Lyrics Generator: Deep Learning for Artist and Sentiment-Driven Lyrics Composition

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Abstract

The problem at the heart of this endeavor revolves around exploring the bounds of AI's creativity. Our primary question is, to what degree can AI emulate the artistry of human lyricists? Generating lyrics of new songs based on a model trained on a particular artist's previous songs has been implemented to answer the above question, various Natural Language Processing (NLP) techniques have been employed to analyze the sentiment, tone, and emotional depth in lyrics. This sentiment analysis serves as a cornerstone for our AI model, enabling it to imitate the emotional nuance found in human-created lyrics. A diversified and boundless dataset is collected for the project to train the model. The dataset is collected from Kaggle website which consist of lyrics from various genres, generations, cultures, and countries. The model is trained on artists too, trying to emulate their lyrics in a similar format. Our approach centers around a combination of Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs).

These deep learning models have been tailored to capture the intricate patterns and emotions prevalent in human lyrics, while also generating original lyrical compositions that resonate with human-like sentiment. By exploring the divide between human creativity and artificial intelligence, this project contributes to our understanding of the current capabilities and limitations of AI in the domain of creative expression, showcasing the promise of AI in generating lyrics while also acknowledging the room for growth and refinement. Future scope includes training the model on the audio discography dataset of different artists to sing the verse with the lyrics generated in the artist's voice and also adding background music to the verse which would completely revolutionize the music industry.

1. Introduction

1.1 Project Background

In the ever-evolving landscape of music and technology, the intersection of artificial intelligence and creativity has given rise to innovative applications in the realm of music composition. Our project, titled "Lyrics Generator: Deep Learning for Artist and Sentiment-Driven Music Composition," aims to explore the fascinating world of text generation using Recurrent Neural Networks (RNNs) to craft lyrics inspired by specific artists and perform sentiment analysis based on a specified artist.Language is a fundamental element in the expression of artistic creativity, and exploring the intricacies of song lyrics can offer insights into the cultural and social dimensions of music. The Genius Song Lyrics dataset, sourced from Kaggle, serves as the foundation for this exploration, providing a rich repository of lyrics along with associated language information.

1.2 Project Motivation, Objective, and Goals

The motivation behind this project stems from a desire to push the boundaries of AI applications in the creative domain, specifically in the field of music. While there are various AI-driven text generation models, the focus on generating lyrics tailored to the distinctive style and themes of individual artists adds a unique dimension to the creative process. This project seeks to bridge the gap between technology and artistry, offering a tool that not only aids songwriters but also serves as a source of inspiration for new and aspiring artists.

As the music industry also continuously embraces digital transformation, the project seeks to contribute a tool that empowers artists, songwriters, and enthusiasts alike, providing them with a source of inspiration and a means to analyze the emotional tone of their compositions.

Objective

1. Text Generation with RNN: Utilizing Recurrent Neural Networks, the project aims to create a model capable of learning the distinctive lyrical style of a given artist. The RNN will be trained on a diverse dataset of the artist's lyrics to capture the nuances of their language, rhythm, and thematic elements.
2. Sentiment Analysis: In parallel with text generation, the system will conduct sentiment analysis on the generated lyrics. This analysis will provide insights into the emotional tone conveyed by the lyrics, such as joy, sadness, anger, etc. This dual functionality aims to offer users a comprehensive understanding of the emotional context of the generated content.

Project Goals

1. Text Generation with RNN: Develop a robust Recurrent Neural Network (RNN) model capable of learning and emulating the distinct linguistic style of a given artist. Achieve a high level of accuracy in generating coherent and artistically relevant lyrics that closely resemble the chosen artist's unique lyrical patterns.
2. Training Data Acquisition: Curate a diverse and representative dataset of the selected artist's lyrics to ensure the RNN model captures the full spectrum of their creative expression. Compile a comprehensive and well-structured dataset that reflects the artist's evolution in style and thematic elements over time.
3. Model Optimization: Fine-tune the RNN model parameters to enhance its ability to capture subtle nuances, rhythms, and contextual intricacies present in the artist's lyrical compositions. Achieve a balance between model complexity and efficiency, ensuring optimal performance in generating artistically coherent lyrics.

4. Sentiment Analysis Integration: Implement sentiment analysis algorithms to evaluate the emotional tone and mood expressed in the generated lyrics. Develop an accurate sentiment analysis module that provides insights into the emotional landscape of the lyrics, including joy, sadness, anger, etc.
5. Validation and Evaluation: Conduct thorough validation and evaluation processes to assess the authenticity and artistic fidelity of the generated lyrics. Establish metrics and benchmarks for evaluating the success of the text generation model, ensuring it consistently produces high-quality and artistically resonant content.

By achieving these goals, the project aims to create a powerful and versatile tool that not only assists artists in their creative process but also contributes to the broader exploration of AI's role in artistic expression and emotional communication through music.

1.3 Project Application and Impact

Applications

- Artistic Inspiration: Lyricists and Songwriters: The project serves as a creative assistant for lyricists and songwriters, offering them a wellspring of inspiration by generating lyrics in the style of their favorite artists. It becomes a valuable resource for overcoming creative blocks and exploring new thematic dimensions.
- Content Customization: Musical Collaborations: Artists collaborating on a project can use the system to merge their distinct styles, creating a fusion of their lyrical nuances. This promotes innovation and diversity in collaborative musical endeavors.
- Marketing and Branding: Music Labels and Agencies: The system can be utilized to analyze and generate lyrics in alignment with an artist's established brand and image.

This ensures consistency in messaging and enhances the marketability of the artist's work.

- Audience Engagement: Fan Engagement: Fans can experience personalized content in the style of their favorite artists, deepening their connection with the music. This fosters a sense of exclusivity and engagement within the artist-fan relationship.
- Content Recommendation Systems: The project's insights into linguistic features, sentiment, and cultural context can be integrated into content recommendation systems. By incorporating language analysis, these systems can offer more personalized and emotionally resonant music recommendations to users.
- Cultural and Historical Studies: The linguistic analysis of song lyrics contributes to cultural and historical studies. Researchers and scholars can use the findings to explore linguistic shifts over time, understand the evolution of cultural narratives through music, and analyze the impact of language in reflecting societal changes.
- Educational Resources: The project outcomes can serve as valuable educational resources. Teachers and students in music, linguistics, and cultural studies can use the linguistic sentimental analysis to deepen their understanding of the relationship between language and music, fostering a richer appreciation of both disciplines.
- Genre-specific Insights: The project can provide genre-specific insights into language use, aiding music producers, and artists in tailoring their compositions to align with the linguistic expectations and preferences of popular genres. This can enhance the authenticity and resonance of musical creations.

Projected Impact

1. Enhanced Creativity: The project enables artists to overcome creative barriers and explore new artistic directions by providing them with a tool for generating lyrics that resonate with their preferred styles.
2. Efficiency in Content Creation: Songwriters can use the system to expedite the initial stages of songwriting, allowing them to focus more on melody, arrangement, and overall musical composition.
3. Data-Driven Insights: The sentiment analysis component offers artists valuable insights into the emotional impact of their lyrics. This data-driven approach enhances self-awareness and helps in tailoring content to resonate with specific emotional themes.
4. Diverse Artistic Expressions: The system encourages the exploration of diverse artistic expressions by allowing artists to experiment with different lyrical styles and themes, contributing to the overall innovation in the music industry.

In summary, the project's application and impact extend across various domains, including the music industry, education, therapy, cultural studies, and technology. Our project aspires to not only revolutionize the creative process for artists but also contribute to a more dynamic and innovative landscape within the music industry, enhancing the overall experience for both creators and consumers of music.

1.4 Expected Deliverables

Table 1

Listing of project deliverables with dates.

Phase	Deliverables	Description	Date
Project Understanding	Literature Survey report	Summarizes the findings and conclusions from related research papers	Sep-13-2023
	Technology and data requirements report	Evaluates technology and data requirements for the project	Oct-18-2023
	Project Plan	Outlines development methodology, milestones, and data management.	Oct-25-2023
Data Preparation	Data Collection, EDA	Gathers data and conducts data exploration and preprocessing	Nov-01-2023
	Data Modelling Report	Finalizing the data and processing the data to feed into deep learning models	Nov-08-2023
Model building	Model Proposal and development	Proposal for models to address the problem, including model architecture, data flow and technologies used for development.	Nov-15-2023
	Model accuracy and evaluation	Report on model accuracy and evaluation using selected performance metrics.	Nov-22-2023
Data Documentation	Fall Semester report	Detailed report of the project progress until fall semester	Dec-06-2023

Evaluation	Comparison report	Reporting the results of the developed models and the evaluation metrics	Dec-06-2023
Deployment	Presentation	Presentation of the project using Microsoft PowerPoint.	Dec-06-2023
	Final Report	Final documentation of the whole project	Dec-06-2023

2. Background and Related Work

2.1 Literature Review

The purpose of this section is to structure the literature review on the AI-generated song lyrics. While referring to several relevant previous studies, to establish a benchmark for evaluating the performance of the model. The approach is to comprehensively evaluate these methodologies to identify the strengths and weaknesses. The studies reviewed in this survey explain various techniques like GAN based transfer learning, Long Short-term based deep learning models etc.

In the paper DopeLearning: A computational Approach to rap lyrics generation (Malmi et al., 2016), the authors tried to describe the structure of the rap lyrics based on different rap types. They automatically detected the rhyme of the lyrics by using text- to- phonemes functionality. Rhythm density of each lyric is calculated to quantify the technical quality. The skill of a human rapper is evaluated based on the quality of the rhymes. Feature extraction is done in various methods. Endrum is a method where the matching vowel phonemes at the end of the previous line. The authors used a neural language model to predict the next lines of the lyrics. The network architecture consists of multi-layered, fully connected neural networks trained with back propagation. The deep neural network model for semantic features outperformed by 17%

accuracy in predicting next lines from existing rap songs, surpassing human rappers by 21% in rhyme density.

In the paper Can a machine win a Grammy? An evaluation of AI-generated song lyrics (Lu & Eirinaki, 2021), authors designed and trained two neural network models for composing lyrics in three genres and proposed scoring functions to select and evaluate the generated songs. They treated the problem as a text generation task, and optimized for features particular to song lyrics, including lyrics' quality, rhyme density, and sentiment ratio, for lyrics in different genres. The neural networks that were experimented with are generative adversarial network (GAN)-based transfer learning for a deep learning model and long short-term memory (LSTM)-based deep learning model. The first language model was trained based on the generative pretrained transformer (GPT-2)1 deep learning model. The second language model was trained on a traditional long short-term memory (LSTM)-based deep learning model. The two types of language models were trained with three lyrics' genres, resulting in six models. Sequence data processing has been used for text processing and text prediction. An early-stage recurrent neural networks (RNN) model is the bidirectional recurrent neural network (BiRNN). BiRNN splits the RNN's nodes into forwarding computation direction and backward computation direction.

Recently, most RNN models use the long short-term memory (LSTM) network in which they can learn long-term dependencies and predict the sequence data much better. The model uses character-level models, that tokenized each character into vectors from the corpus of letters and train the model with the LSTM networks. Author obtained a pre-trained text generator model, GPT-2 Text Generation Model trained on an enormous dataset, as the base model. Then, trained and produced several newer models that can generate song lyrics by retraining the original model with our datasets, which include lyrics (text). which kept the middle layer parameters of the GPT-2 model and changed the parameters in the last layer of the neural network. Authors evaluated lyrics on three parameters, which are a) Lyrics Quality Analysis which yields a quality score for each lyric b) Rhyme density analysis c) Sentiment Score. Based on above scores, Lyrics scoring metrics were generated. The generators were fed into a seed of random words as inputs to start with and processed. Then scored each piece by using the lyrics evaluation metrics that were designed and called this scoring process automatic evaluation. Then picked top-scored songs for each genre and mixed them with real songs and conducted a user study presenting them blindly to users to evaluate.

Based on the paper AI-Lyricist: Generating Music and Vocabulary Constrained Lyrics (Ma et al., 2021), the authors propose a system for generating novel and meaningful lyrics given a required vocabulary and a MIDI file as inputs. The system consists of four modules: a music structure analyzer, a SeqGAN-based lyrics generator, a deep coupled music-lyrics embedding model, and a Polisher module. The music structure analyzer identifies melody and extracts a syllable template, while the lyrics generator ensures syllable alignment and text quality. The deep coupled music-lyrics embedding model compares music and lyrics for style and constraint matching. The Polisher module applies vocabulary constraints and personalized language learning requirements. The paper discusses related work in lyrics generation and poetry generation, highlighting the lack of research on generating lyrics from whole music and the absence of application-oriented constraints in existing models. Several baseline models, including machine translation, encoder-decoder, and SeqGAN, are compared to the proposed system in terms of novelty, informative density, relevance, BLEU scores, and application-oriented satisfaction. The objective evaluation shows the superiority of the proposed system, while the subjective evaluation confirms its effectiveness in terms of fluency, coherence, meaningfulness, aesthetics, syllable alignment, relevance, and overall quality. The authors conclude by suggesting future research directions, including deeper music structure analysis for better topic transition in lyrics generation, controlled language generation techniques, and end-to-end architectures. Overall, the paper provides insights into generating lyrics from multi-channel music and offers a promising solution for language learning applications.

The paper Melody Generation from Lyrics Using Three Branch Conditional LSTM-GAN (Srivastava et al., 2022) presents a novel architecture, Three Branch Conditional (TBC) LSTM-GAN, for melody generation conditioned on lyrics. The proposed model consists of a LSTM-based generator and discriminator. The generator is composed of three branches of independent lyrics-conditioned LSTM-based sub-networks, responsible for generating different attributes of a melody. The GAN framework is trained using the Gumbel-Softmax technique for discrete-valued sequence generation. Extensive experiments demonstrate that the TBC LSTM-GAN model generates tuneful and plausible melodies from given lyrics, surpassing the current state-of-the-art models in terms of both quantitative and qualitative performance metrics. The key contributions of this work include leveraging paired lyrics-melody dataset and advancements in artificial intelligence techniques to enable melody generation conditioned on lyrics. The proposed TBC LSTM-GAN architecture utilizing multiple branches of sub-networks allows for generating different melody attributes, resulting in more diverse and expressive melodies. The Gumbel-Softmax technique enables training the GAN model for discrete-valued sequence generation, enhancing the quality of the generated melodies. The paper highlights the superiority of the TBC LSTM-GAN model through extensive experiments and evaluations. The quantitative evaluation demonstrates that the proposed model outperforms the state-of-the-art models in terms of various metrics. Moreover, the qualitative evaluation reveals that the melodies generated by the TBC LSTM-GAN model are tuneful and plausible, capturing the essence of the provided lyrics effectively. Overall, this work contributes to the field of melody generation by introducing a robust and effective architecture, the TBC LSTM-GAN, that generates high-quality melodies conditioned on lyrics. The experimental results validate the superiority of the proposed model and its potential for various applications in music composition, production, and creative systems.

The paper A Systematic Literature Review on Text Generation Using Deep Neural Network Models (Fatima et al., 2022) presents a systematic literature review (SLR) on text generation usingdeep neural network models. The review aims to bring together the relevant work in this field, highlighting key contributions and identifying research gaps. The SLR covers five aspects: deep learning approaches, quality metrics, datasets, languages, and applications of text generation. The findings show that traditional deep learning models, such as LSTM and RNN, have been widely used for text generation, but advanced models like transformer-based architectures have gained popularity. Evaluation of generated text has been done using both machine-centric and human-centric approaches, with BLEU being the most used metric. Publicly available datasets have been used in most studies, but there is a need for more benchmark datasets, especially for low-resource languages. The applications of text generation encompass various domains, including data balancing, data-to-text, script writing, machine translation, and text summarization. English is the most studied language for text generation, while low-resource languages have received less attention. The study highlights gaps and provides recommendations for future research, such as focusing on complex language constructs, diversifying the generated text, improving the selection of quality metrics, and addressing resource and dataset limitations.

3. Data Preparation

3.1 Data Description

The foundation for the lyric's generation is started with collecting a vast and varied dataset comprising lyrics written by multiple artists from an array of genres, languages, and themes. This immense collection is sourced from Kaggle (Carlosgdcj, n.d.) and originating from Genius, a collaborative platform for annotating creative works, consisting of a tremendous amount of 5 million songs. This dataset contains information as recent as 2022 scraped from Genius (Genius, n.d.), a place where people can upload and annotate songs, poems and even books (but mostly songs).

The dataset collected is in CSV format, with column names as shown below:

- Title - Title of the piece. Most entries are songs, but there are also some books, poems and even some other stuff.
- Tag - Genre of the piece. Most non-music pieces are "misc", but not all. Some songs are also labeled as "misc"
- Artist - Person or group the piece is attributed to.
- Year - Release year
- Views - Number of page views
- Features - Other artists that contributed.
- Lyrics - Lyrics of songs
- id - Genius identifier
- language_cld3 - Lyrics language according to CLD3. Not reliable results are NaN
- language_ft - Lyrics language according to FastText's langid. Values with low confidence (<0.5) are NaN

3.2 Data Storage

The dataset has been downloaded from Kaggle and loaded in a AWS S3 bucket. Using the access_key and secret_key they have related to a PySpark in Jupyter notebook to perform rest operations on them.

3.3 Data Cleaning and Exploration

Cleaning involves addressing the inconsistencies in data, while organizing adds a coherent structure for subsequent analysis. The lyrics data that is collected also consists of books. Removing the books from the data is one of the steps in preprocessing.

To just keep the music lyrics data and to remove other books and poem data the below PySpark Code has been implemented. Figure 1 Misc. contains books too, using only the tags which have music lyrics in it,

Figure 1

Code to remove miscellaneous tags

```
music = df.filter(df["tag"] != "misc")
```

The preprocessing is continued by looking for null values in the dataset and removing them. Figure 2 displays the number of null values for each column. Removing those columns helps in training a better model as shown in Figure 3.

Figure 2

Null values

```
title              165
tag                  0
artist               0
year                 0
views                0
features             0
lyrics               0
id                   0
language_cld3    90966
language_ft     134322
language        226918
dtype: int64
```

Figure 3

Filling the missing null values with fillna() and na.fill()

```
music.fillna("language_cld3", "language_ft").show()
```

```
music.na.fill("language_cld3", "language").show()
```

Figure 4

Number of songs collected for each tag

```
music.groupBy('tag').count().show()
```

```
[Stage 8:>
+----+-------+
| tag|  count|
+----+-------+
| pop|2138587|
| rap|1724816|
|rock| 793220|
```

The above figure 4 explains that the data collected consists of more pop songs followed by rap.

Removing the white spaces, new line characters, and brackets is also part of preprocessing for this project. After various steps of preprocessing and extracting the required features like artist and lyrics, the dataset is converted into a text file from csv file to access the model as shown in the figure 5.

Figure 5

Grouping by artist and saving the lyrics in a .txt format to access from the model

```python
# Loop through artists and write lyrics to text files
for artist in artists:
    text = imp_features.filter(col("artist") == artist).select("lyrics").collect()

    if text:
        text = text[0][0]
        # print(text)
        file_name = "data/TextData/" + artist + ".txt"

        with open(file_name, "w+") as file:
            file.write(str(text))
            file.close()
```

The structured dataset supplies the raw material for training the model. The objective is to collect accurate features which can generate lyrics that synchronize with the diversity of real-world music based on the artist given.

3.4 EDA

The word cloud shown in figure 6 visually encapsulates the prominent terms in Coldplay's lyrics, providing an immediate snapshot of recurring words, emphasizing the thematic essence of his music.

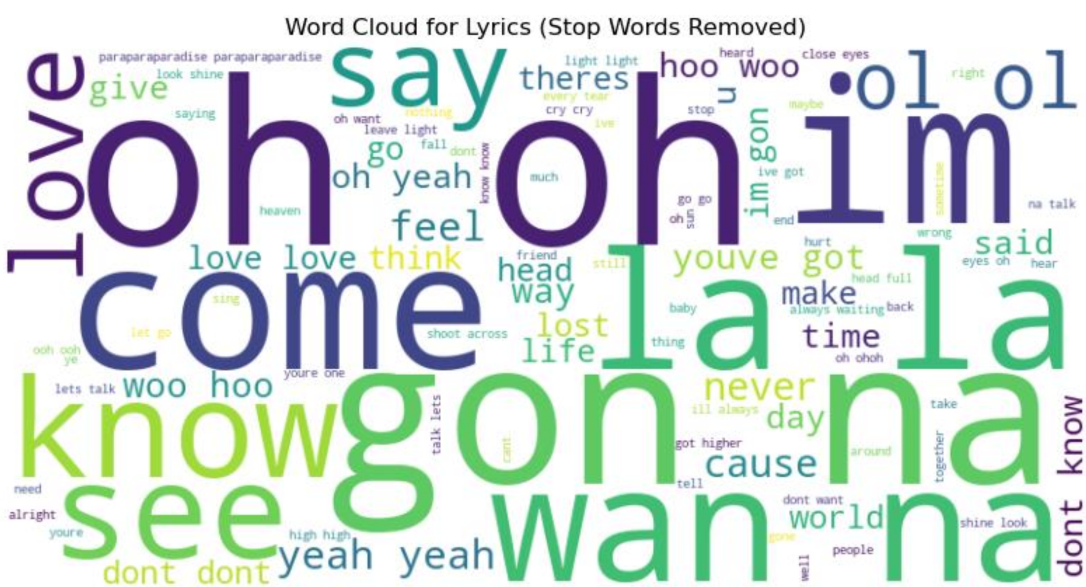
Figure 6

Word Cloud for Lyrics

By excluding common stop words, the refined word cloud offers a more focused representation, Figure 7 shows substantive and distinctive vocabulary within Coldplay's lyrical content.

Figure 7

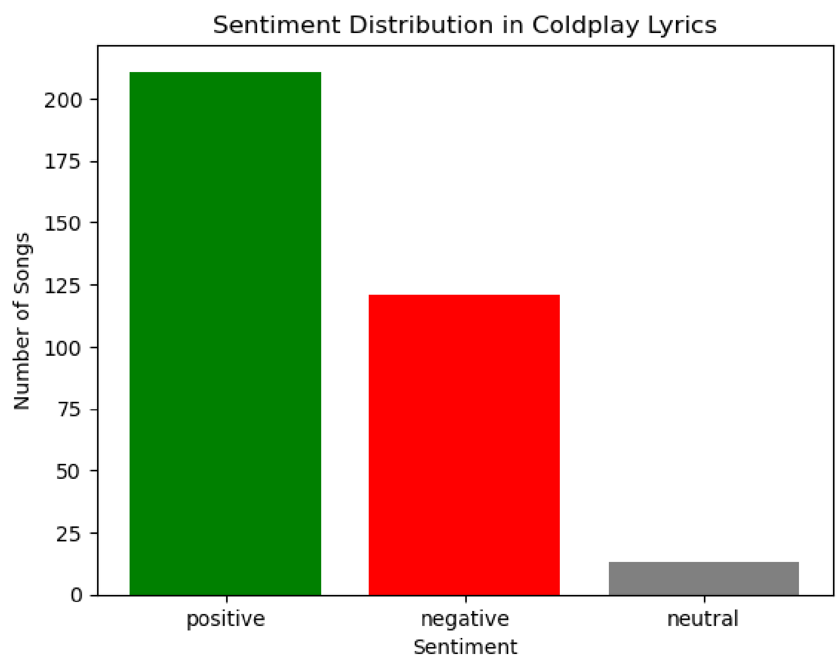
Word Cloud for lyrics without Stopwords



The code combines sentiment analysis with word frequency distribution to provide insights into the emotional tone and frequently used words in different sentiment categories within Coldplay's lyrics. The bar charts in figure 8 help visualize the distribution of sentiments, and the word frequency distributions offer a glimpse into the most common words associated with positive and negative sentiments.

Figure 8

Sentiment Analysis of Coldplay

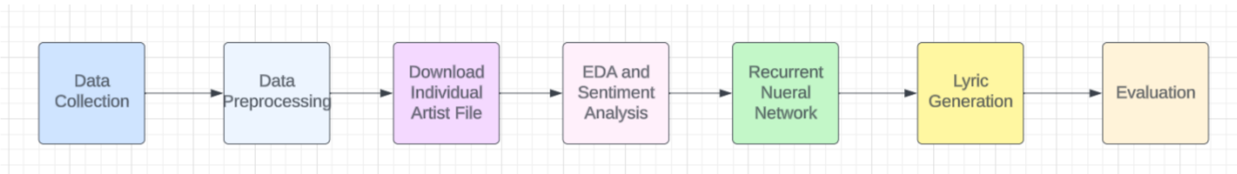


4. Proposed Methodology/Architecture

4.1 Project Workflow

Figure 9

Model Workflow



The project encompasses a structured workflow aimed at creating a lyrics text generation model using Recurrent Neural Networks (RNN) which is seen in Figure 9. The journey begins with data collection from Kaggle, acquiring a diverse dataset comprising lyrics from various artists. Subsequent to this, the data undergoes preprocessing, where irrelevant content, such as poems and books, is filtered out. Duplicates and missing values are also addressed during this phase.

Following data preprocessing, the project delves into Exploratory Data Analysis (EDA) to gain insights into the dataset's distribution and characteristics. wordclouds and barplots have been created to see the most used words of artists. Additionally, sentiment analysis is performed on the lyrics, categorizing them into positive, negative, or neutral sentiments using Natural Language Processing (NLP) techniques.

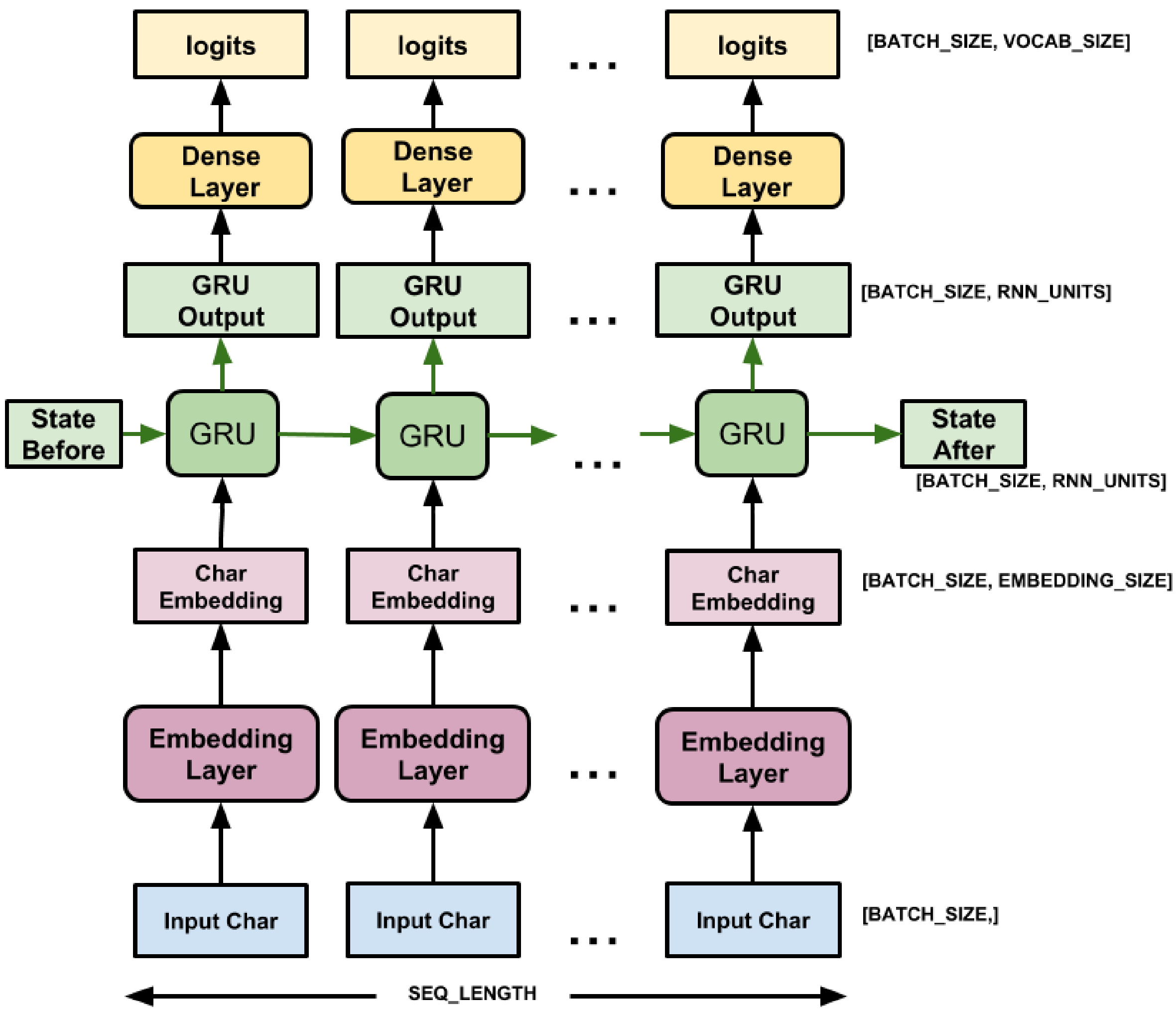
Transitioning into model implementation, the project leverages TensorFlow to construct a Recurrent Neural Network (RNN). The model architecture of the RNN itself is given in the next section.

Once the model is trained, a mechanism is implemented for generating lyrics. This involves seeding the model with an initial input and iteratively generating subsequent characters or words.

4.2 Architecture

Figure 10

Model Architecture of the RNN



The Model Architecture as shown in Figure 10 includes an embedding layer for character embeddings, which translates characters into numerical vectors allowing the model to grasp intricate relationships between characters and facilitate effective information representation within the neural network. This layer enhances the model's ability to understand the contextual nuances of lyrics by mapping each character to a continuous vector space.

A Gated Recurrent Unit (GRU) layer is employed, a type of recurrent neural network (RNN) layer that excels in capturing dependencies within the lyrics. It efficiently addresses the vanishing gradient problem, enabling effective modeling of intricate patterns within the temporal context of the lyric's dataset.

Following the GRU layer, a Dense layer is introduced to the Recurrent Neural Network (RNN) architecture. This fully connected layer processes the GRU outputs, providing the final layer of abstraction and generating logits that contribute to the prediction of the next character in the lyrics generation process.

Evaluation

Five different evaluation methods have been used for evaluating the model, which are BLEU Score, Sentiment Score, Rhyme & Rhythm Score, Subjective Score and Overlap Score.

BLEU (Bilingual Evaluation Understudy) is a metric commonly used for evaluating the quality of machine-generated text, including translations. It calculates the precision of n-grams (contiguous sequences of n items) in the generated text compared to reference text. Higher BLEU scores indicate better agreement with reference text.

Sentiment analysis aims to determine the sentiment expressed in a piece of text, typically classified as positive, negative, or neutral. It relies on natural language processing techniques to understand the emotions conveyed through the language.

SequenceMatcher is a method for comparing sequences, such as strings, and determining the similarity ratio. It can be used to measure how similar the generated lyrics are to the reference lyrics in terms of overall structure and rhythm. Very low similarity score.

Subjectivity refers to the degree to which a piece of text expresses opinions, personal beliefs, or emotions rather than objective facts. TextBlob is a natural language processing library that can assess subjectivity based on linguistic patterns. The lyrics generated are more subjective, as is the case with most pop songs.

Comparing generated lyrics to a reference dataset involves measuring the overlap or similarity in terms of vocabulary. This can provide insights into how well the generator captures the language style and richness of existing high-quality lyrics.

In Table 2, the evaluation metrics for the artist Coldplay at epoch 20 is given.

Table 2

Evaluation Metrics of the artist "Coldplay"

Evaluation Metrics	Evaluation Score
BLEU Score	0.004
Sentiment Score	0.69
Rhyme and Rhythm Score	0.000019
Subjectivity Score	0.67
Overlap Score	0.0048

Results

Figure 11

Generated lyrics of artist Kanye West with 20 and 30 epochs

```
kanye west off i dropped my new jesus
i will feel yeah i done feel all
day nigga take you they dont get down
get up oh oh these ares one mess
with an esport hold up uh fame is
the kingdom and the power no one can
say you will never play some she want
some integrate young baradabbleg and bibblegar bid chickget
get you go nna get hard bared a
fuck and roll a cop god got no
clothes one day you just know the cameras
on it huh bullshit just to mess with
these drunk all of thes not hurt some
runer

Run time: 2.044405698776245
```

```
kanye west without you he esh i run uh
i feel like you better make it on
up back at what up i just want
your ds a hands and lines ooh off
thats a strike ass i see the big
maybe im yellin ye yall got stick to
the ground to blow uh my dick had
to step back cameras on me
who can i run talk and talk my
shit again can you hear me yeah yeah
  yeah youre lookin everything upma eurs
ya sis broke i just wait for a
suched be tight get your keep us clear
  its 4 am the girl i
must have fall barney we

Run time: 2.177551507949829
```

As seen from the figure 11, for the artist Kanye West the lyrics generated with 20 epochs are better than the ones generated using 30 epochs. It is possible because sometimes it overfits and hence it makes the model learn the noise from the data rather than the underlying patterns in lyrics resulting in poor generalization to new data.

Also, as seen from the figure 12 and 13 for the artist Ed Sheeran and Coldplay lyrics generated using 30 epochs are far better than ones using 20 epochs. This is because it fits properly and is able to clearly find out underlying lyric patterns in the data rather than making the model learn the noise from the data.

Figure 12

Generated lyrics of artist Ed Sheeran with 20 and 30 epochs

```
ed sheeran  im aund out of three bags
no talk about my cash flows devember when
you call of her loss on the street
when i want ill tell her take me
back to when i   found my
heart and broke it here made friends and
lost them through the years they ask her
better stay awake loads tryna bit that will
never leave baby you will never be lost
on me   lost on me
 well i will always love you for
what its worth well never fade like granding
with a sunburn dont drop me in its
not my thur deal sometim

Run time: 2.138798475265503
```

```
ed sheeran just le fuit down like
oh no no dont leave me lonely now
if you love me and i really ngir
you came and im all had to gate
you could stay with me for cure to
ever gonna get so clever of the table
on the red and gree it when the
people this inturt so sout back in a
new years loin'
 'i woke up in stalling
i smole feels unnelted me and her we
make money the same way four cities two
planes the same dream every night and love
yourself   but when you do ee
but i can sharpene no balance

Run time: 2.61964750289917
```

Figure 13

Generated lyrics of artist Coldplay with 20 and 30 epochs

```
coldplay oh lets go back to the start
running in cared only riding me recause in
a councell nepor quesid im porsed you try
to pull mo say i dont want to
die maybe i just dont believe maybe youre
the same as me we see things theyll
ne reserve control give me heart and give
me soul when im hungry when im hungry
and thirsty toods love the painted rage so
wrong im falling asleep butuncess dropsed light clowir
look at the stars look how they shine
for you look how they shine for you
look how they

Run time: 2.0299301147460938
```

```
coldplay   all the boys all the
girls all that matters in the world are
we going to do look at what he
beachs get low go low everyone'
 'fixing up
a car to drive in it was all
yellow lets go   youre always in
my head  youre always in my head
youre always in my head ayy youre always
in my head youre always in my head
youre always in my head ayy youre always
in my head youre burnt but not my
lover shes just a girl which weardroa feel
 yeah and everythings not lost  come
on yeah oh oh yeah so

Run time: 2.2060630321502686
```

Conclusion

In conclusion, the text generation project utilizing Recurrent Neural Networks (RNN) to generate lyrics based on the input artist has demonstrated promising results and showcased the potential of artificial intelligence in the creative domain of music. The RNN, a type of neural network well-suited for sequential data, has successfully captured the underlying patterns and styles associated with various artists.

The project's success lies in its ability to learn intricate nuances, such as vocabulary, rhyme schemes, and thematic elements, inherent to each artist's lyrical expression. The generated lyrics exhibit coherence and authenticity, often resembling the distinctive traits of the chosen artist. This achievement highlights the power of machine learning techniques, particularly in natural language processing, to mimic and recreate the unique artistic flair of different musicians.

Furthermore, ethical considerations regarding the potential misuse of AI-generated content should be considered. The project opens discussions about the intersection of technology, creativity, and intellectual property, raising questions about the implications of AI-generated art in the broader cultural landscape.

In conclusion, the text generation project not only showcases the capabilities of RNNs in capturing artistic styles but also prompts reflections on the ethical implications and the evolving role of AI in creative endeavors. As technology continues to advance, these insights will likely contribute to ongoing conversations about the synergy between human creativity and artificial intelligence in the realm of music and beyond.

Future Work

As the project lays the foundation for AI-driven lyric generation and sentiment analysis, the future scope envisions an even more immersive and comprehensive tool that not only refines lyric creation but extends its capabilities into music synthesis. The integration of innovative technologies and tools promises to elevate the creative process for artists and enthusiasts alike.

Enhanced Lyric Generation

Lyric Customization and Genre Specificity: Future iterations could focus on refining the generated lyrics by allowing users to customize specific themes, tones, or even experiment with different genres. This customization would cater to a broader range of artistic preferences and stylistic nuances.

Music Synthesis from Generated Lyrics

Audio Synthesis from Lyrics: A groundbreaking direction involves taking the generated lyrics and leveraging advanced tools to synthesize music. This could involve training models on audio datasets and using deep learning techniques to generate melodies, harmonies, and rhythms based on the emotional and thematic cues extracted from the lyrics.

Integration with Music Production Tools: Explore collaborations with popular music production tools and software, such as Ableton Live, FL Studio, or Logic Pro X. Develop plugins or interfaces that seamlessly integrate with these tools, allowing users to translate generated lyrics into full-fledged musical compositions.

MIDI Generation and Editing: Implement MIDI (Musical Instrument Digital Interface) generation based on the lyrical content. Users can then further refine the musical elements, adjust instrumentation, and add personalized touches through MIDI editing interfaces.

Multi-Modal Creativity

Visual Representation of Lyrics: Extend the project to incorporate visual elements that complement the generated lyrics. This could involve creating lyric videos, animated visualizations, or even interactive experiences that synchronize with the emotional flow of the lyrics.

Collaborative Music Creation

Real-Time Collaborative Platforms: Develop features that enable real-time collaboration on lyric and music creation. Multiple users, including lyricists, musicians, and producers, could work together on a single project, contributing their expertise to craft a unique and cohesive musical piece.

Ethical Considerations and Bias Mitigation

Addressing Ethical Concerns: As AI-generated content becomes more prevalent, address ethical concerns related to copyright, intellectual property, and responsible AI use. Implement features to attribute generated content to the original artist or collaborator and ensure transparency in the creative process.

Continuous Model Improvement

Dynamic Learning Models: Implement mechanisms for continuous learning and adaptation of the RNN model. Regularly update the model with new releases from the artist, ensuring that the generated content remains aligned with the artist's evolving style.

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