

```

1 import pandas as pd
2 data = pd.read_csv('/content/all_songs_data.csv')
3 print(data.head())
4

```

```

0           Album \
1           Battle of New Orleans
2           That's All
3           "Mr Personality's" 15 Big Hits
4           The Greatest Hits Of Frankie Avalon
5           Paul Anka Sings His Big 15

0           Album URL           Artist \
1 https://genius.com/albums/Johnny-horton/Battle... Johnny Horton
2 https://genius.com/albums/Bobby-darin/That-s-all Bobby Darin
3 https://genius.com/albums/Lloyd-price/Mr-perso... Lloyd Price
4 https://genius.com/albums/Frankie-avalon/The-g... Frankie Avalon
5 https://genius.com/albums/Paul-anka/Paul-anka-... Paul Anka

0           Featured Artists           Lyrics \
1           [] [Verse 1] In 1814 we took a little trip Along ...
2           [] Oh the shark, babe Has such teeth, dear And he...
3           [] Over and over I tried to prove my love to you ...
4           [] Hey, Venus! Oh, Venus! Venus, if you will Ple...
5           [] I'm just a lonely boy Lonely and blue I'm all ...

0           Media Rank Release Date \
1 [{"native_uri": "spotify:track:0dwpcQkeZqpuoA..."} 1 1959-04-01
2 [{"native_uri": "spotify:track:3E5ndy0f06vFDEI..."} 2 NaN
3 [{"provider": "youtube", "start": 0, "type": "..."} 3 NaN
4           [] 4 NaN
5           [] 5 NaN

0           Song Title \
1           The Battle Of New Orleans
2           Mack The Knife
3           Personality
4           Venus
5           Lonely Boy

0           Song URL \
1 https://genius.com/Johnny-horton-the-battle-of...
2 https://genius.com/Bobby-darin-mack-the-knife-...
3 https://genius.com/Lloyd-price-personality-lyrics
4 https://genius.com/Frankie-avalon-venus-lyrics
5 https://genius.com/Paul-anka-lonely-boy-lyrics

0           Writers           Year
1 [{"api_path": "/artists/561913", "header_image..."} 1959.0
2 [{"api_path": "/artists/218851", "header_image..."} 1959.0
3 [{"api_path": "/artists/355804", "header_image..."} 1959.0
4 [{"api_path": "/artists/1113175", "header_imag..."} 1959.0
5           [] 1959.0

```

```

1 # Descriptive statistics for numerical columns
2 print(data.describe())
3
4 # Descriptive statistics for categorical columns
5 print(data.describe(include='object'))
6

```

```

0           Rank           Year
1 count 6500.000000 6500.000000
2 mean 50.500000 1991.000000
3 std 28.868291 18.763106
4 min 1.000000 1959.000000
5 25% 25.750000 1975.000000
6 50% 50.500000 1991.000000
7 75% 75.250000 2007.000000
8 max 100.000000 2023.000000

0           Album           Album URL \
1 count 6036 6036
2 unique 4202 4285
3 top Greatest Hits https://genius.com/albums/Morgan-wallen/One-th...
4 freq 21 9

0           Artist Featured Artists           Lyrics Media Release Date \
1 count 6500 6384 6384 4563
2 unique 3181 612 6044 5054 3233
3 top Madonna [] [Instrumental] [] 2022-05-06
4 freq 35 5492 21 1043 10

```

	Song Title	Song URL	Writers
count	6500	6384	6384
unique	5798	6065	4184
top	Stay	https://genius.com/Billboard-hot-rap-songs-cha...	[]
freq	7	5	971

```

1 rank_stats = data['Rank'].describe()
2 rank_frequency = data['Rank'].value_counts().sort_index()
3 top_artists = data['Artist'].value_counts().head(10)
4
5 print("Descriptive Statistics for Song Ranks:")
6 print(rank_stats)
7 print("\nFrequency of Songs by Rank:")
8 print(rank_frequency)
9 print("\nTop 10 Artists by Number of Songs:")
10 print(top_artists)
11

```

→ Descriptive Statistics for Song Ranks:

```

count    6500.000000
mean      50.500000
std       28.868291
min        1.000000
25%       25.750000
50%       50.500000
75%       75.250000
max       100.000000
Name: Rank, dtype: float64

```

Frequency of Songs by Rank:

```

Rank
1      65
2      65
3      65
4      65
5      65
..
96     65
97     65
98     65
99     65
100    65
Name: count, Length: 100, dtype: int64

```

Top 10 Artists by Number of Songs:

```

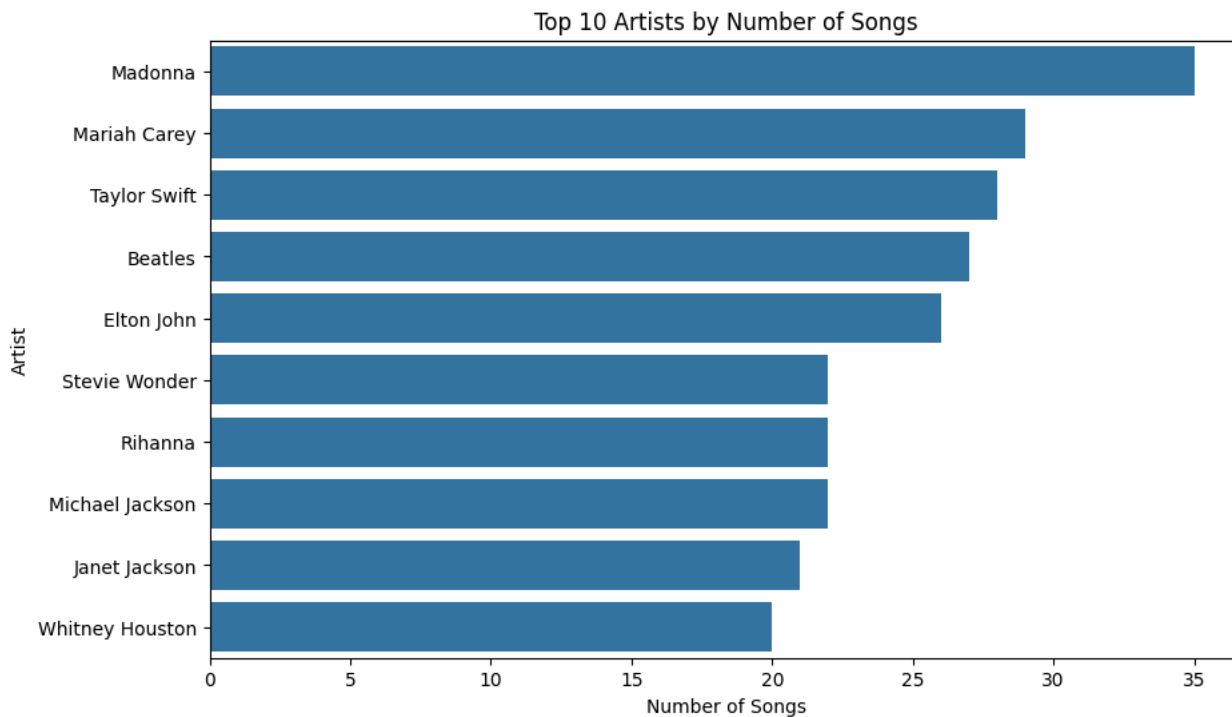
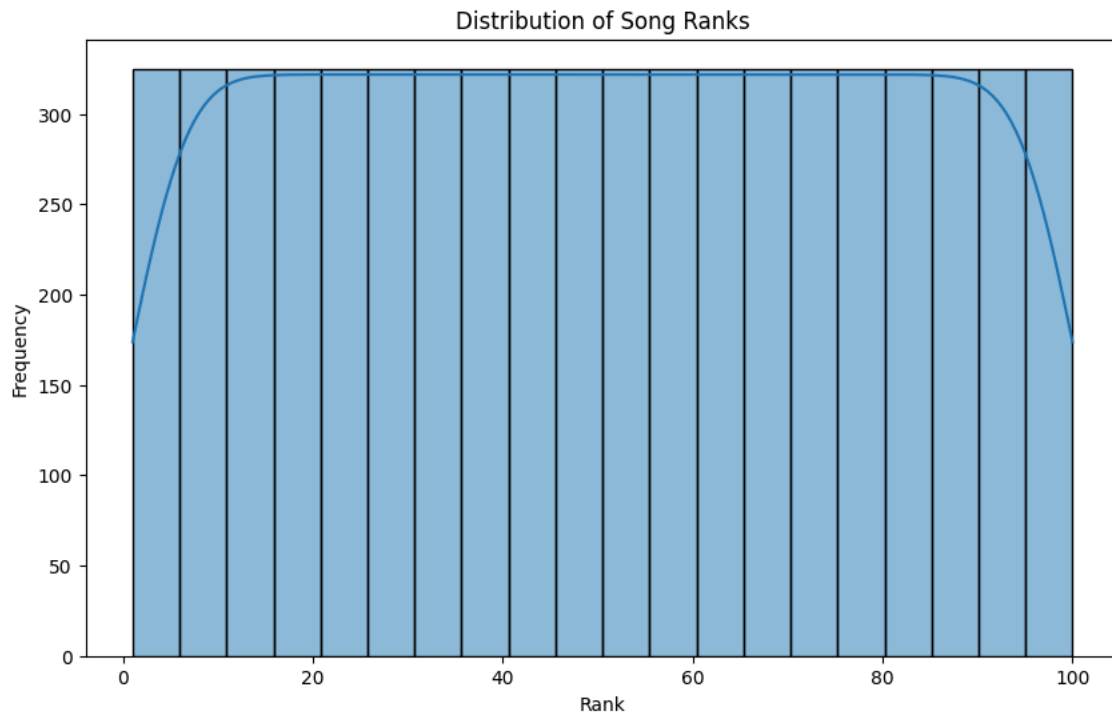
Artist
Madonna      35
Mariah Carey  29
Taylor Swift  28
Beatles      27
Elton John   26
Stevie Wonder 22
Rihanna      22
Michael Jackson 22
Janet Jackson 21
Whitney Houston 20
Name: count, dtype: int64

```

```

1 import matplotlib.pyplot as plt
2 import seaborn as sns
3
4 plt.figure(figsize=(10, 6))
5 sns.histplot(data['Rank'], bins=20, kde=True)
6 plt.title('Distribution of Song Ranks')
7 plt.xlabel('Rank')
8 plt.ylabel('Frequency')
9 plt.show()
10
11 top_artists = data['Artist'].value_counts().head(10)
12 plt.figure(figsize=(10, 6))
13 sns.barplot(x=top_artists.values, y=top_artists.index)
14 plt.title('Top 10 Artists by Number of Songs')
15 plt.xlabel('Number of Songs')
16 plt.ylabel('Artist')
17 plt.show()
18

```



```

1 # Converting 'Release Date' to datetime
2 data['Release Date'] = pd.to_datetime(data['Release Date'])
3
4 data['Year'] = data['Release Date'].dt.year
5
6
7
8
9 rank_year_corr = data[['Year', 'Rank']].groupby('Year').mean().reset_index()
10 rank_year_corr['Rank'] = rank_year_corr['Rank'].round(2)
11
12 correlation = data['Year'].corr(data['Rank'])
13
14 top_artists = data['Artist'].value_counts().head(10).index
15 rank_distribution_top_artists = data[data['Artist'].isin(top_artists)].groupby('Artist')['Rank'].describe()
16
17 print("Average Rank by Year:")
18 print(rank_year_corr)
19 print("\nCorrelation between Year and Rank:")

```

```

12 print(correlation)
13 print("\nRank Distribution by Top 10 Artists:")
14 print(rank_distribution_top_artists)
15

```

➦ Average Rank by Year:

	Year	Rank
0	1877.0	26.00
1	1922.0	70.00
2	1955.0	52.00
3	1957.0	77.00
4	1958.0	72.00
..
66	2020.0	52.36
67	2021.0	45.94
68	2022.0	48.67
69	2023.0	53.90
70	2024.0	82.00

[71 rows x 2 columns]

Correlation between Year and Rank:
0.04014067434061861

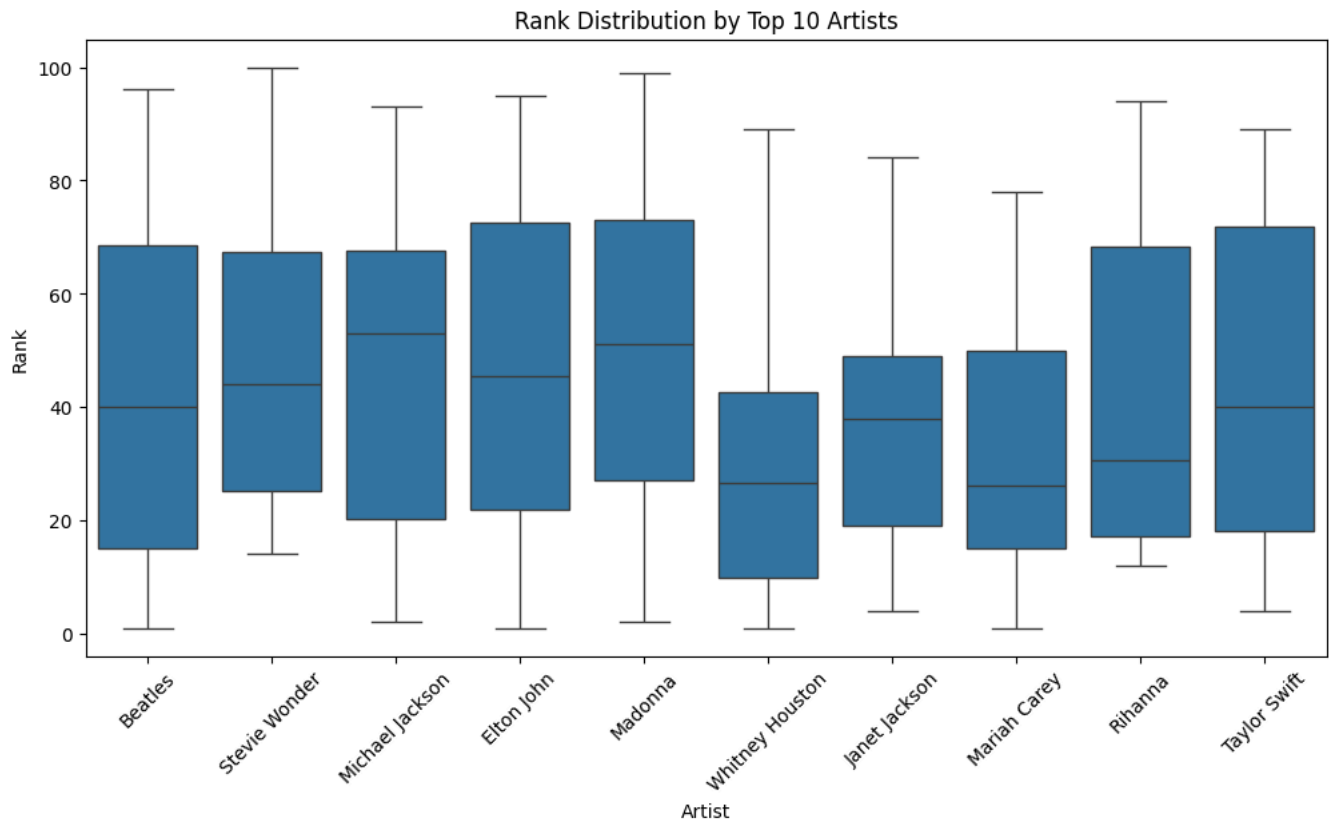
Rank Distribution by Top 10 Artists:

	count	mean	std	min	25%	50%	75%	max
Artist								
Beatles	27.0	42.777778	31.624398	1.0	15.00	40.0	68.50	96.0
Elton John	26.0	47.038462	29.200659	1.0	21.75	45.5	72.50	95.0
Janet Jackson	21.0	38.619048	21.973794	4.0	19.00	38.0	49.00	84.0
Madonna	35.0	49.285714	28.678308	2.0	27.00	51.0	73.00	99.0
Mariah Carey	29.0	33.724138	24.335301	1.0	15.00	26.0	50.00	78.0
Michael Jackson	22.0	47.409091	30.316833	2.0	20.25	53.0	67.50	93.0
Rihanna	22.0	42.090909	29.012163	12.0	17.25	30.5	68.25	94.0
Stevie Wonder	22.0	48.318182	26.141349	14.0	25.25	44.0	67.25	100.0
Taylor Swift	28.0	43.642857	27.214123	4.0	18.00	40.0	71.75	89.0
Whitney Houston	20.0	29.200000	23.625588	1.0	9.75	26.5	42.50	89.0

```

1 top_artists = data['Artist'].value_counts().head(10).index
2 plt.figure(figsize=(12, 6))
3 sns.boxplot(x='Artist', y='Rank', data=data[data['Artist'].isin(top_artists)])
4 plt.title('Rank Distribution by Top 10 Artists')
5 plt.xlabel('Artist')
6 plt.ylabel('Rank')
7 plt.xticks(rotation=45)
8 plt.show()
9

```



At this stage, I am moving on to exploring the categorical data and cleaning/preprocessing the text

```

1 # Checking for missing values
2 print(f"Missing Lyrics: {data['Lyrics'].isnull().sum()}")
3 empty_lyrics = data[data['Lyrics'].apply(lambda x: isinstance(x, str) and len(x) == 0)]
4 print(f"Empty Lyrics: {empty_lyrics.shape[0]}")
5 invalid_lyrics = data[data['Lyrics'].apply(lambda x: not isinstance(x, str))]
6 print(f"Invalid Lyrics (Non-string values): {invalid_lyrics.shape[0]}")
7

```

Missing Lyrics: 116
Empty Lyrics: 0
Invalid Lyrics (Non-string values): 116

```

1 # Removing missing values
2 data_cleaned = data.dropna(subset=['Lyrics'])
3
4 data_cleaned = data_cleaned[data_cleaned['Lyrics'].apply(lambda x: isinstance(x, str))]
5
6 print(f"Data after cleaning: {data_cleaned.shape[0]} rows")
7 print(data_cleaned['Lyrics'].isnull().sum()) # Check if there are any missing lyrics
8

```

Data after cleaning: 6384 rows
0

```

1 !pip install spacy
2 !python -m spacy download en_core_web_sm

```



```
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.11 in /usr/local/lib/python3.10/dist-packages (from spacy<3.0.0,>=3.0.0)
Requirement already satisfied: spacy-loggers<2.0.0,>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: thinc<8.3.0,>=8.2.2 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: wasabi<1.2.0,>=0.9.1 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: srsly<3.0.0,>=2.4.3 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: catalogue<2.1.0,>=2.0.6 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: weasel<0.5.0,>=0.1.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: typer<1.0.0,>=0.3.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: requests<3.0.0,>=2.13.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: pydantic!=1.8,!<1.8.1,<3.0.0,>=1.7.4 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: Jinja2 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: langcodes<4.0.0,>=3.2.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: numpy>=1.19.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.8.0,>=3.0.0)
Requirement already satisfied: language-data>=1.2 in /usr/local/lib/python3.10/dist-packages (from langcodes<4.0.0,>=3.2.0)
Requirement already satisfied: annotated-types>=0.6.0 in /usr/local/lib/python3.10/dist-packages (from pydantic!=1.8,!<1.8.1,<3.0.0,>=1.7.4)
Requirement already satisfied: pydantic-core==2.27.1 in /usr/local/lib/python3.10/dist-packages (from pydantic!=1.8,!<1.8.1,<3.0.0,>=1.7.4)
Requirement already satisfied: typing-extensions>=4.12.2 in /usr/local/lib/python3.10/dist-packages (from pydantic!=1.8,!<1.8.1,<3.0.0,>=1.7.4)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0)
Requirement already satisfied: blis<0.8.0,>=0.7.8 in /usr/local/lib/python3.10/dist-packages (from thinc<8.3.0,>=8.2.2)
Requirement already satisfied: confection<1.0.0,>=0.0.1 in /usr/local/lib/python3.10/dist-packages (from thinc<8.3.0,>=8.2.2)
Requirement already satisfied: click>=8.0.0 in /usr/local/lib/python3.10/dist-packages (from typer<1.0.0,>=0.3.0)
Requirement already satisfied: shellingham>=1.3.0 in /usr/local/lib/python3.10/dist-packages (from typer<1.0.0,>=0.3.0)
Requirement already satisfied: rich>=10.11.0 in /usr/local/lib/python3.10/dist-packages (from typer<1.0.0,>=0.3.0)
Requirement already satisfied: cloudpathlib<1.0.0,>=0.7.0 in /usr/local/lib/python3.10/dist-packages (from weasel<0.5.0,>=0.1.0)
Requirement already satisfied: smart-open<8.0.0,>=5.2.1 in /usr/local/lib/python3.10/dist-packages (from weasel<0.5.0,>=0.1.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from Jinja2)
Requirement already satisfied: marisa-trie>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from language-data>=1.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.10/dist-packages (from rich>=10.11.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.10/dist-packages (from rich>=10.11.0)
Requirement already satisfied: wrapt in /usr/local/lib/python3.10/dist-packages (from smart-open<8.0.0,>=5.2.1)
Requirement already satisfied: mdurl~0.1 in /usr/local/lib/python3.10/dist-packages (from markdown-it-py>=2.2.0)
```

✓ Download and installation successful

You can now load the package via `spacy.load('en_core_web_sm')`

▲ Restart to reload dependencies

If you are in a Jupyter or Colab notebook, you may need to restart Python in order to load all the package's dependencies. You can do this by selecting the 'Restart kernel' or 'Restart runtime' option.

1 Start coding or generate with AI.

Next, I am loading the necessary tools to preprocess the lyrical data

```
1 import spacy
2 import re
3 import nltk
4 from nltk.corpus import stopwords
5 from nltk.stem import WordNetLemmatizer
6 nltk.download('wordnet')
7 nltk.download('stopwords')
8
9
10
11 # Implementing custom stopwords
12 custom_stopwords = set(stopwords.words('english')).union({'chorus', 'verse', 'bridge', 'hook', 'intro', 'outro', 'nt'})
13 nlp = spacy.load("en_core_web_sm")
14 lemmatizer = WordNetLemmatizer()
15
16 #in the first round, i noticed contractions were not removed properly so I used a dictionary to ensure removal
17 def expand_contractions(text):
18     contractions_dict = {
19         "don't": "do not", "can't": "cannot", "won't": "will not", "didn't": "did not",
20         "isn't": "is not", "aren't": "are not", "wasn't": "was not", "weren't": "were not",
21         "hasn't": "has not", "haven't": "have not", "hadn't": "had not", "doesn't": "does not",
22         "didn't": "did not", "couldn't": "could not", "shouldn't": "should not", "mightn't": "might not",
23         "mustn't": "must not", "let's": "let us", "i'm": "i am", "you're": "you are", "he's": "he is",
24         "she's": "she is", "it's": "it is", "we're": "we are", "they're": "they are", "that's": "that is",
25         "what's": "what is", "who's": "who is", "where's": "where is", "how's": "how is"
26     }
27     for word, expansion in contractions_dict.items():
28         text = re.sub(r'\b' + word + r'\b', expansion, text)
29     return text
```

```

30
31 def preprocess_text(text):
32     text = expand_contractions(text)
33
34     # Converting to lowercase
35     text = text.lower()
36
37     # Removing non-alphanumeric characters (keeping spaces and words)
38     text = re.sub(r'^a-zA-Z\s|', '', text)
39
40     # Tokenizing the text using spaCy
41     doc = nlp(text)
42
43     words = [token.text for token in doc if token.text not in custom_stopwords and not token.is_punct]
44
45     # Lemmatizing words
46     words = [lemmatizer.lemmatize(word) for word in words]
47
48     # Rejoining words
49     cleaned_text = ' '.join(words)
50
51     return cleaned_text
52 data_cleaned['cleaned_lyrics'] = data_cleaned['Lyrics'].apply(preprocess_text)
53
54 print(data_cleaned[['Song Title', 'Lyrics', 'cleaned_lyrics']].head())
55

```

```

[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Unzipping corpora/stopwords.zip.
Song Title \
0 The Battle Of New Orleans
1 Mack The Knife
2 Personality
3 Venus
4 Lonely Boy

Lyrics \
0 [Verse 1] In 1814 we took a little trip Along ...
1 Oh the shark, babe Has such teeth, dear And he...
2 Over and over I tried to prove my love to you ...
3 Hey, Venus! Oh, Venus! Venus, if you will Ple...
4 I'm just a lonely boy Lonely and blue I'm all ...

cleaned_lyrics
0 took little trip along colonel jackson mig...
1 oh shark babe teeth dear show pearly white jac...
2 tried prove love friend say fool ill fool ...
3 hey venus oh venus venus please send little ...
4 lonely boy lonely blue alone nothin got ever...

```

Now that the data is preprocessed, we move on to vectorizing the text data to fit the LDA model

```

1 import pandas as pd
2 from sklearn.feature_extraction.text import CountVectorizer
3 from sklearn.decomposition import LatentDirichletAllocation
4 import matplotlib.pyplot as plt
5 import seaborn as sns
6
7 texts = data_cleaned['cleaned_lyrics'].dropna()
8
9 vectorizer = CountVectorizer(stop_words='english', max_features=5000)
10
11 X = vectorizer.fit_transform(texts)
12
13 lda = LatentDirichletAllocation(n_components=5, random_state=42)
14 lda.fit(X)
15
16 # Retrieving the words for with each topic
17 words = vectorizer.get_feature_names_out()
18
19 #display/interpret top words/topic
20 def print_top_words(model, feature_names, n_top_words=10):
21     topic_labels = {}
22     for topic_idx, topic in enumerate(model.components_):
23         top_words_idx = topic.argsort()[::-n_top_words - 1:-1]
24         top_words = [feature_names[i] for i in top_words_idx]

```

```
25
26
27     print(f"Topic {topic_idx + 1}:")
28     print(" ".join(top_words))
29
30     #Labels/category interpretations were created by human coder after first iteration retrieved top words
31     if topic_idx == 0:
32         topic_labels[topic_idx] = "Reflections and Life Experiences"
33     elif topic_idx == 1:
34         topic_labels[topic_idx] = "Communication and Family Dynamics"
35     elif topic_idx == 2:
36         topic_labels[topic_idx] = "Love and Emotional Longing"
37     elif topic_idx == 3:
38         topic_labels[topic_idx] = "Street Culture and Raw Emotions"
39     elif topic_idx == 4:
40         topic_labels[topic_idx] = "Romantic Desire and Affection"
41
42     return topic_labels
43
44 topic_labels = print_top_words(lda, words)
45
46 # Adding the dominant topic for each song
47 topic_probabilities = lda.transform(X)
48 dominant_topic = topic_probabilities.argmax(axis=1)
49 data_cleaned['dominant_topic'] = dominant_topic
50
51 # Mapping topic labels to the songs
52 data_cleaned['topic_label'] = data_cleaned['dominant_topic'].map(topic_labels)
53
54 print(data_cleaned[['Song Title', 'dominant_topic', 'topic_label']].head())
55
56 # Visualizing topic distribution across songs
57 plt.figure(figsize=(10, 6))
58 sns.countplot(x='topic_label', data=data_cleaned, palette='viridis')
59 plt.title('Distribution of Topics Across Songs')
60 plt.xlabel('Topic Label')
61 plt.ylabel('Number of Songs')
62 plt.xticks(rotation=45)
63 plt.show()
64
```



```

Topic 1:
said like man day time old know hand make say
Topic 2:
say tell mr know mam like boy come dad want
Topic 3:
love time night heart day away ill know life let
Topic 4:
like nigga got la bitch shit know love ai fuck
Topic 5:
baby yeah love oh know got like na want girl

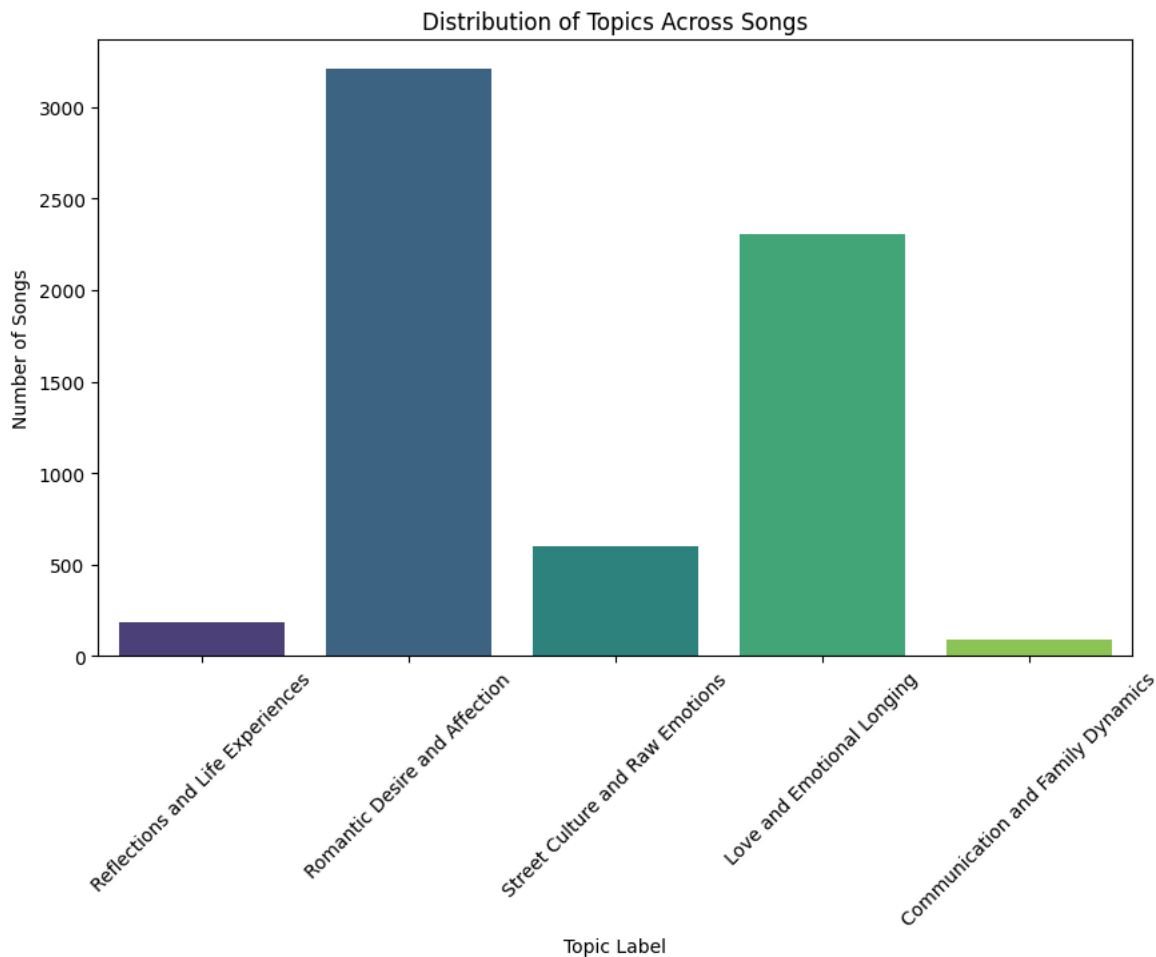
```

	Song Title	dominant_topic	topic_label
0	The Battle Of New Orleans	0	Reflections and Life Experiences
1	Mack The Knife	4	Romantic Desire and Affection
2	Personality	3	Street Culture and Raw Emotions
3	Venus	0	Reflections and Life Experiences
4	Lonely Boy	2	Love and Emotional Longing

<ipython-input-13-e7fbc0700270>:58: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and

```
sns.countplot(x='topic_label', data=data_cleaned, palette='viridis')
```



Testing the coherence score to confirm quality of topics

```

1 from gensim.models import CoherenceModel
2 from gensim.corpora import Dictionary
3 import numpy as np
4
5 # Convert the feature matrix back to text format
6 texts = [text.split() for text in data_cleaned['cleaned_lyrics']]
7 dictionary = Dictionary(texts)
8 corpus = [dictionary.doc2bow(text) for text in texts]
9
10 # Map sklearn LDA topics to Gensim format
11 lda_sklearn_topics = []
12 for topic in lda.components_:
13     topic_words = np.argsort(topic)[-10:] # Top 10 words for each topic
14     lda_sklearn_topics.append([words[i] for i in topic_words])

```

```

15
16 # Compute coherence score
17 coherence_model = CoherenceModel(topics=lda_sklearn_topics, texts=texts, dictionary=dictionary, coherence='c_v')
18 coherence_score = coherence_model.get_coherence()
19
20 print(f"Coherence Score of LDA Model: {coherence_score}")
21

```

→ Coherence Score of Existing LDA Model: 0.5165370826945308

0.51 coherence score represents moderate coherence

Comparing ML models for classifying the dominant topic of song lyrics

```

1 from sklearn.model_selection import train_test_split, cross_val_score
2 from sklearn.linear_model import LogisticRegression
3 from sklearn.ensemble import RandomForestClassifier
4 from sklearn.svm import SVC
5 from sklearn.metrics import classification_report, accuracy_score
6 from scipy.stats import ttest_rel
7 import time
8
9 #Preprocessing
10 vectorizer = CountVectorizer(stop_words='english', max_features=5000)
11 X = vectorizer.fit_transform(data_cleaned['cleaned_lyrics'].dropna())
12 y = data_cleaned['dominant_topic']
13
14 #Splitting the data
15 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
16
17 # Logistic Regression
18 start_train = time.time()
19 logreg = LogisticRegression(max_iter=1000)
20 logreg_cv_scores = cross_val_score(logreg, X_train, y_train, cv=5)
21 logreg.fit(X_train, y_train)
22 end_train = time.time()
23
24 start_predict = time.time()
25 logreg_preds = logreg.predict(X_test)
26 end_predict = time.time()
27
28 print("\nLogistic Regression")
29 print("Cross-validation scores:", logreg_cv_scores)
30 print("Accuracy:", accuracy_score(y_test, logreg_preds))
31 print(classification_report(y_test, logreg_preds))
32 print(f"Training time: {end_train - start_train:.4f} seconds")
33 print(f"Prediction time: {end_predict - start_predict:.4f} seconds")
34
35 # Random Forest
36 start_train = time.time()
37 rf = RandomForestClassifier(random_state=42)
38 rf_cv_scores = cross_val_score(rf, X_train, y_train, cv=5)
39 rf.fit(X_train, y_train)
40 end_train = time.time()
41
42 start_predict = time.time()
43 rf_preds = rf.predict(X_test)
44 end_predict = time.time()
45
46 print("\nRandom Forest")
47 print("Cross-validation scores:", rf_cv_scores)
48 print("Accuracy:", accuracy_score(y_test, rf_preds))
49 print(classification_report(y_test, rf_preds))
50 print(f"Training time: {end_train - start_train:.4f} seconds")
51 print(f"Prediction time: {end_predict - start_predict:.4f} seconds")
52
53 # SVM
54 start_train = time.time()
55 svm = SVC(kernel='linear', random_state=42)
56 svm_cv_scores = cross_val_score(svm, X_train, y_train, cv=5)
57 svm.fit(X_train, y_train)
58 end_train = time.time()
59
60 start_predict = time.time()
61 svm_preds = svm.predict(X_test)

```

```

62 end_predict = time.time()
63
64 print("\nSupport Vector Machine (SVM)")
65 print("Cross-validation scores:", svm_cv_scores)
66 print("Accuracy:", accuracy_score(y_test, svm_preds))
67 print(classification_report(y_test, svm_preds))
68 print(f"Training time: {end_train - start_train:.4f} seconds")
69 print(f"Prediction time: {end_predict - start_predict:.4f} seconds")
70
71 # Comparing stability between models
72 t_stat_lr_rf, p_value_lr_rf = ttest_rel(logreg_cv_scores, rf_cv_scores)
73 t_stat_lr_svm, p_value_lr_svm = ttest_rel(logreg_cv_scores, svm_cv_scores)
74 t_stat_rf_svm, p_value_rf_svm = ttest_rel(rf_cv_scores, svm_cv_scores)
75
76 print("\nStatistical comparisons between models:")
77 print(f"Logistic Regression vs Random Forest - T-statistic: {t_stat_lr_rf:.4f}, p-value: {p_value_lr_rf:.4f}")
78 print(f"Logistic Regression vs SVM - T-statistic: {t_stat_lr_svm:.4f}, p-value: {p_value_lr_svm:.4f}")
79 print(f"Random Forest vs SVM - T-statistic: {t_stat_rf_svm:.4f}, p-value: {p_value_rf_svm:.4f}")
80

```



1	0.33	0.14	0.20	7
2	0.88	0.86	0.87	296
3	0.91	0.82	0.86	109
4	0.88	0.94	0.91	483

accuracy			0.88	912
macro avg	0.75	0.59	0.62	912
weighted avg	0.87	0.88	0.87	912

Training time: 13.3434 seconds
Prediction time: 0.0037 seconds

Random Forest
Cross-validation scores: [0.75890411 0.75616438 0.77777778 0.75308642 0.74485597]
Accuracy: 0.7587719298245614

	precision	recall	f1-score	support
0	0.00	0.00	0.00	17
1	0.00	0.00	0.00	7
2	0.80	0.65	0.72	296
3	0.90	0.43	0.58	109
4	0.73	0.94	0.82	483

accuracy			0.76	912
macro avg	0.49	0.40	0.42	912
weighted avg	0.76	0.76	0.74	912

Training time: 19.4241 seconds
Prediction time: 0.0502 seconds

```

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-de
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-de
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-de
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

```

Support Vector Machine (SVM)
Cross-validation scores: [0.80958904 0.84520548 0.82853224 0.82441701 0.80932785]
Accuracy: 0.8574561403508771

	precision	recall	f1-score	support
0	0.20	0.18	0.19	17
1	0.00	0.00	0.00	7
2	0.85	0.85	0.85	296
3	0.90	0.78	0.84	109
4	0.89	0.92	0.90	483

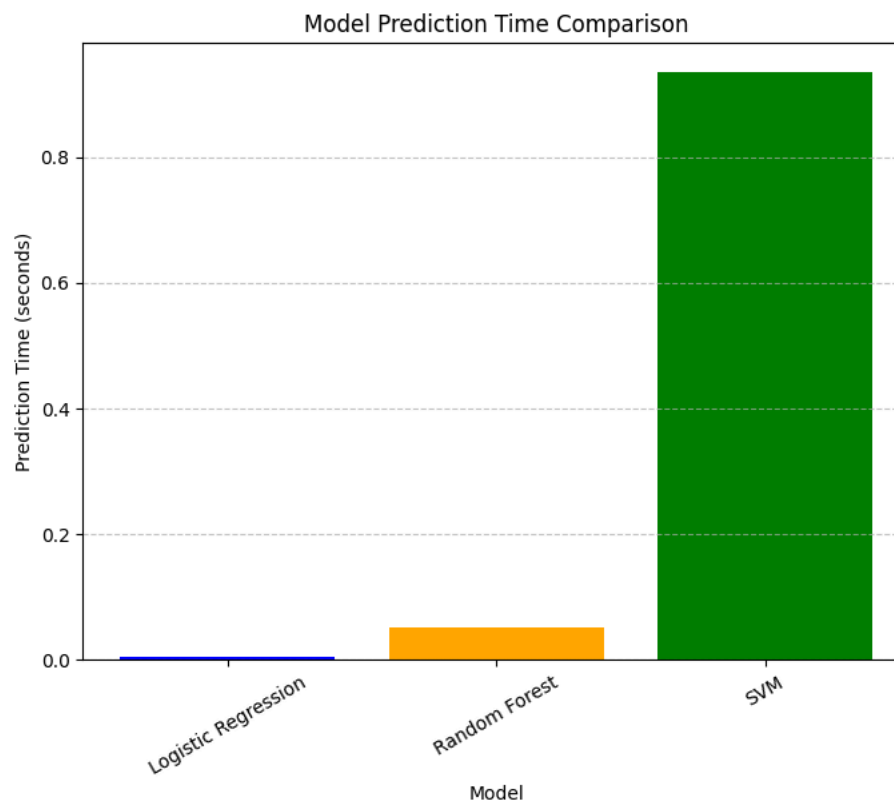
accuracy			0.86	912
macro avg	0.57	0.54	0.56	912
weighted avg	0.86	0.86	0.86	912

Training time: 25.4661 seconds
Prediction time: 0.9349 seconds

Statistical comparisons between models:
Logistic Regression vs Random Forest - T-statistic: 12.3769, p-value: 0.0002
Logistic Regression vs SVM - T-statistic: 7.3006, p-value: 0.0019
Random Forest vs SVM - T-statistic: -9.1116, p-value: 0.0008

creating visualizations for model comparisons

```
1 import matplotlib.pyplot as plt
2
3 # Model names and training times
4 models = ['Logistic Regression', 'Random Forest', 'SVM']
5 training_times = [13.3434, 19.4241, 25.4661] # Training times in seconds
6
7 # Plotting
8 plt.figure(figsize=(8, 6))
9 plt.bar(models, training_times, color=['blue', 'orange', 'green'])
10 plt.title('Model Training Time Comparison')
11 plt.xlabel('Model')
12 plt.ylabel('Training Time (seconds)')
13 plt.xticks(rotation=30)
14 plt.grid(axis='y', linestyle='--', alpha=0.7, which='both')
15
16 plt.show()
17
18 import matplotlib.pyplot as plt
19
20 # Model names and prediction times
21 models = ['Logistic Regression', 'Random Forest', 'SVM']
22 prediction_times = [0.0037, 0.0502, 0.9349] # Prediction times in seconds
23
24 # Plotting
25 plt.figure(figsize=(8, 6))
26 plt.bar(models, prediction_times, color=['blue', 'orange', 'green'])
27 plt.title('Model Prediction Time Comparison')
28 plt.xlabel('Model')
29 plt.ylabel('Prediction Time (seconds)')
30 plt.xticks(rotation=30)
31 plt.grid(axis='y', linestyle='--', alpha=0.7, which='both')
32
33 plt.show()
34
```

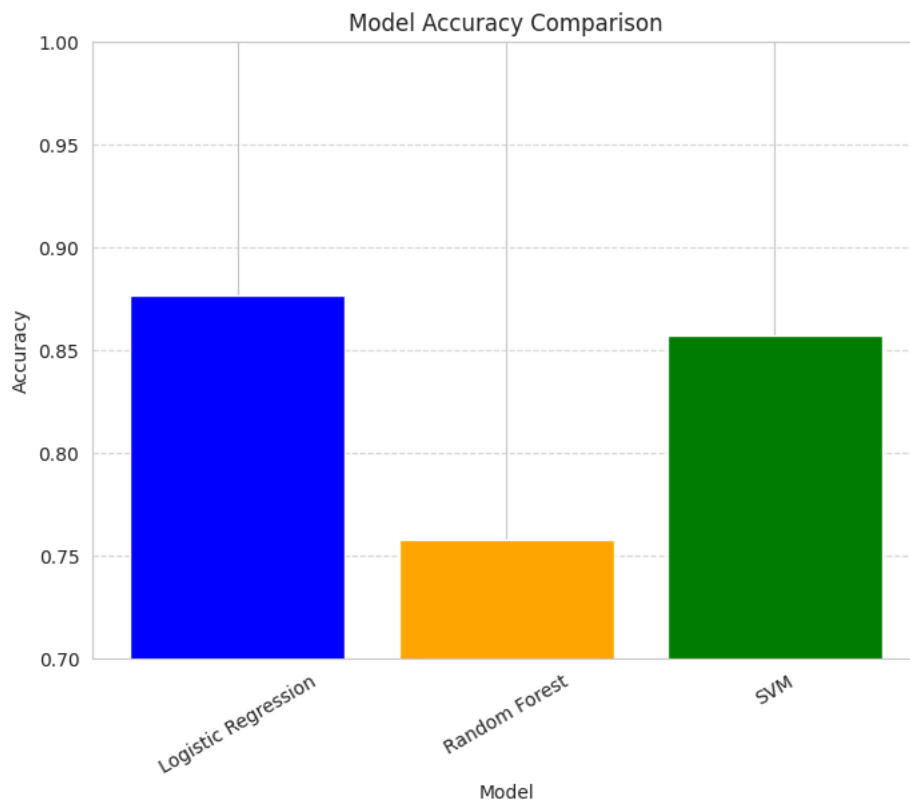


```
1 import matplotlib.pyplot as plt
2
3 # Model names and accuracy scores
4 models = ['Logistic Regression', 'Random Forest', 'SVM']
5 accuracy_scores = [0.877, 0.758, 0.857] # Accuracy values
6
7 # Plotting
8 plt.figure(figsize=(8, 6))
9 plt.bar(models, accuracy_scores, color=['blue', 'orange', 'green'])
10 plt.title('Model Accuracy Comparison')
11 plt.xlabel('Model')
```

```

12 plt.ylabel('Accuracy')
13 plt.xticks(rotation=30)
14 plt.ylim(0.7, 1) # Adjust Y-axis to make comparisons clearer
15 plt.grid(axis='y', linestyle='--', alpha=0.7, which='both')
16
17 plt.show()
18
19

```



1 #I have selected Logistic Regression to continue topic predictions in my analysis

```

1 vectorizer = CountVectorizer(stop_words='english', max_features=5000)
2 X = vectorizer.fit_transform(data_cleaned['cleaned_lyrics'].dropna())
3 y = data_cleaned['dominant_topic']
4
5 # Retraining Logistic Regression model
6 logreg = LogisticRegression(max_iter=1000)
7 logreg.fit(X, y)
8
9 # Get predictions
10 data_cleaned['predicted_topic'] = logreg.predict(X)
11
12 # Map the predicted topic to a label
13 topic_labels = {
14     0: "Reflections and Life Experiences",
15     1: "Communication and Family Dynamics",
16     2: "Love and Emotional Longing",
17     3: "Street Culture and Raw Emotions",
18     4: "Romantic Desire and Affection"
19 }
20 data_cleaned['predicted_topic_label'] = data_cleaned['predicted_topic'].map(topic_labels)
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```

```
9 print(predicted_label_counts)
10
```

```
→ Counts for LDA-Derived Labels:
topic_label
Romantic Desire and Affection      3207
Love and Emotional Longing         2308
Street Culture and Raw Emotions     597
Reflections and Life Experiences    185
Communication and Family Dynamics   87
Name: count, dtype: int64
```

```
Counts for Logistic Regression Predicted Labels:
predicted_topic_label
Romantic Desire and Affection      3205
Love and Emotional Longing         2313
Street Culture and Raw Emotions     597
Reflections and Life Experiences    183
Communication and Family Dynamics   86
Name: count, dtype: int64
```

Using the logistic regression model, continue visualizations

```
1 #grouping by decade
2 data_cleaned['Decade'] = (data_cleaned['Year'] // 10) * 10
3 decade_topic_distribution = data_cleaned.groupby(['Decade', 'predicted_topic']).size().unstack(fill_value=0)
4 decade_topic_distribution_normalized = decade_topic_distribution.div(decade_topic_distribution.sum(axis=1), axis=0)
5
```

```
1 # Plotting topic distribution trends over time
2
3 print("Decade-Topic Distribution:")
4 print(decade_topic_distribution)
5
6 print("\nNormalized Decade-Topic Distribution:")
7 print(decade_topic_distribution_normalized)
8
9 plt.figure(figsize=(12, 8))
10 decade_topic_distribution_normalized.plot(kind='line', marker='o', figsize=(12, 8))
11 plt.title('Topic Distribution Trends Over Time')
12 plt.xlabel('Decade')
13 plt.ylabel('Proportion of Topic')
14 plt.legend(title='Topic')
15 plt.show()
16
```

```

Decade-Topic Distribution:
predicted_topic  0    1    2    3    4
Decade
1950.0           2    0    9    1    9
1960.0          18    8  149   14  120
1970.0          16   13  212   33  188
1980.0          16    7  286   19  354
1990.0           8    4  290   61  459
2000.0          10    9  230   93  572
2010.0          13    4  250  208  568
2020.0           0    2   65   86  153

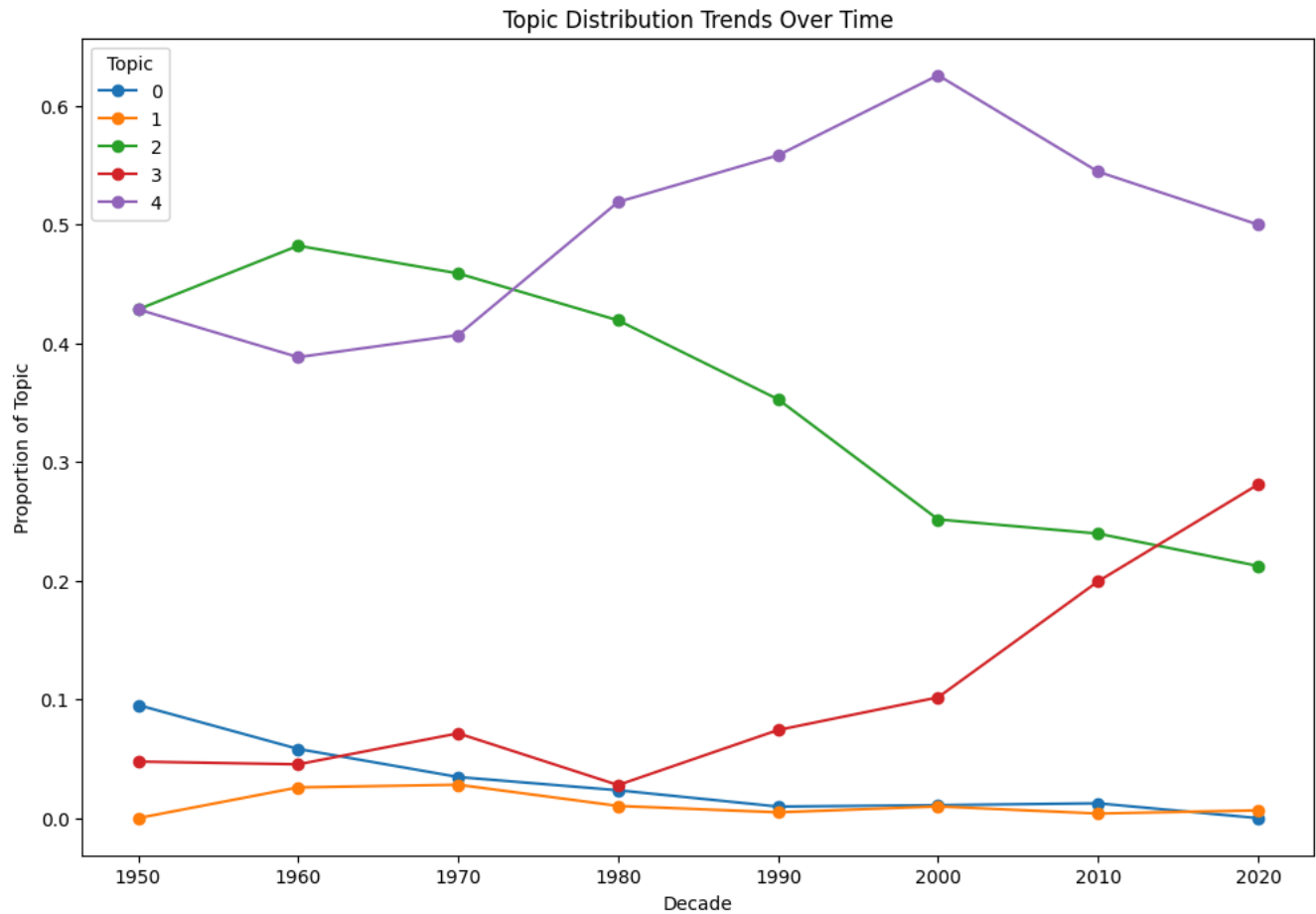
```

```

Normalized Decade-Topic Distribution:
predicted_topic      0      1      2      3      4
Decade
1950.0      0.095238  0.000000  0.428571  0.047619  0.428571
1960.0      0.058252  0.025890  0.482201  0.045307  0.388350
1970.0      0.034632  0.028139  0.458874  0.071429  0.406926
1980.0      0.023460  0.010264  0.419355  0.027859  0.519062
1990.0      0.009732  0.004866  0.352798  0.074209  0.558394
2000.0      0.010941  0.009847  0.251641  0.101751  0.625821
2010.0      0.012464  0.003835  0.239693  0.199425  0.544583
2020.0      0.000000  0.006536  0.212418  0.281046  0.500000

```

<Figure size 1200x800 with 0 Axes>



```

1 from textblob import TextBlob
2
3 #sentiment polarity
4 def calculate_sentiment(text):
5     return TextBlob(text).sentiment.polarity
6
7 data_cleaned['sentiment'] = data_cleaned['cleaned_lyrics'].apply(calculate_sentiment)
8
9 topic_sentiment_by_decade = data_cleaned.groupby(['Decade', 'dominant_topic'])['sentiment'].mean().unstack()
10
11 print("Average Sentiment by Topic Over Time:")
12 print(topic_sentiment_by_decade)
13
14 # Visualizing sentiment trends by decade
15 plt.figure(figsize=(12, 8))
16 topic_sentiment_by_decade.plot(kind='line', marker='o')

```



```

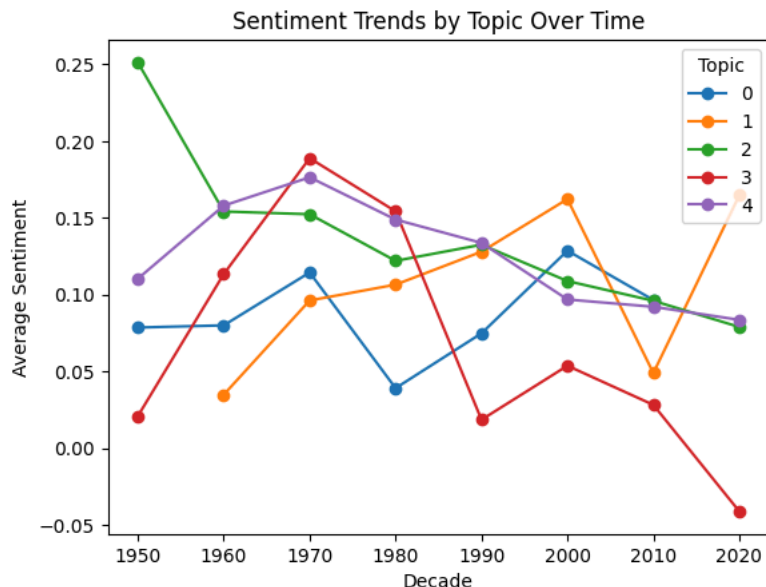
17 plt.title('Sentiment Trends by Topic Over Time')
18 plt.xlabel('Decade')
19 plt.ylabel('Average Sentiment')
20 plt.legend(title='Topic')
21 plt.show()
22

```

↗ Average Sentiment by Topic Over Time:

dominant_topic	0	1	2	3	4
Decade					
1950.0	0.078558	NaN	0.251256	0.020833	0.110333
1960.0	0.079980	0.034834	0.154139	0.113395	0.157962
1970.0	0.114420	0.096173	0.152343	0.188864	0.176406
1980.0	0.039078	0.106487	0.121993	0.154228	0.148873
1990.0	0.074801	0.127951	0.132499	0.018507	0.133668
2000.0	0.128607	0.162236	0.108828	0.053687	0.096815
2010.0	0.096497	0.048946	0.095966	0.028188	0.092077
2020.0	NaN	0.164625	0.078928	-0.041167	0.083543

<Figure size 1200x800 with 0 Axes>



I had an issue with the order of the topics in visualizations and wanted to ensure they were consistent

```

1
2 # Correctly map numerical topics to their intended descriptive labels
3 topic_labels = {
4     0: "Reflections and Life Experiences",
5     1: "Communication and Family Dynamics",
6     2: "Love and Emotional Longing",
7     3: "Street Culture and Raw Emotions",
8     4: "Romantic Desire and Affection"
9 }
10
11 # Map topic indices to their respective string labels
12 data_cleaned['topic_label'] = data_cleaned['dominant_topic'].map(topic_labels)
13
14 # Calculate the overall average sentiment by topic
15 average_sentiment_overall = data_cleaned.groupby('dominant_topic')['sentiment'].mean().reset_index()
16
17 ordered_topics = {
18     0: "Reflections and Life Experiences",
19     1: "Communication and Family Dynamics",
20     2: "Love and Emotional Longing",
21     3: "Street Culture and Raw Emotions",
22     4: "Romantic Desire and Affection"
23 }
24
25 # Reindex the DataFrame to enforce order
26 average_sentiment_overall['topic_label'] = average_sentiment_overall['dominant_topic'].map(ordered_topics)
27 average_sentiment_overall = average_sentiment_overall.sort_values('dominant_topic')
28
29 # Print results for debugging
30 print("Reordered Average Sentiment by Topic:")
31 print(average_sentiment_overall)

```

```

32
33 # Visualize the average sentiment using a bar chart
34 plt.figure(figsize=(12, 6))
35 sns.barplot(
36     x='sentiment',
37     y='topic_label',
38     data=average_sentiment_overall,
39     palette='coolwarm'
40 )
41 plt.title('Average Sentiment by Topic')
42 plt.xlabel('Average Sentiment')
43 plt.ylabel('Topic')
44 plt.grid(axis='x')
45 plt.show()
46
47
48

```

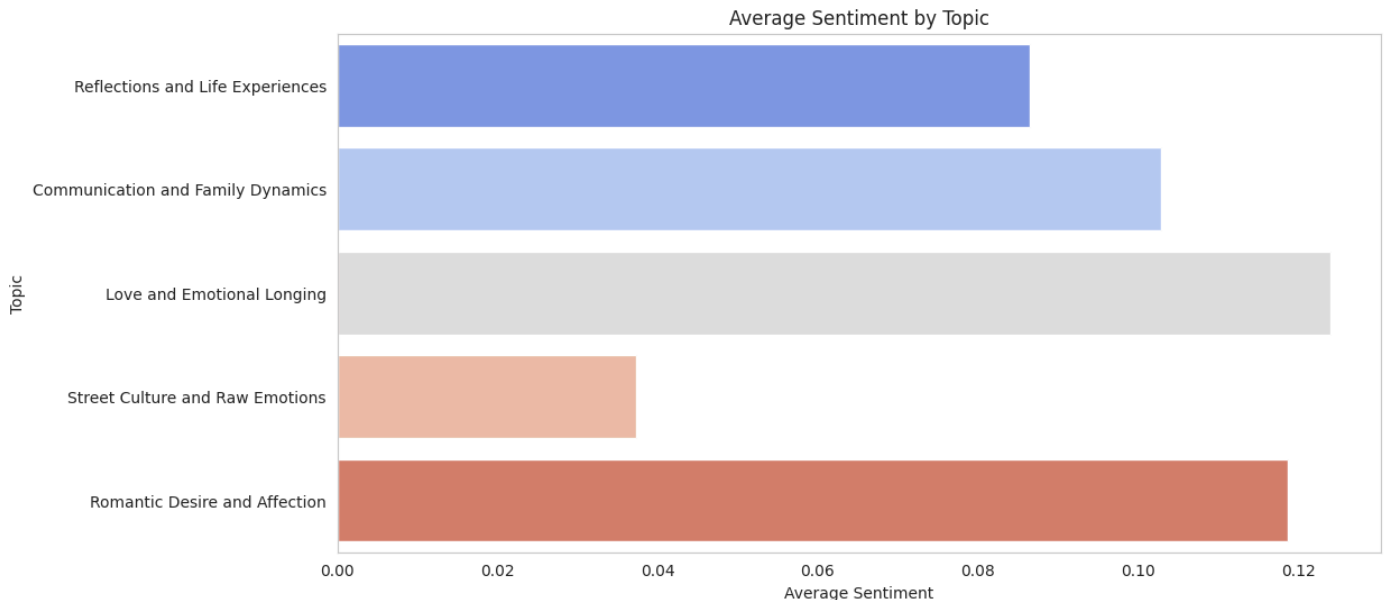
```

↗ Reordered Average Sentiment by Topic:
  dominant_topic  sentiment  topic_label
0              0   0.086567  Reflections and Life Experiences
1              1   0.102831  Communication and Family Dynamics
2              2   0.124082    Love and Emotional Longing
3              3   0.037312  Street Culture and Raw Emotions
4              4   0.118707  Romantic Desire and Affection
<ipython-input-73-d4307c5c71ca>:34: FutureWarning:

```

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and

```
sns.barplot(
```



```

1 import matplotlib.pyplot as plt
2 import seaborn as sns
3
4 print("Sentiment Summary Statistics:")
5 print(sentiment_stats)
6
7 # Plot the distribution of sentiment
8 plt.figure(figsize=(10, 6))
9 sns.histplot(data_cleaned['sentiment'], kde=True, color='skyblue')
10 plt.title('Sentiment Distribution of Song Lyrics')
11 plt.xlabel('Sentiment Score')
12 plt.ylabel('Frequency')
13 plt.show()
14

```