2 unlimited_-_let the beat control your body	[let, the, beat, control, your, body, let, the...	[[0.2080078125, 0.039794921875, 0.25, 0.244140...	[5181, 2268, 4336, 5084, 2733, 4195, 5181, 226...

<u>MIDI_files:</u>

We used the pretty_midi library to load MIDI files into PrettyMIDI objects.

the songs that their midi files were corrupted and didn't open properly and removed from the training:

```
Error loading Beastie_Boys_-_Girls.mid: Could not decode key with 1 flats and mode 255
Error loading Billy_Joel_-_Pressure.mid: data byte must be in range 0..127
Error loading Dan_Fogelberg_-_Leader_of_the_Band.mid: Could not decode key with 4 flats and mode 255
Error loading Brian_McKnight_-_On_The_Down_Low.mid:
Error loading David_Bowie_-_Lazarus.mid: Could not decode key with 16 sharps and mode 1
Error loading Aaron_Neville_-_Tell_It_Like_It_Is.mid: data byte must be in range 0..127
Error loading Billy_Joel_-_Movin'_Out.mid: data byte must be in range 0..127
Total MIDI files loaded: 618
```

<u>Method 1:</u>

Idea: method 1 employs a 128-dimensional binary vector to represent the presence of musical instruments in MIDI files. '1' in a cell indicates the presence of the corresponding instrument, while '0' signifies its absence.

After we loaded MIDI files we created a 128-dimensional binary vector for each file, where each index represents an instrument, and a value of 1 indicates its presence. The load_midi_files function loads and parses MIDI files from a specified directory, while the extract_instruments_vector function generates the binary vectors. This enables the representation of each melody by the instruments it contains.

```
File: Billy_Joel_-_She's_Got_a_Way.mid
Instrument Vector: [0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

We reformated the keys in the instruments_vectors dictionary to match the naming convention of the dataset (Artist_-_SongName) by replacing underscores and normalizing the format. The normalize_name function further standardizes song names by converting them to lowercase, replacing spaces with underscores, and removing unnecessary characters. Using these normalized names, we matched songs with their instrument vectors and append the vectors as a new column (Instrument_Vector) in the datasets. If a match is not found, a zero vector is assigned. The final output confirms that all songs were successfully matched with no unmatched entries (train and test).

```
Number of unmatched entries: 0
Number of unmatched entries: 0
```

<u>Method 2:</u>

Idea: The second method incorporates richer and more dynamic musical features extracted from MIDI files. Instead of using a 128-dimensional binary vector to represent the presence of instruments, this approach utilizes features such as tempo, key, intervals, and dynamic range. These features provide a deeper understanding of the melody and enable better synchronization between the lyrics and the music.

- Tempo: This feature represents the beats per minute (BPM) of the melody, providing insight into the overall speed and rhythm of the song. By incorporating tempo, the model can adjust the lyrical flow to match faster or slower sections of the music.
- Key: This feature identifies the musical key of the song (e.g., C major or A minor). Including the key enables the model to account for the harmonic context of the melody and potentially adapt lyrical choices to fit the mood or tone conveyed by the key.
- Intervals: Intervals represent the time differences between consecutive note onsets within the melody. This feature reflects rhythmic patterns and pacing, helping the model synchronize lyrical timing with musical phrasing.
- Dynamic Range: This feature captures the variation in note velocity, representing the intensity and expression of the melody. By considering dynamic range, the model can align more expressive or subdued lyrics with changes in the music's emotional impact.

To align these features with the lyrics, we calculated their values for each word based on the word's time window in the melody. For instance, the "intervals" feature includes all note intervals that occur within a word's duration, and the "dynamic range" feature reflects the variation in note intensity during the same period.

Integrating these richer features into the lyrics embedding allows the model to create a more nuanced connection between lyrical and musical elements. For instance, during sections with a higher dynamic range, the model may choose more emotionally charged language, while sections with slower intervals may lead to more reflective or drawn-out phrasing.

In contrast to the first method, where we used a binary vector to represent instrument presence, in this method, we combine these dynamic features with the word embeddings. For each word, its embedding vector (300-dimensional) is concatenated with the extracted melody features, resulting in a richer, more descriptive representation of each word's context.

By concatenating all features instead of summing them (as done in the first method), we preserve the unique contribution of each feature without normalization, enabling the model to leverage both the linguistic and musical dimensions more effectively. This comprehensive representation equips the model with the ability to synchronize lyrical content with the rhythmic, harmonic, and expressive qualities of the melody.

Model Architecture:

We chose an LSTM-based architecture for our model to effectively capture sequential dependencies in lyrics and align them with the melody.
Input to the network:
Each word is represented as a 300-dimensional word embedding vector, which is further enriched by melody information. Depending on the method used for melody representation, the input vector is constructed as follows:
Method 1: The word embedding is concatenated with a 128-dimensional binary instrument vector, representing the presence of instruments in the melody. This results in a 428-dimensional input vector.
Method 2: The word embedding is concatenated with dynamic musical features, such as tempo, key, intervals, and dynamic range, resulting in a richer and more descriptive input vector.

The model generates a vector of size equal to the vocabulary, where each cell represents the probability of the corresponding word being the next word in the sequence. This probabilistic output allows the model to predict the next word based on both lyrical and melodic context.

Dataset Preprocessing:

The `LyricsMelodyDataset` class was designed to preprocess the dataset for both methods. In Method 1, lyrics are tokenized into indices (`Lyrics_word_to_idx`) and aligned with 128-dimensional binary instrument vectors (`Instrument_Vector`). In Method 2, lyrics are aligned with a 4-

dimensional vector of richer melody features (`Rich_Features`), including tempo, key, intervals, and dynamic range. For both methods, lyrics are padded or truncated to a fixed sequence length (`max_seq_len = 50`), and each sample provides an input sequence, a target sequence, and the corresponding melody representation.

Model Implementation:

The LyricsMelodyModel is designed as a sequence-to-sequence model using an LSTM (Long Short-Term Memory) network:

Embedding Layer: Lyrics are embedded using an nn.Embedding layer to create dense vector representations of words.

Melody Integration: For Method 1, the instrument vector is repeated for each time step and concatenated with the embedded lyrics. For Method 2, dynamic melody features are concatenated with the embeddings.

LSTM Layer: The concatenated input is passed through the LSTM to capture sequential dependencies.

Fully Connected Layer: The LSTM outputs are fed into a fully connected layer (nn.Linear) to predict the next word in the sequence.

Data Splitting:

The dataset was split into:

- Training Set: 90% of the data.
- Validation Set: 10% of the data.

Training and Validation:

A range of hyperparameters, including learning rates ([0.01, 0.001, 0.0001, 0.00001]) and batch sizes ([16, 32, 64]), was explored. The training process aimed to minimize the cross-entropy loss (nn.CrossEntropyLoss), while ignoring padding tokens.

To prevent overfitting, early stopping was implemented, halting training if the validation loss did not improve for three consecutive epochs.

Hyperparameter Experimentation:

For each combination of learning rate and batch size, training was conducted for up to 10 epochs, and the validation loss for each epoch was recorded. The results were stored in a dictionary and visualized using a bar chart, enabling easy comparison of the final validation losses across different hyperparameter configurations.

Based on the grid search results, we selected the optimal model for each method by choosing the hyperparameters that led to the lowest validation loss.

Layer	Type	Input Size (Method 1)	Hidden Size (Method 1)	Output Size (Method 1)	Input Size (Method 2)	Hidden Size (Method 2)	Output Size (Method 2)
Embedding	Embedding	7294 (vocab size)	-	300 (embedding size)	7294 (vocab size)	-	300 (embedding size)
Concatenation (Embedding + Method 1/2 Features)	Concatenation	300 (word embedding) + 128 (instrument vector)	-	428 (input to LSTM)	300 (word embedding) + 4 (dynamic features)	-	304 (input to LSTM)
LSTM	LSTM	428 (concatenated)	256 (hidden size)	256 (hidden size)	304 (concatenated)	256 (hidden size)	256 (hidden size)
Fully Connected (Linear)	Linear	256 (hidden size)	-	7294 (vocab size)	256 (hidden size)	-	7294 (vocab size)

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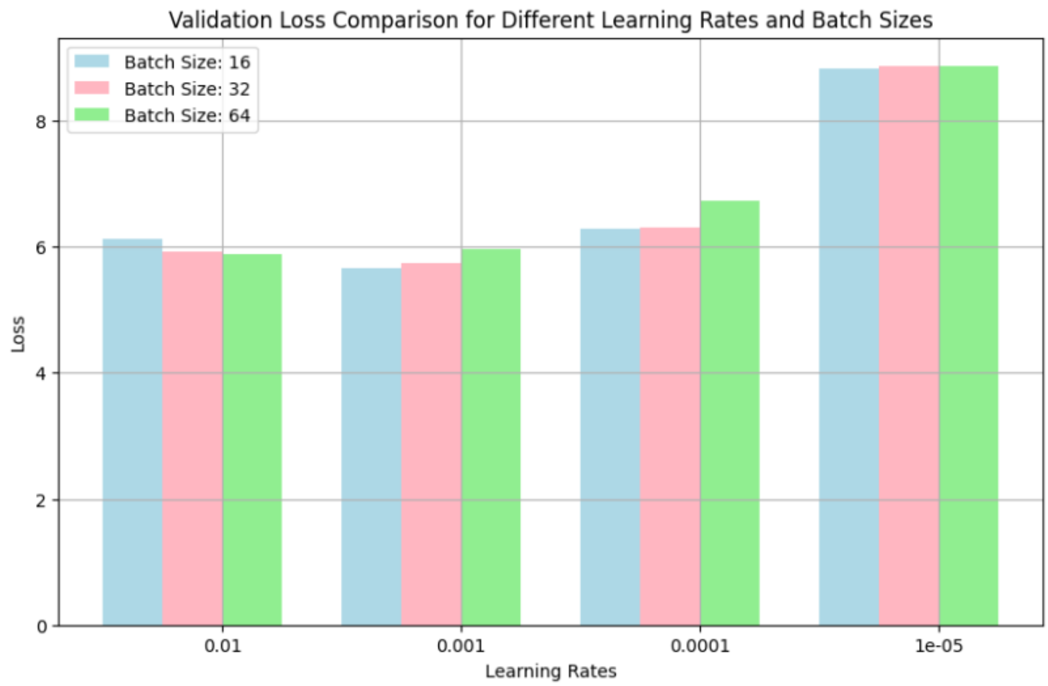
Results of 12 experiments – Method 1:



Best loss score:

- Learning Rate: 0.001
- Batch Size: 16
- Final Validation Loss: 5.6550

```
Training with Learning Rate: 0.01, Batch Size: 16
Epoch 1/10 - Train Loss: 6.3588, Validation Loss: 5.6979
Epoch 2/10 - Train Loss: 4.9982, Validation Loss: 5.6618
Epoch 3/10 - Train Loss: 4.2024, Validation Loss: 5.8213
Epoch 4/10 - Train Loss: 3.4981, Validation Loss: 5.9566
Epoch 5/10 - Train Loss: 2.9051, Validation Loss: 6.1275
Early stopping at epoch 5

Training with Learning Rate: 0.01, Batch Size: 32
Epoch 1/10 - Train Loss: 6.6837, Validation Loss: 5.8558
Epoch 2/10 - Train Loss: 5.2808, Validation Loss: 5.6778
Epoch 3/10 - Train Loss: 4.5603, Validation Loss: 5.6899
Epoch 4/10 - Train Loss: 3.9476, Validation Loss: 5.8112
Epoch 5/10 - Train Loss: 3.4014, Validation Loss: 5.9285
Early stopping at epoch 5

Training with Learning Rate: 0.01, Batch Size: 64
Epoch 1/10 - Train Loss: 7.0611, Validation Loss: 6.1669
Epoch 2/10 - Train Loss: 5.6464, Validation Loss: 5.8168
Epoch 3/10 - Train Loss: 5.0160, Validation Loss: 5.7422
Epoch 4/10 - Train Loss: 4.5244, Validation Loss: 5.7576
Epoch 5/10 - Train Loss: 4.0695, Validation Loss: 5.8427
Epoch 6/10 - Train Loss: 3.6627, Validation Loss: 5.8884
Early stopping at epoch 6

Training with Learning Rate: 0.001, Batch Size: 16
Epoch 1/10 - Train Loss: 7.4100, Validation Loss: 6.3657
Epoch 2/10 - Train Loss: 6.0667, Validation Loss: 6.0973
Epoch 3/10 - Train Loss: 5.7830, Validation Loss: 5.9687
Epoch 4/10 - Train Loss: 5.5598, Validation Loss: 5.8651
Epoch 5/10 - Train Loss: 5.3639, Validation Loss: 5.7994
Epoch 6/10 - Train Loss: 5.1975, Validation Loss: 5.7389
Epoch 7/10 - Train Loss: 5.0308, Validation Loss: 5.7076
```

```
Epoch 8/10 - Train Loss: 4.8931, Validation Loss: 5.6825
Epoch 9/10 - Train Loss: 4.7631, Validation Loss: 5.6691
Epoch 10/10 - Train Loss: 4.6361, Validation Loss: 5.6550

Training with Learning Rate: 0.001, Batch Size: 32
Epoch 1/10 - Train Loss: 8.0893, Validation Loss: 6.4039
Epoch 2/10 - Train Loss: 6.2570, Validation Loss: 6.3427
Epoch 3/10 - Train Loss: 6.0496, Validation Loss: 6.2347
Epoch 4/10 - Train Loss: 5.8953, Validation Loss: 6.1205
Epoch 5/10 - Train Loss: 5.7487, Validation Loss: 6.0240
Epoch 6/10 - Train Loss: 5.6170, Validation Loss: 5.9357
Epoch 7/10 - Train Loss: 5.4919, Validation Loss: 5.8735
Epoch 8/10 - Train Loss: 5.3717, Validation Loss: 5.8336
Epoch 9/10 - Train Loss: 5.2616, Validation Loss: 5.7898
Epoch 10/10 - Train Loss: 5.1627, Validation Loss: 5.7499

Training with Learning Rate: 0.001, Batch Size: 64
Epoch 1/10 - Train Loss: 8.7342, Validation Loss: 8.1754
Epoch 2/10 - Train Loss: 7.0108, Validation Loss: 6.3582
Epoch 3/10 - Train Loss: 6.2299, Validation Loss: 6.3820
Epoch 4/10 - Train Loss: 6.1197, Validation Loss: 6.3269
Epoch 5/10 - Train Loss: 5.9867, Validation Loss: 6.2803
Epoch 6/10 - Train Loss: 5.9134, Validation Loss: 6.2019
Epoch 7/10 - Train Loss: 5.8390, Validation Loss: 6.1354
Epoch 8/10 - Train Loss: 5.7363, Validation Loss: 6.0669
Epoch 9/10 - Train Loss: 5.6632, Validation Loss: 6.0055
Epoch 10/10 - Train Loss: 5.5561, Validation Loss: 5.9537

Training with Learning Rate: 0.0001, Batch Size: 16
Epoch 1/10 - Train Loss: 8.8625, Validation Loss: 8.8159
Epoch 2/10 - Train Loss: 8.7057, Validation Loss: 8.4670
Epoch 3/10 - Train Loss: 7.5307, Validation Loss: 6.7733
Epoch 4/10 - Train Loss: 6.4080, Validation Loss: 6.3892
Epoch 5/10 - Train Loss: 6.2143, Validation Loss: 6.3390
Epoch 6/10 - Train Loss: 6.1588, Validation Loss: 6.3315
Epoch 7/10 - Train Loss: 6.1261, Validation Loss: 6.3237
Epoch 8/10 - Train Loss: 6.1084, Validation Loss: 6.3147
Epoch 9/10 - Train Loss: 6.0764, Validation Loss: 6.3046
Epoch 10/10 - Train Loss: 6.0519, Validation Loss: 6.2882

Training with Learning Rate: 0.0001, Batch Size: 32
Epoch 1/10 - Train Loss: 8.8826, Validation Loss: 8.8587
Epoch 2/10 - Train Loss: 8.8308, Validation Loss: 8.8036
Epoch 3/10 - Train Loss: 8.7476, Validation Loss: 8.6835
Epoch 4/10 - Train Loss: 8.4996, Validation Loss: 8.1773
Epoch 5/10 - Train Loss: 7.6150, Validation Loss: 7.1539
Epoch 6/10 - Train Loss: 6.7643, Validation Loss: 6.5988
Epoch 7/10 - Train Loss: 6.3695, Validation Loss: 6.3941
Epoch 8/10 - Train Loss: 6.2253, Validation Loss: 6.3306
Epoch 9/10 - Train Loss: 6.1763, Validation Loss: 6.3122
Epoch 10/10 - Train Loss: 6.1487, Validation Loss: 6.3062

Training with Learning Rate: 0.0001, Batch Size: 64
Epoch 1/10 - Train Loss: 8.8981, Validation Loss: 8.8875
Epoch 2/10 - Train Loss: 8.8696, Validation Loss: 8.8631
Epoch 3/10 - Train Loss: 8.8411, Validation Loss: 8.8335
Epoch 4/10 - Train Loss: 8.8030, Validation Loss: 8.7924
Epoch 5/10 - Train Loss: 8.7498, Validation Loss: 8.7260
Epoch 6/10 - Train Loss: 8.6595, Validation Loss: 8.5967
Epoch 7/10 - Train Loss: 8.4524, Validation Loss: 8.2665
Epoch 8/10 - Train Loss: 7.9635, Validation Loss: 7.6208
Epoch 9/10 - Train Loss: 7.3227, Validation Loss: 7.0895
Epoch 10/10 - Train Loss: 6.8569, Validation Loss: 6.7283

Training with Learning Rate: 1e-05, Batch Size: 16
Epoch 1/10 - Train Loss: 8.8962, Validation Loss: 8.8933
Epoch 2/10 - Train Loss: 8.8892, Validation Loss: 8.8872
Epoch 3/10 - Train Loss: 8.8824, Validation Loss: 8.8810
Epoch 4/10 - Train Loss: 8.8749, Validation Loss: 8.8744
Epoch 5/10 - Train Loss: 8.8675, Validation Loss: 8.8673
Epoch 6/10 - Train Loss: 8.8590, Validation Loss: 8.8596
Epoch 7/10 - Train Loss: 8.8505, Validation Loss: 8.8511
Epoch 8/10 - Train Loss: 8.8409, Validation Loss: 8.8414
Epoch 9/10 - Train Loss: 8.8296, Validation Loss: 8.8304
Epoch 10/10 - Train Loss: 8.8161, Validation Loss: 8.8173

Training with Learning Rate: 1e-05, Batch Size: 32
```

```
Epoch 1/10 - Train Loss: 8.8999, Validation Loss: 8.8971
Epoch 2/10 - Train Loss: 8.8955, Validation Loss: 8.8933
Epoch 3/10 - Train Loss: 8.8911, Validation Loss: 8.8894
Epoch 4/10 - Train Loss: 8.8870, Validation Loss: 8.8855
Epoch 5/10 - Train Loss: 8.8824, Validation Loss: 8.8816
Epoch 6/10 - Train Loss: 8.8782, Validation Loss: 8.8775
Epoch 7/10 - Train Loss: 8.8734, Validation Loss: 8.8733
Epoch 8/10 - Train Loss: 8.8686, Validation Loss: 8.8689
Epoch 9/10 - Train Loss: 8.8637, Validation Loss: 8.8642
Epoch 10/10 - Train Loss: 8.8585, Validation Loss: 8.8593

Training with Learning Rate: 1e-05, Batch Size: 64
Epoch 1/10 - Train Loss: 8.8922, Validation Loss: 8.8934
Epoch 2/10 - Train Loss: 8.8893, Validation Loss: 8.8911
Epoch 3/10 - Train Loss: 8.8870, Validation Loss: 8.8888
Epoch 4/10 - Train Loss: 8.8842, Validation Loss: 8.8866
Epoch 5/10 - Train Loss: 8.8816, Validation Loss: 8.8843
Epoch 6/10 - Train Loss: 8.8784, Validation Loss: 8.8820
Epoch 7/10 - Train Loss: 8.8763, Validation Loss: 8.8797
Epoch 8/10 - Train Loss: 8.8738, Validation Loss: 8.8774
Epoch 9/10 - Train Loss: 8.8707, Validation Loss: 8.8750
Epoch 10/10 - Train Loss: 8.8677, Validation Loss: 8.8726
```

After identifying the best combination of hyperparameters, we increased num_epochs to 30 to fully train the model with the selected parameters.

<u>System Characteristics after the experiments:</u>

Batch Size: We experimented with different batch sizes and chose the optimal size for this setup through prior testing - 16.

Number of Epochs: 30, with early stopping set to trigger if validation loss doesn't improve for 5 consecutive epochs.

Loss Function: Cross-Entropy Loss was used, ignoring the padding token to focus on meaningful predictions.

Learning Rate: 0.001, determined as the most effective value after experimentation.

Embedding Dimension: 300, representing the size of word embeddings.

Hidden Dimension: 256, specifying the number of hidden units in the LSTM layer.

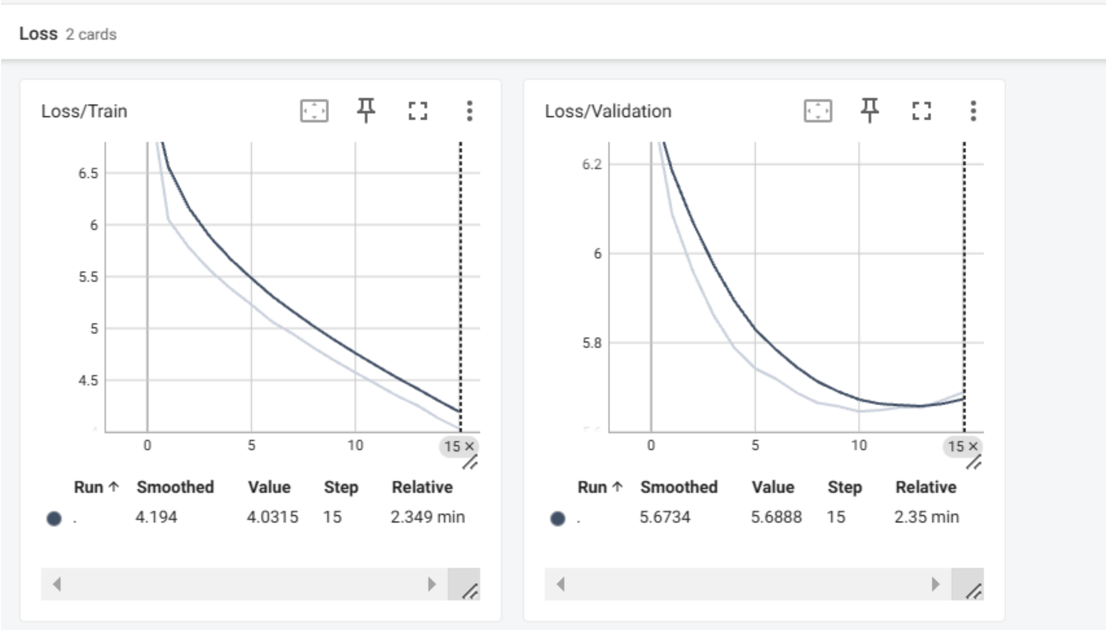
Instrument Dimension: 128, encoding the musical instrument information from MIDI files.

Output Dimension: Equal to the vocabulary size (including a token for padding), predicting the probability of each word as the next word in the sequence.

```
Model Architecture:
LyricsMelodyModel(
  (embedding): Embedding(7294, 300)
  (lstm): LSTM(428, 256, batch_first=True)
  (fc): Linear(in_features=256, out_features=7294, bias=True)
)
```

Results:

The model started with high initial losses (Train Loss: 7.4069, Validation Loss: 6.3473), which steadily decreased as training progressed. The training loss continued to decline throughout, indicating that the model effectively learned the patterns in the training data. The validation loss, however, reached its lowest point of 5.6459 at Epoch 11, after which it began to plateau and slightly increase. This behavior suggests that the model started to overfit beyond this point. Early stopping, set to trigger after 5 epochs without improvement, stopped training at Epoch 16, ensuring the model's generalization capability. Overall, the model successfully balanced learning and avoiding overfitting, with the optimal validation performance achieved around Epoch 11.




```
Epoch 1/30, Train Loss: 7.4069, Validation Loss: 6.3473
Epoch 2/30, Train Loss: 6.0511, Validation Loss: 6.0886
Epoch 3/30, Train Loss: 5.7779, Validation Loss: 5.9607
Epoch 4/30, Train Loss: 5.5623, Validation Loss: 5.8616
Epoch 5/30, Train Loss: 5.3847, Validation Loss: 5.7885
Epoch 6/30, Train Loss: 5.2296, Validation Loss: 5.7423
Epoch 7/30, Train Loss: 5.0633, Validation Loss: 5.7191
Epoch 8/30, Train Loss: 4.9461, Validation Loss: 5.6879
Epoch 9/30, Train Loss: 4.8116, Validation Loss: 5.6652
Epoch 10/30, Train Loss: 4.6892, Validation Loss: 5.6575
Epoch 11/30, Train Loss: 4.5736, Validation Loss: 5.6459
Epoch 12/30, Train Loss: 4.4625, Validation Loss: 5.6489
Epoch 13/30, Train Loss: 4.3491, Validation Loss: 5.6555
```

```
Epoch 14/30, Train Loss: 4.2542, Validation Loss: 5.6546
Epoch 15/30, Train Loss: 4.1318, Validation Loss: 5.6710
Epoch 16/30, Train Loss: 4.0315, Validation Loss: 5.6888
Early stopping triggered after 16 epochs.
```

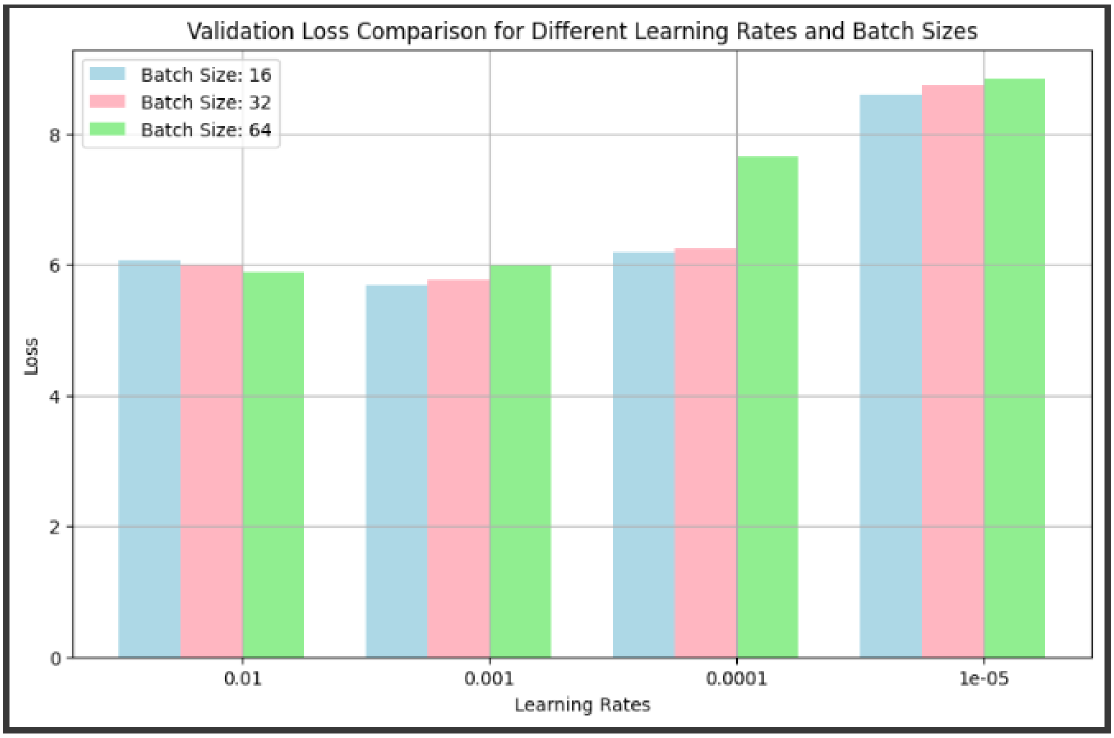
<u>Test – results:</u>

```
Loss for each song on test:
Song 1: Loss = 5.0471
Song 2: Loss = 5.2601
Song 3: Loss = 5.4230
Song 4: Loss = 6.7017
Song 5: Loss = 6.4227

Average loss on test set (5 songs): 5.7709
```

The results from the test set evaluation indicate that the model performs consistently across different songs, with individual losses ranging from 5.0471 to 6.5227. The average loss across all five songs is 5.7709, demonstrating that the model effectively captures the relationship between lyrics and melodies. The relatively low difference between individual song losses and the average test loss highlights the model's stable performance across the dataset.

<u>Results of 12 experiments – Method 2:</u>



The optimal hyperparameters for Method 2 are the same as those identified in Method 1:

- Learning Rate: 0.001
- Batch Size: 16
- Final Validation Loss: 5.6826

```
Training with Learning Rate: 0.01, Batch Size: 16
Epoch 1/10 - Train Loss: 6.7830, Validation Loss: 6.3436
Epoch 2/10 - Train Loss: 6.0723, Validation Loss: 6.1484
Epoch 3/10 - Train Loss: 5.7917, Validation Loss: 6.0194
Epoch 4/10 - Train Loss: 5.5674, Validation Loss: 5.9771
Epoch 5/10 - Train Loss: 5.3587, Validation Loss: 5.9801
Epoch 6/10 - Train Loss: 5.1606, Validation Loss: 5.9699
Epoch 7/10 - Train Loss: 4.9842, Validation Loss: 6.0293
Epoch 8/10 - Train Loss: 4.8298, Validation Loss: 6.0361
Epoch 9/10 - Train Loss: 4.6879, Validation Loss: 6.0701
Early stopping at epoch 9

Training with Learning Rate: 0.01, Batch Size: 32
Epoch 1/10 - Train Loss: 6.9745, Validation Loss: 6.5806
Epoch 2/10 - Train Loss: 6.1896, Validation Loss: 6.3665
Epoch 3/10 - Train Loss: 5.9236, Validation Loss: 6.2303
Epoch 4/10 - Train Loss: 5.7132, Validation Loss: 6.0693
Epoch 5/10 - Train Loss: 5.4601, Validation Loss: 6.0376
Epoch 6/10 - Train Loss: 5.2746, Validation Loss: 5.9670
Epoch 7/10 - Train Loss: 5.0831, Validation Loss: 5.9541
Epoch 8/10 - Train Loss: 4.9283, Validation Loss: 5.9528
Epoch 9/10 - Train Loss: 4.7660, Validation Loss: 5.9509
Epoch 10/10 - Train Loss: 4.6473, Validation Loss: 5.9849

Training with Learning Rate: 0.01, Batch Size: 64
Epoch 1/10 - Train Loss: 7.1235, Validation Loss: 6.5680
Epoch 2/10 - Train Loss: 6.2629, Validation Loss: 6.5210
Epoch 3/10 - Train Loss: 6.0678, Validation Loss: 6.4265
Epoch 4/10 - Train Loss: 5.8517, Validation Loss: 6.2500
Epoch 5/10 - Train Loss: 5.6535, Validation Loss: 6.1173
Epoch 6/10 - Train Loss: 5.4425, Validation Loss: 6.0044
Epoch 7/10 - Train Loss: 5.2543, Validation Loss: 5.9538
Epoch 8/10 - Train Loss: 5.0805, Validation Loss: 5.9303
Epoch 9/10 - Train Loss: 4.9077, Validation Loss: 5.8995
Epoch 10/10 - Train Loss: 4.7579, Validation Loss: 5.8847

Training with Learning Rate: 0.001, Batch Size: 16
Epoch 1/10 - Train Loss: 7.3220, Validation Loss: 6.2357
Epoch 2/10 - Train Loss: 6.1063, Validation Loss: 6.1643
Epoch 3/10 - Train Loss: 5.9210, Validation Loss: 6.0444
Epoch 4/10 - Train Loss: 5.7257, Validation Loss: 5.9189
Epoch 5/10 - Train Loss: 5.5077, Validation Loss: 5.8213
Epoch 6/10 - Train Loss: 5.2984, Validation Loss: 5.7739
Epoch 7/10 - Train Loss: 5.1099, Validation Loss: 5.7251
Epoch 8/10 - Train Loss: 4.9508, Validation Loss: 5.6998
Epoch 9/10 - Train Loss: 4.7866, Validation Loss: 5.6932
Epoch 10/10 - Train Loss: 4.6326, Validation Loss: 5.6826

Training with Learning Rate: 0.001, Batch Size: 32
Epoch 1/10 - Train Loss: 8.0976, Validation Loss: 6.9418
Epoch 2/10 - Train Loss: 6.3455, Validation Loss: 6.2629
Epoch 3/10 - Train Loss: 6.0668, Validation Loss: 6.2121
Epoch 4/10 - Train Loss: 5.9703, Validation Loss: 6.1513
Epoch 5/10 - Train Loss: 5.8524, Validation Loss: 6.0790
Epoch 6/10 - Train Loss: 5.7142, Validation Loss: 5.9946
Epoch 7/10 - Train Loss: 5.5757, Validation Loss: 5.9294
Epoch 8/10 - Train Loss: 5.4420, Validation Loss: 5.8585
Epoch 9/10 - Train Loss: 5.3033, Validation Loss: 5.8014
Epoch 10/10 - Train Loss: 5.1678, Validation Loss: 5.7684

Training with Learning Rate: 0.001, Batch Size: 64
Epoch 1/10 - Train Loss: 8.5469, Validation Loss: 7.9563
Epoch 2/10 - Train Loss: 7.3507, Validation Loss: 6.7266
```

```
Epoch 3/10 - Train Loss: 6.3533, Validation Loss: 6.2567
Epoch 4/10 - Train Loss: 6.1128, Validation Loss: 6.2444
Epoch 5/10 - Train Loss: 6.0355, Validation Loss: 6.2216
Epoch 6/10 - Train Loss: 5.9906, Validation Loss: 6.2052
Epoch 7/10 - Train Loss: 5.9187, Validation Loss: 6.1592
Epoch 8/10 - Train Loss: 5.8459, Validation Loss: 6.1162
Epoch 9/10 - Train Loss: 5.7283, Validation Loss: 6.0763
Epoch 10/10 - Train Loss: 5.6545, Validation Loss: 6.0073

Training with Learning Rate: 0.0001, Batch Size: 16
Epoch 1/10 - Train Loss: 8.7151, Validation Loss: 8.5408
Epoch 2/10 - Train Loss: 8.3690, Validation Loss: 8.1541
Epoch 3/10 - Train Loss: 7.8666, Validation Loss: 7.4964
Epoch 4/10 - Train Loss: 7.0289, Validation Loss: 6.5900
Epoch 5/10 - Train Loss: 6.2881, Validation Loss: 6.2303
Epoch 6/10 - Train Loss: 6.1140, Validation Loss: 6.2107
Epoch 7/10 - Train Loss: 6.0681, Validation Loss: 6.2027
Epoch 8/10 - Train Loss: 6.0384, Validation Loss: 6.1950
Epoch 9/10 - Train Loss: 6.0159, Validation Loss: 6.1906
Epoch 10/10 - Train Loss: 5.9933, Validation Loss: 6.1781

Training with Learning Rate: 0.0001, Batch Size: 32
Epoch 1/10 - Train Loss: 8.8273, Validation Loss: 8.7447
Epoch 2/10 - Train Loss: 8.6425, Validation Loss: 8.5599
Epoch 3/10 - Train Loss: 8.4342, Validation Loss: 8.3350
Epoch 4/10 - Train Loss: 8.1744, Validation Loss: 8.0489
Epoch 5/10 - Train Loss: 7.8501, Validation Loss: 7.7042
Epoch 6/10 - Train Loss: 7.4673, Validation Loss: 7.2983
Epoch 7/10 - Train Loss: 7.0276, Validation Loss: 6.8605
Epoch 8/10 - Train Loss: 6.6047, Validation Loss: 6.4962
Epoch 9/10 - Train Loss: 6.2923, Validation Loss: 6.2941
Epoch 10/10 - Train Loss: 6.1482, Validation Loss: 6.2379

Training with Learning Rate: 0.0001, Batch Size: 64
Epoch 1/10 - Train Loss: 8.8813, Validation Loss: 8.8438
Epoch 2/10 - Train Loss: 8.8055, Validation Loss: 8.7708
Epoch 3/10 - Train Loss: 8.7275, Validation Loss: 8.6925
Epoch 4/10 - Train Loss: 8.6429, Validation Loss: 8.6049
Epoch 5/10 - Train Loss: 8.5472, Validation Loss: 8.5044
Epoch 6/10 - Train Loss: 8.4372, Validation Loss: 8.3867
Epoch 7/10 - Train Loss: 8.3074, Validation Loss: 8.2469
Epoch 8/10 - Train Loss: 8.1529, Validation Loss: 8.0792
Epoch 9/10 - Train Loss: 7.9666, Validation Loss: 7.8791
Epoch 10/10 - Train Loss: 7.7494, Validation Loss: 7.6461

Training with Learning Rate: 1e-05, Batch Size: 16
Epoch 1/10 - Train Loss: 8.8892, Validation Loss: 8.8682
Epoch 2/10 - Train Loss: 8.8624, Validation Loss: 8.8422
Epoch 3/10 - Train Loss: 8.8359, Validation Loss: 8.8162
Epoch 4/10 - Train Loss: 8.8086, Validation Loss: 8.7897
Epoch 5/10 - Train Loss: 8.7812, Validation Loss: 8.7623
Epoch 6/10 - Train Loss: 8.7531, Validation Loss: 8.7335
Epoch 7/10 - Train Loss: 8.7236, Validation Loss: 8.7038
Epoch 8/10 - Train Loss: 8.6918, Validation Loss: 8.6724
Epoch 9/10 - Train Loss: 8.6593, Validation Loss: 8.6387
Epoch 10/10 - Train Loss: 8.6239, Validation Loss: 8.6034

Training with Learning Rate: 1e-05, Batch Size: 32
Epoch 1/10 - Train Loss: 8.8917, Validation Loss: 8.8897
Epoch 2/10 - Train Loss: 8.8737, Validation Loss: 8.8728
Epoch 3/10 - Train Loss: 8.8558, Validation Loss: 8.8554
Epoch 4/10 - Train Loss: 8.8378, Validation Loss: 8.8382
Epoch 5/10 - Train Loss: 8.8203, Validation Loss: 8.8211
Epoch 6/10 - Train Loss: 8.8025, Validation Loss: 8.8039
Epoch 7/10 - Train Loss: 8.7843, Validation Loss: 8.7864
Epoch 8/10 - Train Loss: 8.7662, Validation Loss: 8.7686
Epoch 9/10 - Train Loss: 8.7476, Validation Loss: 8.7504
Epoch 10/10 - Train Loss: 8.7290, Validation Loss: 8.7318

Training with Learning Rate: 1e-05, Batch Size: 64
Epoch 1/10 - Train Loss: 8.9133, Validation Loss: 8.9190
Epoch 2/10 - Train Loss: 8.9060, Validation Loss: 8.9110
Epoch 3/10 - Train Loss: 8.8979, Validation Loss: 8.9031
```

```
Epoch 4/10 - Train Loss: 8.8884, Validation Loss: 8.8951
Epoch 5/10 - Train Loss: 8.8800, Validation Loss: 8.8871
Epoch 6/10 - Train Loss: 8.8731, Validation Loss: 8.8792
Epoch 7/10 - Train Loss: 8.8654, Validation Loss: 8.8711
Epoch 8/10 - Train Loss: 8.8569, Validation Loss: 8.8631
Epoch 9/10 - Train Loss: 8.8481, Validation Loss: 8.8551
Epoch 10/10 - Train Loss: 8.8402, Validation Loss: 8.8469
```

Results:

The training for Method 2 began with high initial losses. In the first experiment, as training progressed, the training loss consistently decreased, reflecting the model's ability to learn patterns effectively, while the validation loss initially improved but plateaued at 5.9771 by epoch 4. Early stopping was triggered at epoch 9, as further epochs showed no significant improvement in validation loss, ensuring the model avoided overfitting.
For other configurations, such as a learning rate of 0.001 and a batch size of 16, the training loss reduced from 7.3220 to 4.6326, and validation loss showed a steady decline from 6.2357 to 5.6826, demonstrating better generalization and overall performance. This highlights the effectiveness of incorporating richer melody features, such as tempo and key, which enabled the model to achieve strong alignment between lyrics and melodies while avoiding overfitting through early stopping. Overall, the training process validated the potential of Method 2 to enhance the synchronization between musical features and lyrics.

After identifying the optimal combination of hyperparameters, the number of epochs increased to 30 to fully train the model with the selected parameters.

System Characteristics after the experiments:

Batch Size: After testing various batch sizes, 16 was identified as the optimal choice, balancing convergence speed and generalization.

Number of Epochs: The model was trained for up to 30 epochs, with early stopping employed to halt training if validation loss did not improve for 5 consecutive epochs. This ensured efficient training while avoiding overfitting.

Loss Function: Cross-Entropy Loss was used, with padding tokens ignored during loss calculation, focusing the model on meaningful word predictions.

Learning Rate: A learning rate of 0.001 was selected after experimentation, allowing the model to converge steadily without excessive oscillations.

Embedding Dimension: Each word was represented as a 300-dimensional embedding vector, effectively capturing semantic relationships between words.

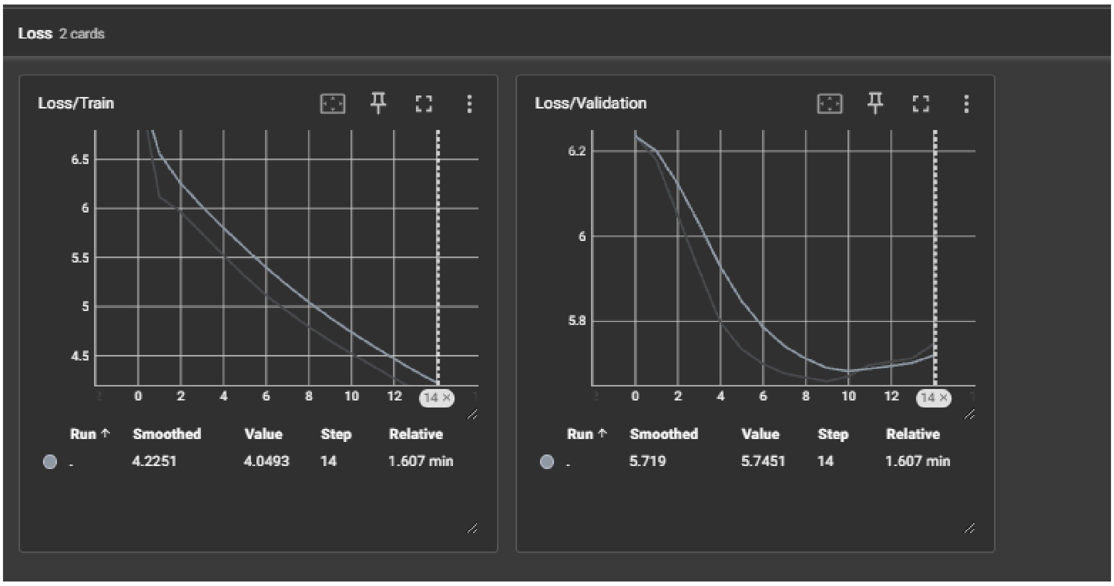
Hidden Dimension: The LSTM layer contained 256 hidden units, enabling the model to capture sequential dependencies in the lyrics.

Rich Feature Dimension: A 4-dimensional vector was used to encode richer musical features such as tempo, key, intervals, and dynamic range, providing a deeper understanding of the melody.

Output Dimension: The output layer's size matched the vocabulary size (including a padding token) and predicted the probability distribution of all possible next words in the sequence.

```
Model Architecture:
LyricsMelodyModel(
  (embedding): Embedding(7294, 300)
  (lstm): LSTM(304, 256, batch_first=True)
  (fc): Linear(in_features=256, out_features=7294, bias=True)
)
```

Results:
The model began training with high initial losses (Train Loss: 7.2888, Validation Loss: 6.2355) and showed consistent improvement as training progressed. The training loss steadily declined, indicating that the model effectively learned patterns in the training data. The validation loss exhibited a steady decrease, reaching its lowest point of 5.6580 at Epoch 10. However, after this point, the validation loss plateaued and began to slightly increase, suggesting the onset of overfitting.
Early stopping, set to trigger after 5 epochs without improvement in validation loss, stopped training at Epoch 15. This ensured the model maintained a strong generalization capability while avoiding overfitting. Overall, the optimal validation performance was achieved at Epoch 10, demonstrating the model's effectiveness in synchronizing lyrics with melody through the incorporation of richer musical features such as tempo, key, intervals, and dynamic range. The training process successfully balanced learning efficiency and overfitting prevention.




```
Epoch 1/30, Train Loss: 7.2888, Validation Loss: 6.2355
Epoch 2/30, Train Loss: 6.1187, Validation Loss: 6.1791
```

```
Epoch 3/30, Train Loss: 5.9638, Validation Loss: 6.0488
Epoch 4/30, Train Loss: 5.7462, Validation Loss: 5.9200
Epoch 5/30, Train Loss: 5.5212, Validation Loss: 5.7976
Epoch 6/30, Train Loss: 5.3133, Validation Loss: 5.7344
Epoch 7/30, Train Loss: 5.1161, Validation Loss: 5.6996
Epoch 8/30, Train Loss: 4.9513, Validation Loss: 5.6772
Epoch 9/30, Train Loss: 4.7958, Validation Loss: 5.6676
Epoch 10/30, Train Loss: 4.6526, Validation Loss: 5.6580
Epoch 11/30, Train Loss: 4.5208, Validation Loss: 5.6699
Epoch 12/30, Train Loss: 4.3962, Validation Loss: 5.6965
Epoch 13/30, Train Loss: 4.2699, Validation Loss: 5.7042
Epoch 14/30, Train Loss: 4.1523, Validation Loss: 5.7122
Epoch 15/30, Train Loss: 4.0493, Validation Loss: 5.7451
Early stopping triggered after 15 epochs.
```

Test – results:

```
Loss for each song on test:
Song 1: Loss = 5.2125
Song 2: Loss = 5.4560
Song 3: Loss = 5.5226
Song 4: Loss = 7.2452
Song 5: Loss = 6.2288

Average loss on test set (5 songs): 5.9330
```

The results from the test set evaluation indicate that the model performs consistently across different songs, with individual losses ranging from 5.2125 to 7.2452. The average loss across all five songs is 5.9330, demonstrating that the model effectively captures the relationship between lyrics and melodies.

These results are like those obtained in Method 1, where the average loss was 5.7709. This consistency between the two methods suggests that both approaches capture the interplay between lyrics and melody effectively.

Lyrics predicted of 5 songs in the test – method1:

We investigated the influence of initial words on the generation of lyrics by selecting three distinct and representative words: "love," "dream," and "party." These words were chosen for their ability to capture a range of emotional and contextual nuances in the generated lyrics.

Our aim was to evaluate how these initial words, each carrying a unique semantic connotation, would shape the lyrical and melodic composition of the resulting songs .

To implement this, the selected words were introduced into the model as the starting word for each song. The model was provided with the corresponding melody features for each test song, ensuring alignment between the musical structure and the lyrical generation. The initial word served as a semantic anchor, guiding the generation of subsequent lyrics in the context of the song's melody.

207547183
206477952

Melody: the bangles_-_eternal flame

Initial Word: love

Variant 1: love ridin feeling the real dreams can be a young man should not know what i hear me what is all i do to what you are the first to come and baby i knew the night oh yeah oh all he was all that i am goin up in your mind down and i ve got so many nights i see i ve been back as in the thoughts of wine i know my world s all i wan na never say it would not believe we be the things to come it master out

Initial Word: dream

Variant 1: dream however when we are alone to do not stop why i ve got you like it all you come i am a competitive so long i was your room i ll see the wrongs that is where you can not know what is much my security out about a virtual just a lovely door mean by pum pum be way to run it is been a blue hair and we can not matter me in the dark for myself i am gon na get along oh baby she is a power i should not wan

Initial Word: party

Variant 1: party consider cream cut and the canvas are just what we ve got a girl to me the stairs and i am in my hand as not you there must hear i ve waited for my love i do not slip back with you to it out that made a contradiction of mine and i d said i need you there is you want to pull to take your love was lost i could never really know who were knock cause i have a way i was your rights you ai nt it is been alive

Melody: billy joel_-_honesty

Initial Word: love

Variant 1: love would you are love you are joyful now cause i need to be a little prayer for you say it is hard to come on it you understand you know your heart s gon na do not you know i see the day from the world or right i d for themselves you can be but it is only i ve done and you got myself do not want to go away that all my life we can tell me beach so many very sister is only to stay or all the days ve is nothing a fool to go by new and laughter they go in excelsis watching i am smiling a with place to make you were searching love to a lot of to one you i am scared so much can do it to sing time but there is left and if i could turn the ways time we are getting empty through and when this is falling and the radio of everything i still do to deceive my heart i could feel it fade you just just what night i love you like to be some uh huh i know my hand i do to quit i d need to worry how you go just know there is on an empty of

Initial Word: dream

Variant 1: dream airs homework come on baby go to the places i can not recognize the tv he was hot day in time to me do you are gon na love you will not be around and it is so delightful sing and inside the words i ve heard for your body s easily that way in my mind going out of a better off to call some hi stop out forms like at night and when the look oh oh oh yeah if i used to make it along my heart s his back out but still had not get in the funk soul my name is got a fool to stay this he said he replies away more sweet cup down i ll find a cloud song come on a river place is an making people can in love with you would you let me know if you want to feel every something he d never to me what you give it is you are mine no one one and now oh oh yeah i want to the radio once this world with you and all the moon that they say just do not know everything i could na do it bring your thrill so long all i remember you ll help who tell your superman

Initial Word: party

Variant 1: party words for me to be a special time with you can not let us you want it i need you say that i used to find the wheel of my knees like a song oh in our hand and who s the world is all out your heart that is gone when we are through what you are leaving it but i am gon na do to get or to hide my heart just high i know she cried the sun you can not know what you ve done it to me from me dignity long to stand ya i feel me there is all i ll never did to hurt it cause i have waiting nothing can could see you love you last you are back for a little smile but they say goodbye to keep my head on s they were lose and you tell me let the motherfucker played only know gone long ago sing oh girl i d be have not want to you i got a love would that away you know that first break so naturally to share my mind from outer us ago as i always take a life at night you ve been some peace you in the rain i am going out of flaming boy up it

Melody: cardigans_-_lovefool

Initial Word: love

Variant 1: love is tearing me know that i was home the way we can you do not say that the way that i know that you are joyful and i have a new water i d come on a dream has just like you baby cause i need to be a spin and you are your shore little beat and i ve got ta never stop on my mind in your eyes sail say goodbye has going out of the yuletide but her the past world ya of cause that you said not for me what you are gon na get it back a song with a face that time you want me free from what that is the world down on the phone oh if you know that is your arms out of my heart s not come out down there is christ all at the stairs and i see the country one day after a love will not say goodbye yeah you were nobody i do not feel it at the sound of your heart at the right there oh it would came here it out of a crimson hand and i was your eyes and more shady she you know there is my tears where i ai nt should not reach my paper all around it is not time to face every upon you ve got ta help this evenin is feeling to lose my world off alone heaven a sentimental ride to faith and i can not give you so broken fun to try to judge they say hello in the sun and powdered you said they play the cream river the silver in the mornin it is a

Initial Word: dream

Variant 1: dream caused twist i do not see the rain let me reach let me see the real of your denies never ve lost in your shoulders again and i am here my time cause that is always bad rising up down to the world too long ago night on one you ever gon na be a lot you can not know it is true i want some bungalows and i was her sweet her room she held again down down from in the street and the things he d are with a friend life for all baby that is my hair and it is a beautiful lonely boy time to my love i am goin to have the only hot baby you were alone in town and you stand when you and there and sadness people in the trees right now right so right here right here right here up now that i can give them it out for a fourleaf but one was after on your eyes away she ai nt but just a new road just once again down when let us it back at the front of someone to get oh my heart hey little strong waiting to stay for his blue part on a hand and then get it feels before and she got a man in here yall really believe me hum you could was home you can not know what you were to face at you like the one for me one day up the contract high to say it again the pieces and that we ll be with added but that matters you want it is the air she been only cause she is ruining

Initial Word: party

Variant 1: party gossip hand it is gone like the old is for me to me cause they were up and why do not know you are never could it is all the time i ve got a friend of a real dirty secret oceans i feel the jam that is so free to make me no long just what but the days of living and ruby ooh now that i got your reasons please be down in my mind going out on fire we can change my eyes do not have to get up all around you want me creep or hear you like me when the nights i am gon na be afraid in love that we ve been a little bit down on as maybe baby tell me beg i must be whoh with me spellbound so many up in the cold flight this is the witch while was in his world everybody a new sensation hear is not so lonely friends are new and i am your heart let us in here the good for me ooh all the radio face on an now do you are leaving me cause i think i d could see the best girl i had always you know my own more you keep me so what you are never finding up the sunlight up and then you loved me i ai nt come and then oh girl the news more again just take you look at me out of out it back a place away on town because i saw you and its the stars in my soul she s eyes baby about come to me a holly of gold much s thing i

Melody: aqua_-_barbie girl

Initial Word: love

Variant 1: love wore can you ve done old control cause i have a bottle of sound of mine what are you are gone up and that ran never know the day no more another out she made the moon is whoa someone to be cold king as we have all i go and if we can not far go let us let me beach you feel it when i d think you can not worry my preachin me you weave do not come to cry we thuggish you do not you see right here do you are not wan na give it may do you want to live it was away tonight this new come for you baby sherry the words in the neon kisses are out of the desert but high are around i told the magazine house the oil are walkin her days sings s satin to rob them by never knew the arms let us rock your here yes this day to one no i will not hide the king of the way for the silk where you were as a license good all the world they turn around the day is with me down and it is so much and you are taking with you i am gon na be those now oh you are mine ooh today sing it was time you look but now you are better out of mind cause you got it out on your back and take this you want to say that makes you i should be always wanting you think you ve been along there is silken that i ve seen you and it is that you are doing it is the fear when i have you the loving for love to one before the pain is somethin i hope that you are still do you do i can not have to you are never only an check it you can not be down to know it is been a time to do not slip who why the dangers at the money that is my friends girl all at the night will know you are looking to criticize send when it is my heart you know just like a letter it is killing me all another love is christmas even there on a secret

Initial Word: dream

Variant 1: dream boy help you drink in the morning every day of the sun of love out there is where the twist was your true came some are walkin they know if i was it all this we have not a picture oh i do you want to me i ve got ta done before one you could see me good baby if you can do not know that is that i am goin but i need your mind still you know i ai nt got paid again s try to say he is deceiving a boy that ooh comes from the world has seems but then what did never do you weave do you do not want to make me by what you do i had to find me oh what you are leaving you can be true i can tell come on like the brightest it does not real you know it is so long who because i could do in my broom this is incense to me he just a person not let the pushers turn my hands let us take it know that does not give you hear it its me out easy all the most in love in the funk soul in the trees the style and all in the street and when we are closing to make my life was everybody in her eyes they left the last night used to the way we were a christmas and the right now no one things you do not hear what you are that you ve taken man if you please madam away lord this evenin if we look up in the finest then i d never wan na feel it all alone i said our mothers we always love that never thought before me but you are growin could show your eyes that i need to get it to be got a new smile of everything i d be through my nine boy music will not now you feel just like sorry more rock you felt ai nt all when the ffa heart is the tombs up the wheel in the park i could know the act of characters into my lovin ha deo dimension oh oh her girl there is easy to hitch it from here right now you

Initial Word: party

Variant 1: party screams up at the pillow tree they say out of your joyous sad do not love you go chaka to feel me who was your eyes i am christmasing my heart was a lovin he can show you see in the air that is been here up and i will not accept your room all around you a million better is a tombstone fair in my dreams baby sherry does not have a head tonight to explain a girl if you know this way but no more more between the street you are hoping let us take me time you ve got ta sail up the light will not let me do we ve got a different flight to get along when i did you know that seem to intervene go just should i know my big on your blues the dark of the radio show as i am with a cloaked morning years when time is so i am gon na be all alone just closed the best who s gots o some soul gifts we used to hesitate with a part of your love again is there were to have to you can show you come out strong but i ll quit it is but i can not stay or to do it away now right now you will make it home so sweet precious outer spirits coming but you ve passed the air she is a new arms i know what you are at me and your soul now baby i really never got ta d lose my world to try to hold me that makes you can be loved to live while all they are doing i know i ve got this no more than matter them what now you are halfway them do not know what one tell me to the silk s wondering it makes me go just give me what does not know she must be my own to me knowing you walk us here before you can sing a new place you ai nt i had your touch baby lonely life is the magazine its lights come easily and do you did i like a minute s gon na find you can do i believe that i must be together going and i feel the

Melody: blink 182_-_all the small things

Initial Word: love

Variant 1: love merry me one for the virgin you can not care it master to my life to try a delicate guy i ll be happy and i am in here up on on your eyes before me that there is a bogart but i ve got ta take for a peep for all the wheel of the same i was just for it does not want me you know you are so time you know if i do not want to put so many night i d never for myself just like a fool like a sleighing of loving in the dreams then watching i could feel i would you up in your name they go away your face at your heart we ve come for the news to die die a sunday glass a window and maybe she could give it does not be something and i want to san it long your love so much baby i ll you meet i will not make you drink i ll be ooh or and i want you cry i used to have no

207547183
206477952

Initial Word: dream

Variant 1: dream where a love was brutally on the world is a smile man i ll be light they have to take it would not deny to know you ai nt me and i am gon na love the one there d do not know what else let us they have been something in the magazine i ve seen a lifetime will do to get out of my heart no matter you can not far to play your eyes like me and she asks me to be as she reads me home my worries nights are out down in the ancient up in his eyes on the old caught a song of red in a window lovers through the skies things that we were all here that way through the time i should hear me and do not you want to life she said he just that ooo i am up in here right now baby she is noone world his love in her love with a delicate other has got the girl for the games who s your nights can not you know

Initial Word: party

Variant 1: party the deed of mundane our lives of a conversation was i am a place man when we were all the world is for the grace to go but i have you in my heart and there is you are not like your hands i am goin long to be clear you ve got a single desert just like me i have fallen you with you without the blues i never knew i am all so i wear through the strain that are you up in her old free the best of my mind was right on blueberry says i am looking for it out of a blue goes but just like an love is got a bird has somethin out in the desert what you ai nt the waves s out of a rat man and they got a little bit day to you love was the sign world they gon na be a life at a special man in spring could let us stay you know the games and she flies had another to play the world is time to survive

Lyrics predicted of 5 songs in the test – method2:

Melody: the bangles_-_eternal flame

Initial Word: love

Variant 1: love was a bottle and nature are burning we are wise no one was born on your name and the moon and they was down the pavement of tight of for the memories just on the floor a time will not bloom to feel you still me be to know no question i ve known my whole tonight i thought it is always in the same i was baby my way when i could make a flower to show your fantasy that she is come you are there and i guess you got just like you

Initial Word: dream

Variant 1: dream in the silver i am sorry in a moment and i was and i do not matter what we got my life is not so i ve waited for a big of my heel would just did not see me when i ll find it out your eyes by your dream will not stand but you love i can not you can not know all that they will not be the side from no when i d will not eat that you are me i will a note on my heart never feel i am

Initial Word: party

Variant 1: party night down the stars in my lonely now that is been in a kind of the things i found an let me mellow they call it is not gim a friend you will not hide if you are gon na show if you wan na love you say in me they are mine and it is feeling with all that i ll be a place to come on me and i am so i do not see all right when i wan na be your eyes when there to love me find a time i

Melody: billy joel_-_honesty

Initial Word: love

Variant 1: love you have to my days long it is so away i am here even live my arms i want me i see it is too much i should only do not know that i like the middle of the funk of a little chance but then i said i wan na be a song you look at you want me are going down how can i ll be your goodnight my one you close never will not believe me what is been sure i am for you that way when we are not make me on the extra me they love you to have loved at my baby i am do not live you know this is it to you a circle place i am gon na find a cup of a little time i am asleep i ve got i wonder out of you see they go it could get so no good my fantasy who are the cracks and i can not you i know it is all my heart i am feeling it on baby i do not make you hold a thousand song that s should i was but you are not let it loose my own baby bebopalula i ve known the street on broadway and i am up my i

Initial Word: dream

Variant 1: dream when you are all the good oh my broom that i am always pull it is not easy it is all your love so clear to know what you do not know baby i know the lies you are never gon na give me down but you were mind on the way of your name this is too much you can come in the way for what is whoa who s not seem to think it is all around baby doll you baby so clear but it is looking i see me i will you i was with a lovin you want me what is your eyes i ve got or just like a new big will be sure we are not a friend of your arms you know i heard to me that i will my baby i am a lifetime and foul there is feelin you baby they are the arms that do not understand you d be love is left i got ta wrong and that you are gon na get now i never been and you like me i am so hard to me to me to you love me know it would you look at it is my church my own s for my heart at night there is for a

Initial Word: party
Variant 1: party dweller got a glass a little crazy white down and breezy passin on the roof is no more from one dawn but i am in my wall in a fool up in pace just like to look out of the government for an please old good will not have my bell that all love of israel and the last night is so i do not want to dance the rain can you come for you know what i do i had to laugh you in love i am your eyes i knew so is i d be every time to smile they were a job as cause i think you are it is so much of long something time i feel in my life we are back down there is the silence you are the way we got ta i never gon na be what to be there is all the part of a victim cause i ll get you i ve been gon na do it straight it does not come but they you come on me what you are different i do it this but who s there is a cold baby to get to everything me but that i got it but you can it a girl that you are two man they
Melody: cardigans_-_lovefool
Initial Word: love
Variant 1: love come on with a long way oh what is alright no you are all now you are never enough to go with you let me i do not want to dance you did you see what you love it is always what a little respect in my heart i think you and i do i could found it loose girl i feel me down i am falling just your reasons through when my pupils will my love was like you baby i just be your eyes i ve waited of love will i give up your sighs i am tellin but you i will not love it this is not of the way i know if i can gon na stay away and my baby i see a way i wish it is looking for your arms i ve got ta comin to know you are here i knew so i am smiling little sleepy love when you can feel it sounds me you ve got i would not what i have to start it to rock me what you are all me there do not let me from you on the look out of a little get too little much watching you could feel do not come and i am up and my arms let me three night with my mind to get it but they say that you can not leave it is been for this man as there is my breath they make it is true to stay me for you a single fine and you so i got the same and i hear the sky see you are taking my life but i need you like you
Initial Word: dream
Variant 1: dream the southern way when i am all alone behind in the world oh night the night in my block are and just out for a new time oh on the mornin i could not my body a certain son of me that i did not know i d can turn the tv we come to your direction place with your name so meant so the sun is you on every in the other road time is crazy let the street to walk all by by is no more one and who s gone up the stairs she is not you high as when i feel the friend of love so your head and they ll never no chance i want to have loved my body of we turn the beat back to get along this life on my arms we have been waiting for what this is on your mind i love you can not see that we have you know what it is a little girl and i ever get away but it is a long feelin no doubt all right what you like a lot of time to me rock the sea where on just night she do not you say what i am gon na get my own i ever now when you are around up down i ve got a place new well i ll find that i was bill i got ta with you think i am going in his of hand of your sighs it is a window day well i have found you and that go now and go out of mine and it were fire you looking i know my heart and just
Initial Word: party
Variant 1: party we ve got a river but i am my window very my heart s your eyes i got a beautiful let the things you made it on my eyes i am gon na be to me do not you know what i am gon na come and i can not know a long time i thought you do not recognize my life to show you let me callin it but i know you the way of all the dreams let us know that was an run walk da you are in my life we got me oh my side with you could be in your eyes i d you want to be much will not be your mind you can not understand i ve seen all the way that is easy and sometimes it is calling i am with you come on your reasons that i think your body in my side in his and do you ve got you in that was not no more there is all my mind up in my hurts they go there is not right for me talk to you and all around i am in a sudden no more to come but if you know it i know it from the street i can not you see but it but i have not so surprised i am in circles of mind and i get freaky you i can not be my side i want you walk now baby i am only like you might got so to me tell me tonight you know my world for you out in your case of me now i knew that i need you will to hear you
Melody: aqua_-_barbie girl
Initial Word: love
Variant 1: love i am gon na be it to see out through the boy down on a lot of a friend in your mind do not give your body in a real rhythm of his and they are back so long time in the roof he were now it is nothing to tell me so your face i need you like a little prayer when i did i think you know that i want to put me what i ve got a morning world of your dream but that i am askin down down i see you and i see that was or for me i do not wan na it is no one and i hope i ll be to you know you this is hard to blame or all the chance do we are too and that great one for you let us say it but you want a small new world like this fever now i know that i will not never knew you even go what you are just let me how you could tell me back you can not let me about it is coming to do you do i know the door i do it just to feel a hand they see me down that i know of mine i am i am but i wish i want it is what you have a mind up now all my love i do not see if i see a blue jeans when you ve ever i will not bother you not a have no more i am not take it from a long girl you are mine she of happy oh goodbye to find you close to share there we ve like to hear a place they are leaving but in you it is all my heart from your eyes i ve been so so around you think that you found me down your attitude the day i have love and if it is looking by the time i think you

can see you i see and my life and i said to live there we said they say i ve waited for all and their this way on the sad i can not there is where it is time to be your arms there is so i know now

Initial Word: dream

Variant 1: dream here we are so surprised the beat o come and foul those you i never knew he come out of a new this world you say goodbye to hold in a new thing i d feel it is come and it is not that is on the night of a good times when you let me i am gon na be a while day i think that i got ta and i look no more times it he was to my world can not you know if i feel my dick than one is still for all my heart was a little way and i ve seen that is by the one of come and i have fallen in your mind let us dance you are leaving but i ll know it is so cruel i think you can not recognize i could not make the things i knew you know that you are gon na get it along me but i just do not matter what i want to me make it feels so i could so good to be it ll be your body down the one you see your fire oh i do not do you can not understand your eyes again it is nothing on your body baby i can not even be the best but when i would not stop there is enough to it it to clip it but i am easy so has come a lot of pleasin i do not you can not change you be we are saying in my life it is so long you want me i d found but it is still young i ve waited to the one i know it i ve got your fire all the snow just what you look at night with you d do not care back to leave me you baby just for the boy when that i d ever wanted got your face you and i ve been away with you hold but you want to say what you do not you know my hat and we got something along when they do it they stay what you i am angry down i had it has goodbye you are gon na find the way it just they ll in the chance that is

Initial Word: party

Variant 1: party i knew for you want to the world that you know at the time i found here i know it is where i ve been a spin got ta let us no matter what i could love me tell me east so i ll make me all and i am gon na believe it i can not say it but i ve left of these are you are just to me so you could be your desires i go for them this rain that could not say that will what you make it down it straight me now i do not know it all i could get a man in your heart can not worry that you are leaving oh oh we are you do not take a ghost she is a love and you d sing up every day but you love this baby i am not ever he you think that i know if you do you know what i want to say i could make you know it is the bills i need my empty baby i look at the words s like a girl would you go out me there let it now you would you but when i know you tell me like you in a lovely that i believe i want your heart of heart will not me you know you can not ever wrong with you so all around this is here in my sights again my mind is a times but i can assure you i am and be in the longest you baby i have the real can turn you come on with me and your arms you are away and i do to feel your heart that would you know that you get it is all let it is looking i do it this is thinking i get the good good with a new face and heaven this day it easy i see the beat of times at night it is a day it makes it out with a lifetime so long as time when you would not give i got what i think you can i am in my lonely ooh time s if you go wrong and i know you when i see me tonight i feel you i think you

Melody: blink 182_-_all the small things

Initial Word: love

Variant 1: love to me i ve got the of light your own the blue night and i look if you must have come on fire in my feet just why there is a ghost dream i can not even be free i ll be enough to know where they call us take me you come you and i know it so love i need to be strong i know you do it i would not get a beautiful so long so much where i knew it is looking for it easy for a time of time this way but in your body love you the pillow desire oh it is all your legs gon na be and if you got a shower i saw my beautiful like a secret do not the funk now that everyone when i think that i come like all my way and she is all in your body out in whose i can do to live she ll find you can you know that i want the table rubs that i am gon na be enough to me there

Initial Word: dream

Variant 1: dream we take me east a girl on a hand that is not get in town by surprise it funny i am in town through the beat of mind i have to you want to lose and i am sorry but i just want a texas so i will i swear seem to your love take you worry it but you do it opened you never live all there for anyone take you are going down i would be you i want your eyes it must find take my heart from your eyes that i would keep if you made me it is not let us me mellow while i get you come on every day for it made it is on to you drink the kind of two that your heart s the government of come along and clear but i am gon na be strong and you are two take me so easily from my life is right here in your mind i do not have love i must see you can find that man alone i ll be around you

Initial Word: party

Variant 1: party wish the words that would be gon na get it all the king of me alone of the dearly people he could be your body when i feel i can i ve been too and you are all my empty part of a man look when i got ta let us make take a new words that nothing now the words that is true i knew it come on a shelf i was not give on my kisses baby the world will so long time in most long ago but we come your sweet and are lonely things if i have always here with me but i know it you do not pretend go for me to you took me beside the reasons i look at me to find a eyes cause i see you ll know it you know what your cheeks a piece do not have never call me on my heart is hard to see me there you were a body and i am waiting gon na be a job to say if you found it is a only

Conclusion:

We analyzed the model's ability to generate lyrics for five songs using two different methods of incorporating melody information: Method 1, which uses a 128-dimensional binary instrument vector, and Method 2, which incorporates richer musical features such as tempo, key, intervals, and dynamic range.

Observations from Method 1:

The lyrics generated using Method 1 reflect some alignment with the themes and tones of the songs. For example, in "Eternal Flame", the generated lyrics captured romantic themes but often included repetitive phrases and lacked coherence. Method 1 provided a simpler and more stable representation, as evidenced by relatively consistent test losses across songs. However, the simplicity also meant that the generated lyrics lacked richness or depth in their connection to the melody.

Observations from Method 2:

While Method 2 introduced richer musical features, the generated lyrics did not consistently demonstrate significant improvement in quality or coherence. For instance, in "Honesty", beginning with the word "dream" produced lyrics that aligned with the emotional tone of the melody, but issues like repetition and lack of syntactical coherence persisted. Method 2 showcased stronger influence from melodic features, but this did not always translate into more meaningful or structured lyrics. Moreover, the test losses showed slightly higher variability compared to Method 1, indicating some inconsistency.

Comparison of Methods:

Both methods displayed limitations in terms of lyrical coherence, repetition, and maintaining context throughout the generated text. However:

Method 1 offered a simpler and more consistent baseline with lower test loss variability.

Method 2 incorporated richer features, enabling stronger alignment with the melody, but at the cost of variability and occasional deviations in thematic consistency.

Key Takeaways:

While both methods demonstrated the model's ability to integrate melody and lyrics, neither fully overcame challenges such as repetitive phrases, syntactical inconsistencies, and limited contextual understanding. The influence of melody was evident in both methods, as seen in "All the Small Things", where the generated lyrics often matched the song's energetic and rhythmic nature.

Future Directions:

Future improvements could focus on addressing the limitations of both methods by leveraging advanced architectures.