



# SONG GENERATION

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# CONTENT

1. MS1 (Data preprocessing and analysis) edits
2. MS2 (Defining a model)
3. MS3 (Using a pre-trained model)



MS1

(Data preprocessing and analysis) edits

Objective:

Prepare, clean, and analyze song lyrics  
dataset

# DATA CLEANING - INITIAL STEPS

- Initial Exploratory Data Analysis
  - Check for null values
  - Examine data types
  - Summarize dataset
- Rename the 'text' column to 'lyrics'
- Remove missing values and duplicates (none found)
- Drop unnecessary columns: 'link' and 'song'



# DATA CLEANING - TEXT PREPROCESSING



- Remove non-alphabetic characters
- Remove repetitive terms: 'chorus', 'verse', 'intro', 'original', 'outro'
- Convert lyrics to lowercase
- Regular expressions for unwanted characters
- Apply the same preprocessing to artist names




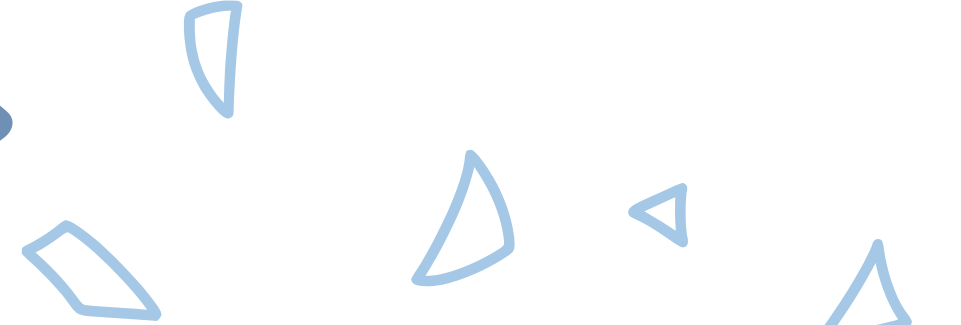

# DATA CLEANING - FINAL STEPS

- The decision against stop words removal and lemmatization
- Preserve sentence structure and rhyme
- Ignore spelling check to maintain the original lyric style



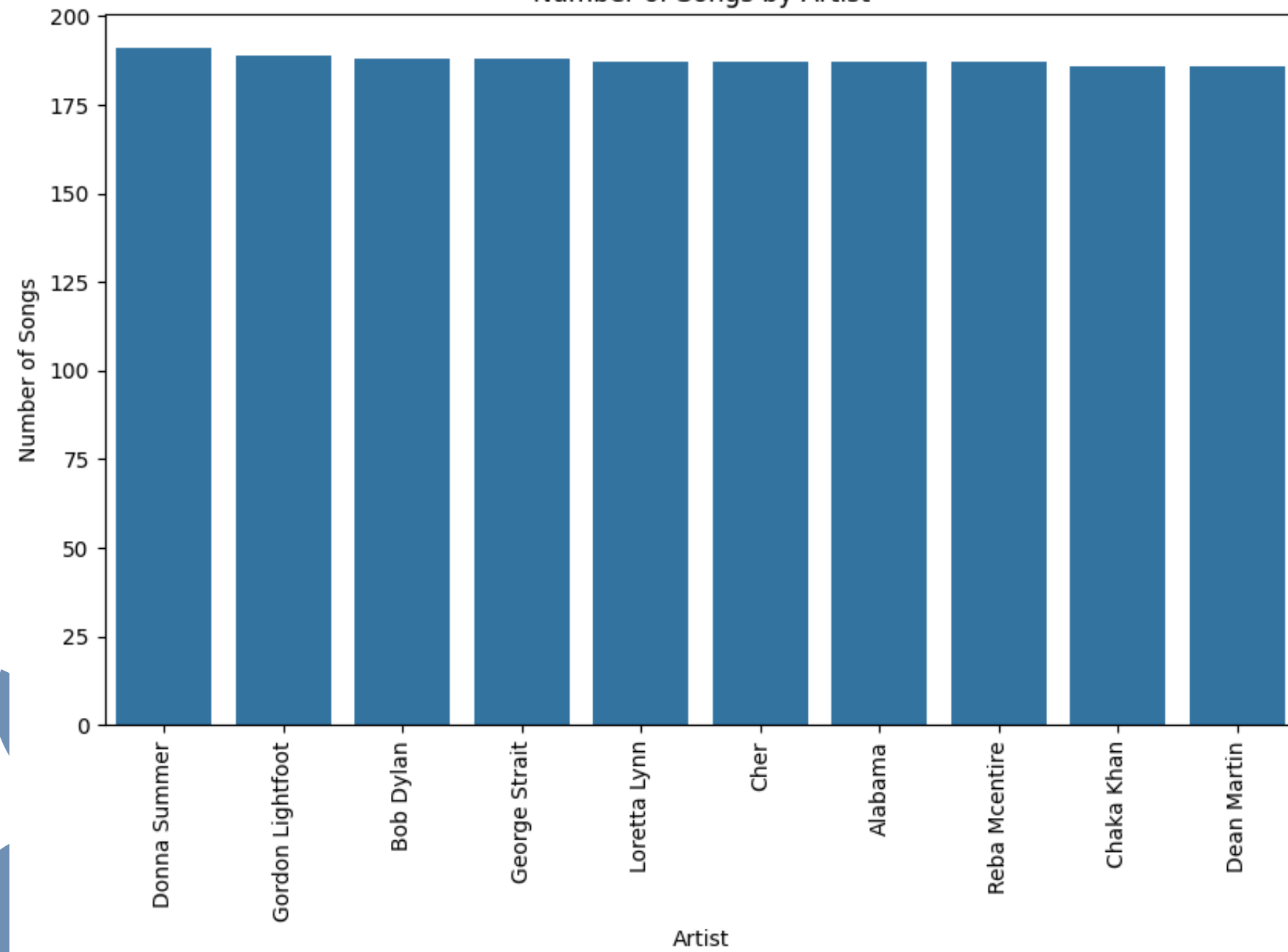
# DATA ANALYSIS - SONG DISTRIBUTION



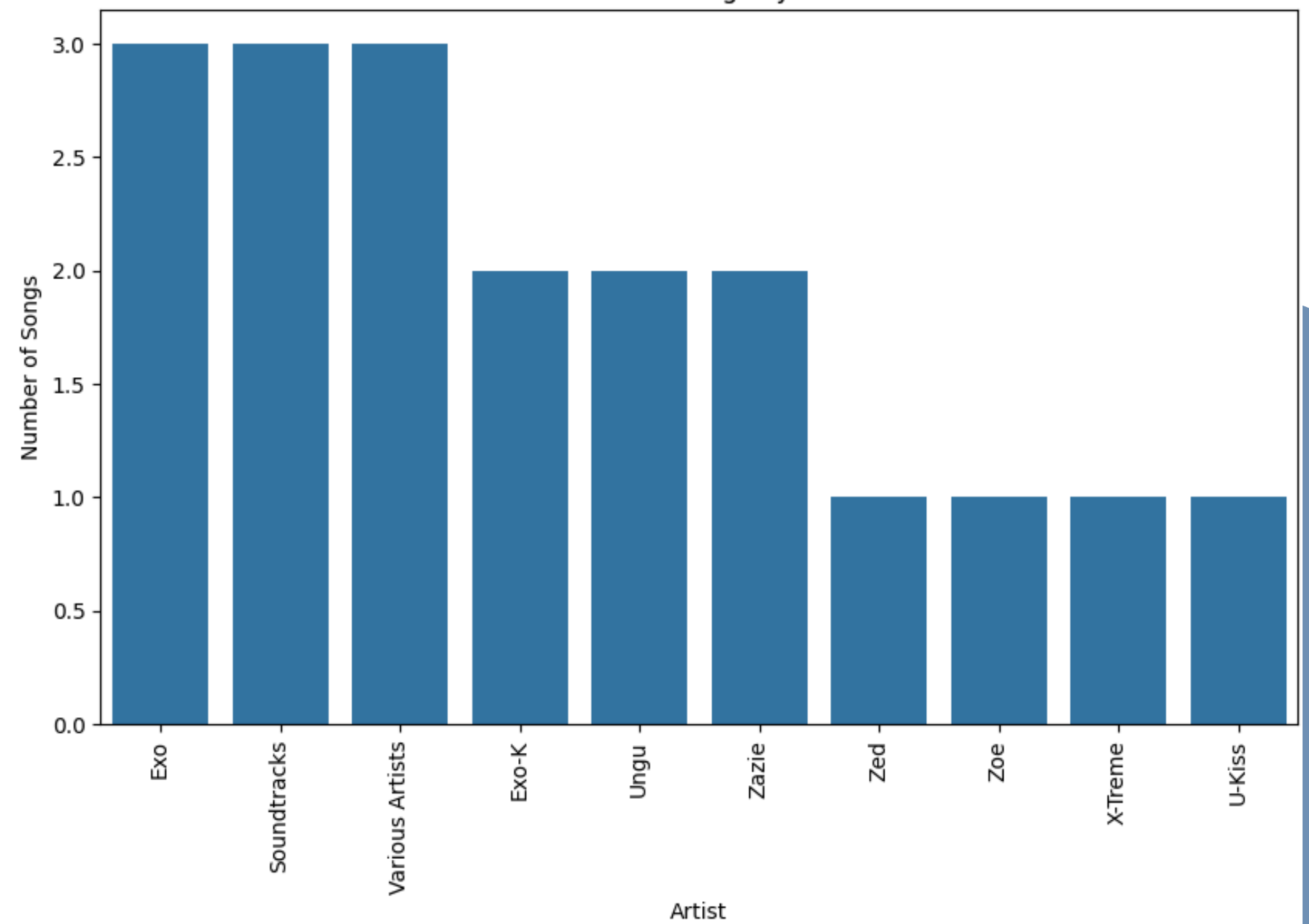
- Visualize the distribution of songs per artist
  - Bar plots: top 10 and bottom 10 artists
  - Insights: dataset composition
  - Top Artist: Donna Summer with 191 songs
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# DATA ANALYSIS - SONG DISTRIBUTION

Number of Songs by Artist




Number of Songs by Artist





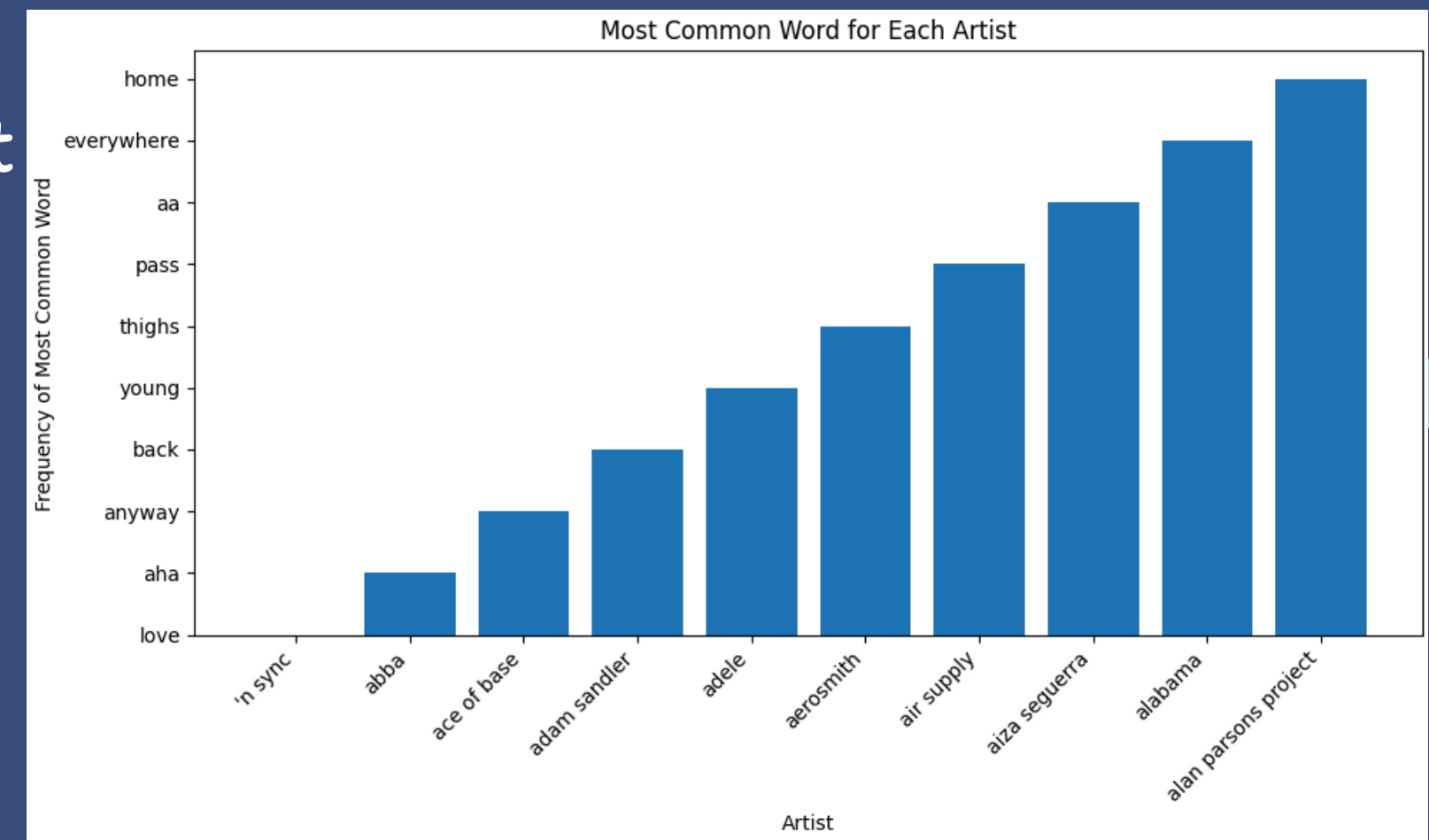
# DATA ANALYSIS - FREQUENT WORDS



- Identify the most frequent word per artist
  - Create a table of artists and their most frequent words
  - Importance: Analyze model output later
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# DATA ANALYSIS - TF-IDF

- Calculate TF-IDF for each artist's frequent word
- Purpose: Keyword extraction, information retrieval
- Remove stop words and determine frequent words
- Visualize frequencies using a bar plot

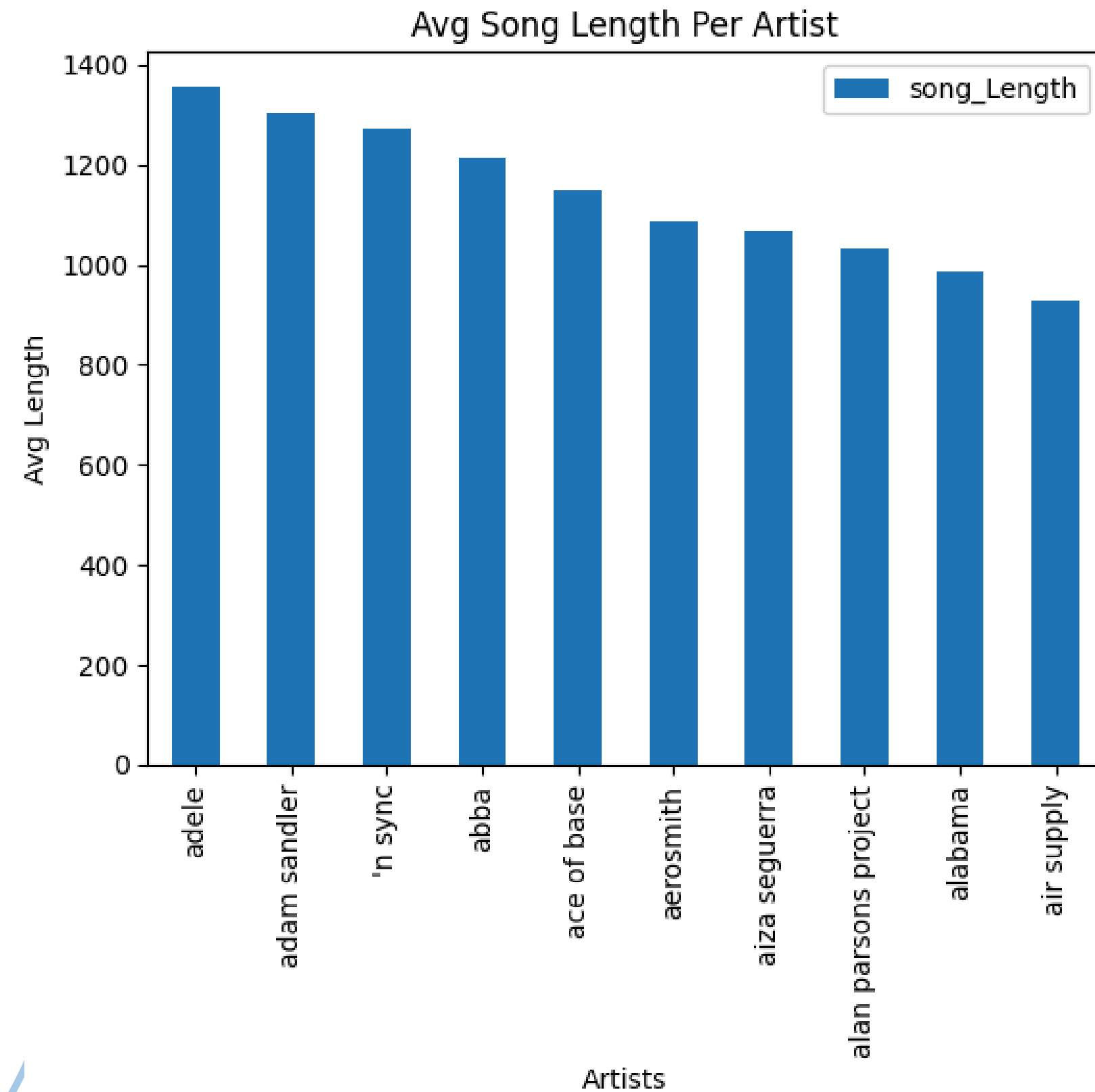




# DATA ANALYSIS - SONG LENGTH

- Analyze average song length per artist
  - Visualize the average song length for the top 10 artists
  - Create histograms for song length distribution
  - Insight: Few songs longer than 1500 words, hence truncated
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# DATA ANALYSIS - SONG LENGTH





MS2

(Defining a model)

Objectives:

Creating neural network

# DATA PREPARATION

- Joined both artist name and song lyrics
- Removed all songs with length >1500
- Eliminated the last word of each song and stored it in a new column
- Converted the lyrics to Ragged Tensor
  - Nested- variable
  - Adapts to varying song length
- One-hot encoded the lyrics





# MODEL SETUP

- We split the data into a training set and a testing set
- Initialized tokenizer
- Converted the lyrics of both sets to sequences
  - Padded the lyrics to a maximum length of 1500
- Defining a sequential model with:
  - Embedding layer
  - GRU layer
  - Dense layer
  - Sigmoid activation function



# MODEL EVALUATION



- The model was trained for 10 epochs
  - Evaluated model based on loss value
  - Defined a function to retrieve the word of the highest probability
  - The function was used to compare actual eliminated word with predicted output
  - The model resulted in a Loss of 6.97
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MS3

(Using a pre-trained model)


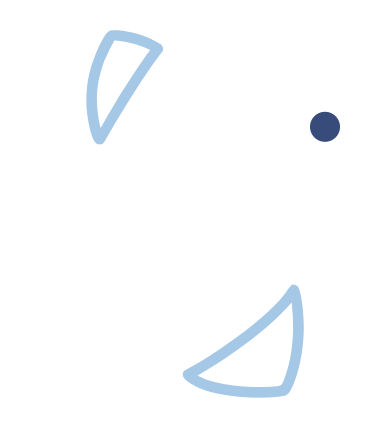
Objective:

Train a BERT2BERT model to generate the second half of song lyrics given the first half



# DATA PREPARATION



- Data Splitting: Each song's lyrics were split into two halves
  - Input Text: Combined artist's name with the first half of the lyrics using BERT2BERT separation token and start/end tokens
  - Output Text: Added start and end tokens to the second half of the lyrics
  - Data Cleaning: Removed songs longer than 1500 characters
  - Training and Test Sets: Data was split into training and test sets
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# MODEL SETUP


- Model Components: Loaded BERT encoder and decoder for BERT2BERT model
- Initialized tokenizer: Chose BERT Tokenizer for seamless pipeline integration
- Version Selection:
  - bert\_large\_uncased not supported due to RAM constraints
  - bert\_tiny\_uncased did not yield optimal results
  - bert\_base\_uncased

# TRAINING PROCESS

- Data Processing:
  - Tokenized training data
  - Converted data to PyTorch tensors
  - Created DataLoader for batching (batch size = 8)
- Training Configuration:
  - Defined optimizer and loss function
  - Trained the model for 10 epochs (approx. 7 hours)
  - Printed loss for each batch

# MODEL EVALUATION




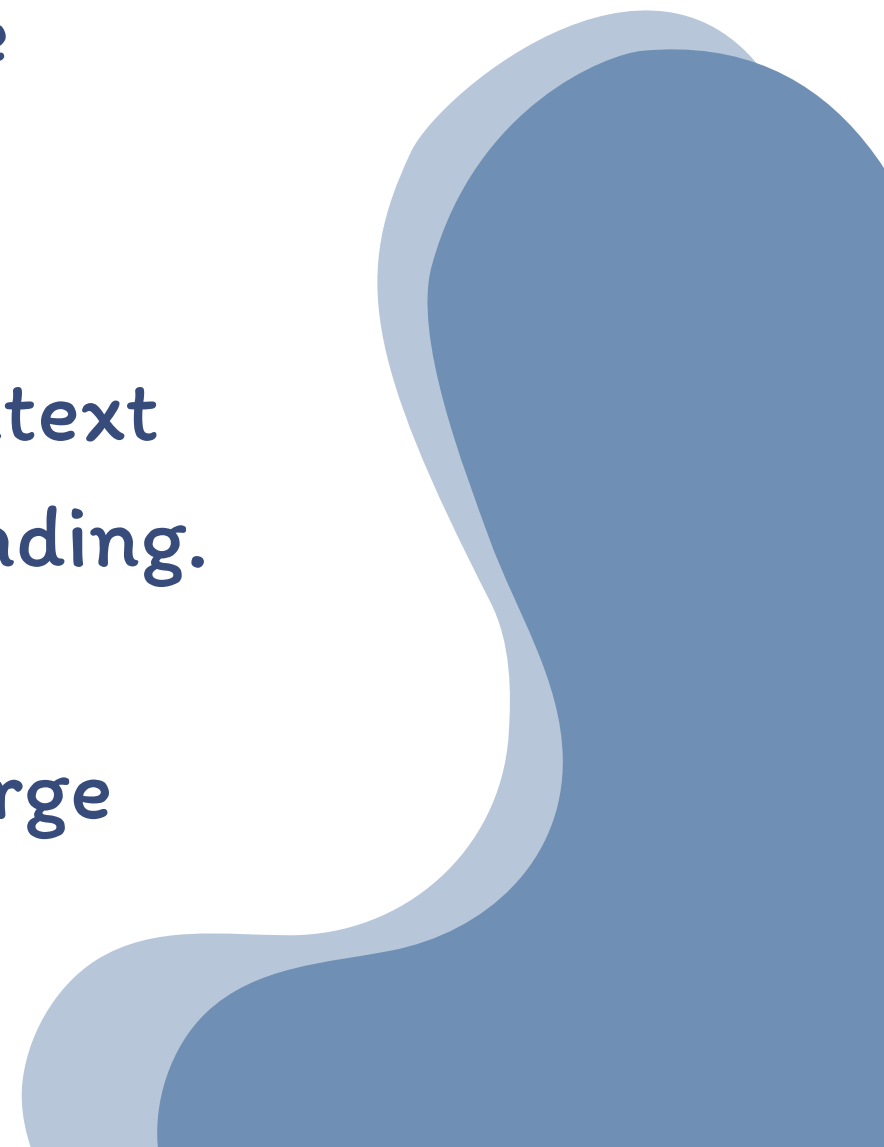
- Test Data Processing:
    - Tokenized test set
    - Converted to PyTorch tensors
    - Created DataLoader
  - Evaluation: Calculated mean loss on the test dataset
  - Result: Mean loss was approximately 0.02
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The background features a light blue and white color scheme. On the left, there are several concentric, wavy lines in a darker blue shade. In the top right corner, there are numerous dark blue dots of varying sizes. In the bottom right corner, there is a stylized leaf or branch shape in a light blue color, with small green dots at the ends of its branches.

Conclusion



# CONCLUSION

- BERT2BERT exhibited a significantly lower loss value compared to our GRU-based model.
  - Bidirectional Processing: BERT is bidirectional, considering both left and right context when encoding a token, unlike GRUs
  - Context Over Long Sequences: BERT can understand context over long sequences providing a more complex understanding.
  - Pre-trained on Large Datasets: BERT's pre-training on large datasets makes it reliable for tasks like lyrics generation
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Thank You