SONG GENERATION

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CONTENT

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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

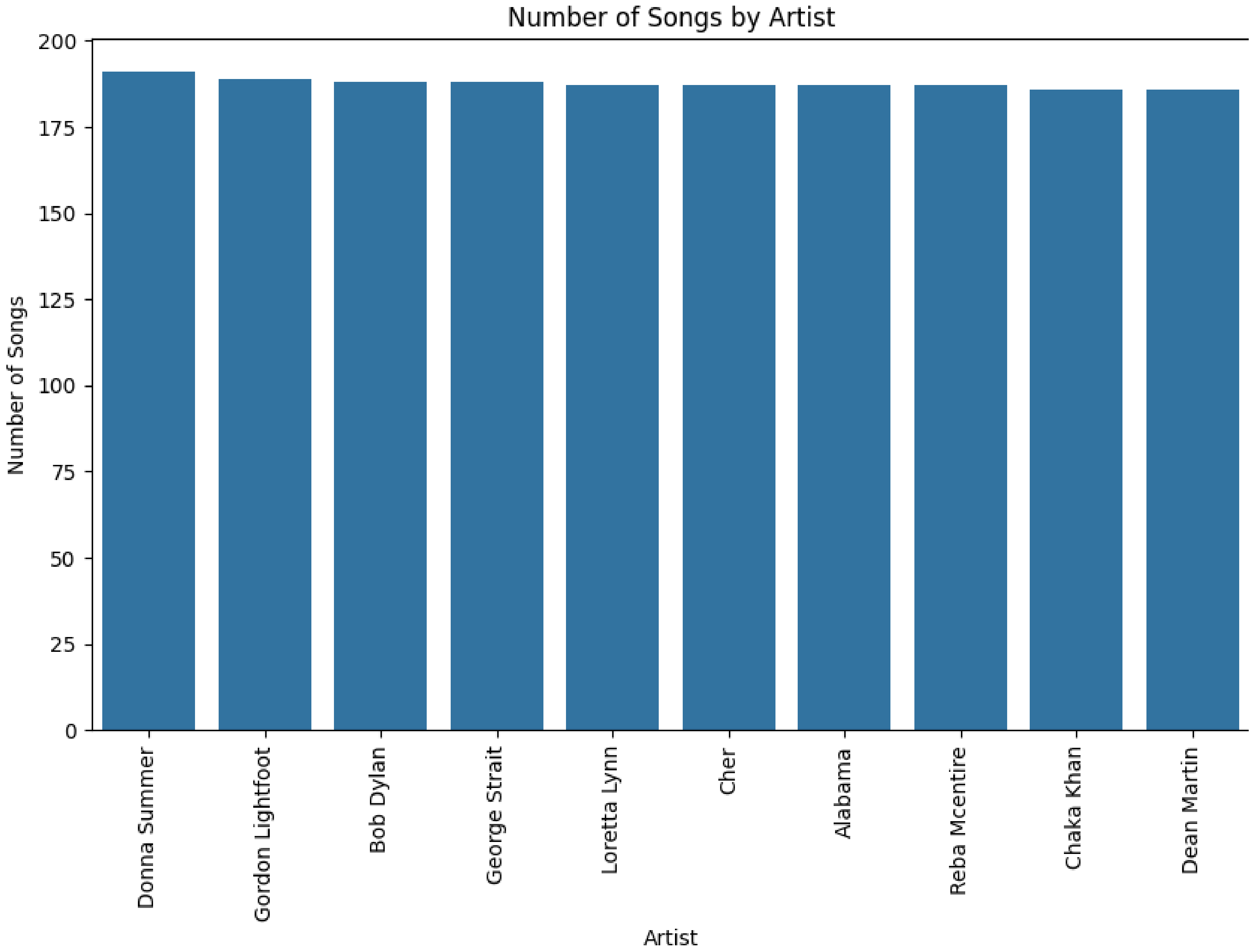
DATA CLEANING - FINAL STEPS

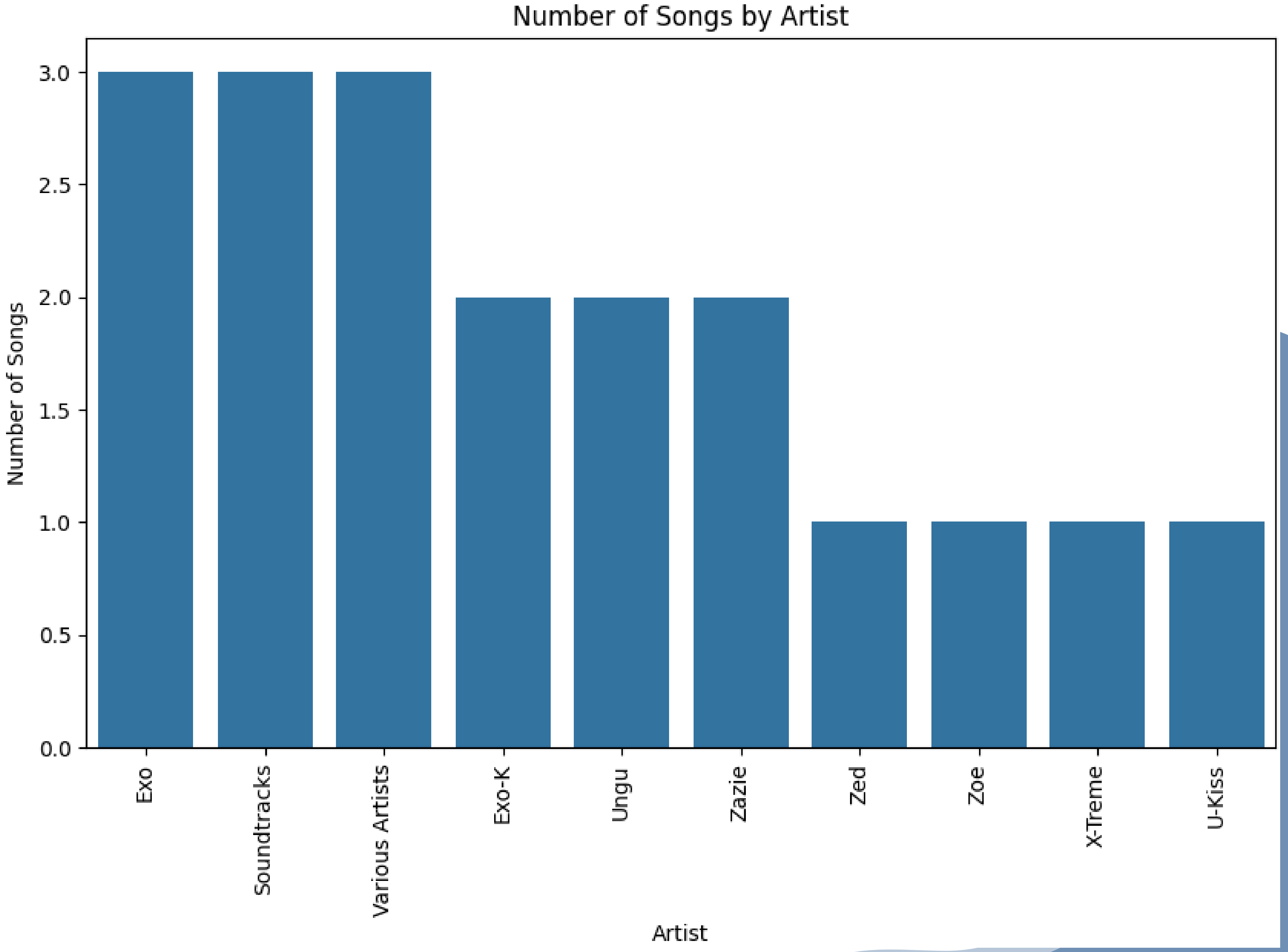
- The decision against stop words removal and lemmatization
- Preserve sentence structure and rhyme
- Ignore spelling check to maintain the original lyric style

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

DATA ANALYSIS - SONG DISTRIBUTION



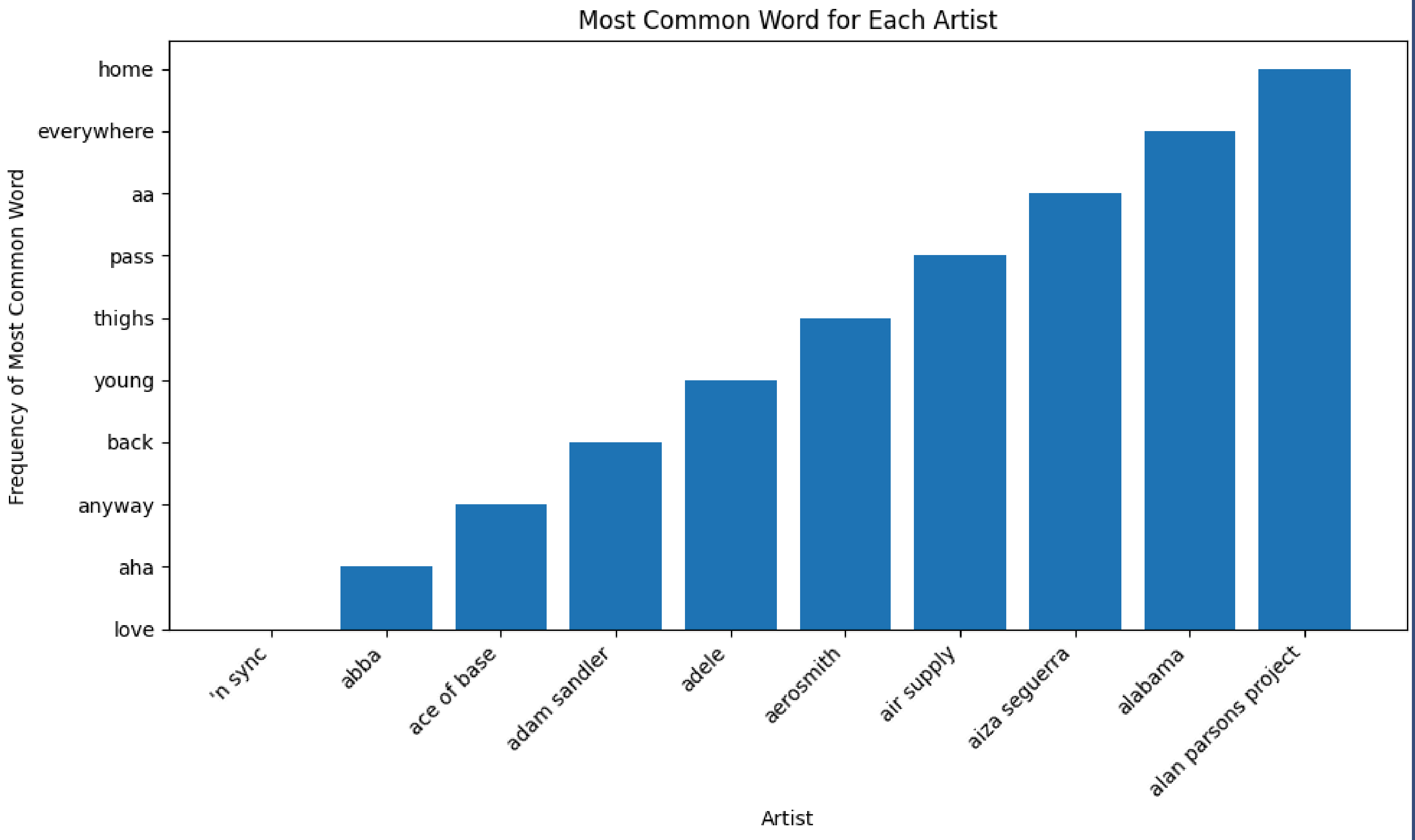


DATA ANALYSIS - FREQUENT WORDS

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

DATA ANALYSIS - TF-IDF

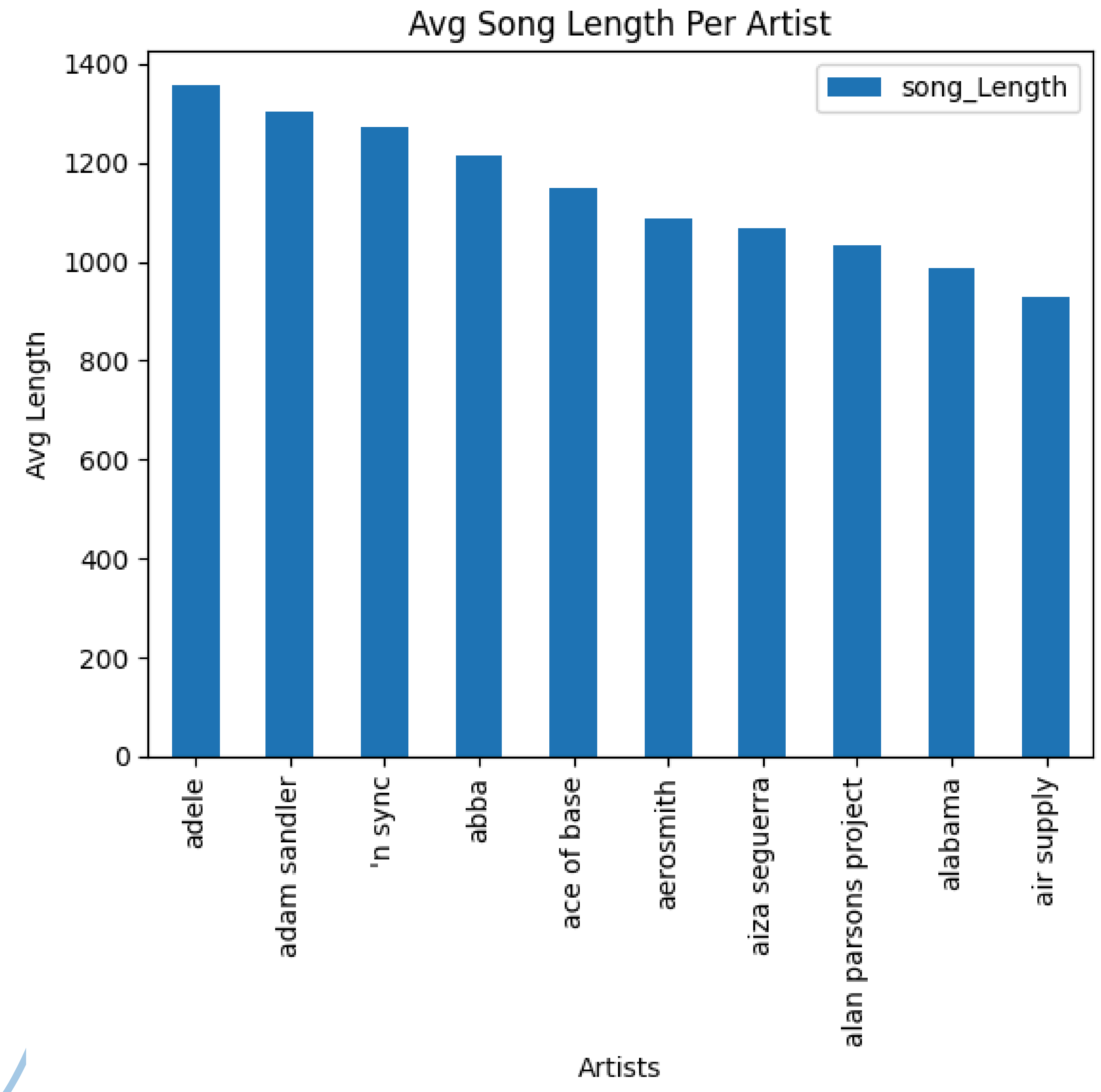
- Calculate TF-IDF for each artist's frequent word
- Purpose: Keyword extraction, information retrieval
- Remove stop words and determine frequent words
- Visualize frequencies using a bar plot



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

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

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

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

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

Thank You