Exploration, Grouping, and Prediction of Genre in Spotify Songs

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- GitHub Link

I

In this project, we predict song genre using a massive dataset of **over 140 thousand songs** from the music streaming platform Spotify. The data set had information about each song's popularity, genre, and other musical qualities. We attempted to classify a song into one of 10 genres by using up to 12 different predictor variables.

- Relevant Predictor Variables: `popularity` , `duration_ms` , `explicit` , `danceability` , `energy` , `loudness` , `speechiness` , `acousticness` , `instrumentalness` , `liveness` , `valence` , `tempo`
- Genres: `classical` , `electronic` , `folk` , `hip-hop` , `jazz` , `metal` , `misc` , `pop` , `rock` , `world`

II

The main feature we are interested in with this dataset is **song genre**, in particular how it relates to other features. We want to test if the musical qualities of a song are strong predictors of its genre. After cleaning, our dataset contained 114 different genres, ranging from emo to classical to industrial and more. We are interested in investigating things such as:

- The qualities of songs that are correlated to genre.
- If certain genres are more similar to each other than others.
- If we can predict a song's genre through its other qualities.

Understanding these relationships is crucial for several reasons. First, accurate genre prediction can *enhance recommendation systems*, providing users with a more personalized and enjoyable listening experience. For artists and producers, insights from our analysis can *guide the creative process*, helping them understand trends and preferences within different genres. Finally, we contribute to the broader field of musicology by providing *data-driven insights* into the characteristics that are different in musical genres.

III

We tried numerous different methodologies, including **linear regression**, **logistic regression**, **decision trees**, **PCA/clustering**, and **neural networks**. Our key methodologies were **decision trees** and **random forest**, which worked most effectively to predict a song's genre through its other qualities.

With decision trees, we were able to obtain a respectable accuracy compared to our other methods. However, due to the depth of the decision trees, these results were not easily interpretable. Finally, after using an ensemble of trees in a **random forest**, we achieved predictions that were significantly more robust and accurate than the previous methods.

Neural networks also appeared to be a viable alternative, however overall accuracy metrics paled in comparison to decision trees. However, recall scores for classical music and metal were better than they were for **random forests**.

IV

Using a train-test split of 60:20:20 and an ensemble of 200 trees, each with a maximum tree depth of 20 (both parameters learned using brute-force cross validation), we were able to achieve a total **Accuracy** of `0.56`. We generated a **Classification Report** showing the `precision`, `recall`, and `F1 score` for each genre, which helped us understand the performance of our model across different genres. In addition, we generated a **Confusion Matrix**, which provided a visual representation of the true positive, true negative, false positive, and false negative prediction rates, allowing us to see what errors our model was making.

Finally, we used **Feature & Permutation Importance** to identify which predictor variables had the most significant impact on genre classification. In particular, we found that `popularity`, `acousticness`, `instramentalness`, and `danceability` were the most important to predict genre. This makes sense because some genres are more appealing to wider audiences and these features could logically seem to be able to predict between genres. Interestingly, mode, time signature, and key had little or negative permutation importances, indicating they are not important to predicting track genre.

While our Random Forest model provided robust and accurate predictions, it also had some limitations. One significant limitation was the model's tendency to overfit (the training accuracy was over 90%), especially with a large number of trees and depth. We tried to combat this by limiting the *maximum tree depth*, which resulted in lower accuracy. In addition, the computational resources required for training and tuning the model were substantial (each run took dozens of minutes) which could be a constraint for larger datasets or more extensive hyperparameter optimization.

All in all, our maximum accuracy was still well below `0.7`, which may be a limitation of our dataset itself; this dataset may not capture all the nuances and variations between genres. Additionally, the subjective nature of genre classification means that there can be overlap and ambiguity between genres, making it challenging to reach high accuracy. Future work could involve refining the genre labels, incorporating more diverse and representative data, and experimenting with different model architectures and techniques to improve performance. Despite these limitations, our project demonstrates the potential of machine learning techniques in predicting song genres and provides a foundation for further exploration and improvement.

V

To run the code in **project_code.ipynb**, ensure that Jupyter Notebook or Jupyter Lab is installed, along with the necessary dependencies. First, clone this repository to the local machine and navigate to the project directory. Launch Jupyter Notebook by running `jupyter notebook` in your terminal, open **project_code.ipynb**, and execute the cells sequentially. Alternatively, use the `Jupyter Notebook` extension and use "Run all cells."

Appendix

I

Boxplots were used to identify the spread of numerical data. Histograms of each feature were created to visualize the frequency of values for the data. By doing this, we determined the skewedness of each feature. A heatmap was used to determine correlations between features. For features that were more correlated, we created scatterplots and used linear and quadratic regressions to find preliminary relationships. We also created histograms of categorical data to see the frequency of each value for the categorical data. Using domain knowledge, we grouped the various genres into 10 overarching genres. Bar graphs were used to visualize mean values for each numerical feature for the overarching genres. A random seed was used to split the data into 60% for training, 20% for validation, and 20% for testing.

II

We realized that many similar genres were classified into different groups, so we grouped the given genres into 10 overarching genres. These grouping are shown below. We removed the "Unnamed: 0" column, any rows with NaN values, and any songs with a duration of less than 30 seconds. We also removed songs with a tempo or time signature of 0, as these values do not make sense for songs.

```
{
    'pop': ['cantopop', 'j-pop', 'j-idol', 'k-pop', 'mandopop', 'pop', 'indie-pop', 'power-pop', 'pop-film', 'synth-pop'],
    'rock': ['alt-rock', 'alternative', 'hard-rock', 'indie', 'punk', 'j-rock', 'punk-rock', 'psych-rock', 'rock', 'rock-n-roll', 'grunge', 'emo', 'rockabilly', 'guitar'],
    'metal': ['black-metal', 'death-metal', 'heavy-metal', 'metal', 'metalcore', 'grindcore'],
    'electronic': ['edm', 'electro', 'electronic', 'house', 'garage', 'j-dance', 'hardcore', 'hardstyle', 'industrial', 'techno', 'trance', 'dubstep', 'idm', 'minimal-techno', 'progressive-house', 'chicago-house', 'deep-house', 'detroit-techno', 'disco', 'drum-and-bass', 'dub', 'club', 'dance', 'dancehall'],
    'hip-hop': ['hip-hop', 'rap', 'r-n-b', 'breakbeat', 'trip-hop'],
    'jazz': ['jazz', 'blues', 'soul', 'funk', 'ska', 'gospel'],
    'classical': ['classical', 'opera', 'piano'],
    'world': ['afrobeat', 'brazil', 'sertanejo', 'british', 'latin', 'latino', 'samba', 'salsa', 'reggae', 'reggaeton', 'tango', 'world-music', 'indian', 'iranian', 'turkish', 'malay', 'mpb', 'pagode', 'forro', 'french', 'german', 'spanish', 'swedish'],
    'folk': ['folk', 'bluegrass', 'country', 'singer-songwriter', 'songwriter', 'honky-tonk'],
    'misc': ['acoustic', 'ambient', 'anime', 'children', 'chill', 'comedy', 'disney', 'happy', 'party', 'study', 'sleep', 'show-tunes', 'new-age', 'kids', 'goth', 'groove', 'romance', 'sad']
}
```

III

Popularity, duration, danceability, energy, loudness, speechiness, acousticness, instrumentalness, liveness, valence, and tempo were used in both linear and quadratic regression. We used a sequential feature selector, forward selection, to determine the most influential features. We used R^2 as the scoring metric for cross-validation to identify optimal features. Because we used this metric, we found that regularization was not necessary. Overall, we determined that the importance of certain features varied by genre group. For example, energy was more prominent for rock and electronic genres, acousticness and liveness were more prominent for folk and classical genres, and danceability was more prominent for pop and hip-hop genres.

IV

For logistic regression, the track-genre column was encoded using a label encoder to map genres to numerical labels. Non-numeric columns were converted via one-hot encoding, and data was standardized. We calculated accuracy, recall, and F1 score and plotted ROC curves and found the AUC to determine the model's ability to distinguish between classes. The default solver lbfgs used L2 regularization, so we did use regularization. However, removing the regularization did not affect the metrics.

We found that there were different key features for each genre. Energy contributed largely to rock, metal, and electronic music. Danceability contributed largely to pop and hip-hop identification. Acousticness contributed largely to classical and folk music. Loudness contributed largely to metal music.

V

We used KNN, a decision tree, and a random forest to try to classify genres of our data. For all of these, we one-hot-encoded all categorical data. While this isn't necessary for the tree models, it is for KNN, since distance between two points for categorical data does not make sense if the data is numeric.

Out of these three, the random forests had the best accuracy on the test set at 0.56, and was the best method by far for classifying the data. As expected, KNN was inefficient in analyzing our data due to the dataset's high dimensionality, and the presence of a lot of categorical data where distance makes much less sense. Decision trees make sense as a good model for the data, since there is a lot of overlap and the decision tree can make minute distinctions at each split. And random forests, as an ensemble version of decision trees, make sense as being more accurate.

VI

We applied one-hot encoding and scaled and mean-centered the data before doing PCA. The scree-plot results were unclear as to how many clusters should be used, but the top 4 principal components accounted for about 30% of the variability. Plotting the principal components showed that there was not clear separation of clusters due to heavy overlap.

After applying logistic regression to the PC-transformed dataset, we still produced relatively low accuracy rate of about 30%; the silhouette scores were also low.

We tried applying a Gaussian Mixture model on the PC-transformed dataset, which resulted in visually similar plots, but very low silhouette score. Even reducing the dimensionality of the GMM resulted in lower silhouette scores. We concluded that PCA transforming the data would not really help with determining genre. Since we did not have many features to begin with, we also believed that feature reduction was not a priority.

We also applied K-means clustering, agglomerative (hierarchical) clustering, and gaussian mixture models to the non-PCA-transformed data. All of these had terrible rand index with genre and <0.25 silhouette scores. Thus, we concluded that clustering would not help us with our problem.

VII

We used the dataset without string features, and one-hot-encoded the categorical features.

We went through a number of models, but ReLU, softmax, and dropout all significantly decreased the accuracy, so we ended up with a simpler model. Our model uses 2 hidden layers of size 64 using sigmoid activation, and log softmax output activation.

We trained using the Adam optimizer using cross entropy loss, and reported accuracy metrics at the end. We also included weights to account for class imbalance. We learned an initial learning rate via pytorch's `lr_find` function, and used the StepLR learning rate scheduler which reduced learning rate by 90% every 10 epochs. Our final accuracy was about 20%.

However, looking at accuracy metrics, recall for some classes like classical and metal was really high, indicating that if the model predicts that a song is classical or metal, then it is likely that it is right.

Interestingly, the model never predicted pop or hip-hop. This might be due to class imbalance, though pop is the most populated class and hip-hop the least. It might also be that the class weights undercompensated for hip-hop and overcompensated for pop. However, this was very common for many runs using many different hyperparameters.

VIII

We primarily used library methods to tune hyperparameters. For random forests and decision trees, we used `GridSearchCV` to tune max depth, critereon (GINI vs entropy), number of estimators (for RF), and other splitting/leaf parameters for decision trees, which checked every combination of hyperparameters. This did not really affect results, however. For neural networks, we used `find_lr` to find our initial learning rate, and used a learning rate scheduler to tune learning rate over the course of the training. We also, over the course of selecting the model, tried different batch sizes, hidden layer sizes, number of hidden layers, activation functions, and loss functions, all of which we "manually tuned" by checking the accuracy results after training.

CSM148 Spotiflies Code

13 December 2024

1 Exploration, Grouping, and Prediction of Genre in Spotify Songs

1.1 Team Spotiflies: Joanna, Aaron, Aubrey, Kennedy, Aster, Ethan

GitHub Link: https://github.com/ketexon/csm148-spotiflies

The data set that we chose for the project was the Spotify dataset, which is a dataset with information about the popularity, genre, and several other musical qualities of over 140K songs on the Spotify music streaming platform. The link to the original dataset can be found here: https://huggingface.co/datasets/maharshipandya/spotify-tracks-dataset.

The main feature we're interested in with this dataset is song genre, and how it relates to other features. We want to see if the musical qualities of a song are strong influences of what genre it's categorized. The dataset has 114 different genres, ranging from emo to classical to industrial and more. We are interested in answering questions regarding what, if anything, in songs may be a predictor of what genre it is, if certain genres are more similar to each other than others, and more.

1.2 First Looks and Cleaning Our Data

We started our project by investigating our data for any obvious cleaning we have to do before EDA, such as missing data or unreasonable values.

```
[50]: %pip install pandas numpy matplotlib seaborn scikit-learn mlxtend
```

```
Requirement already satisfied: pandas in ./.venv/lib/python3.12/site-packages
(2.2.3)
Requirement already satisfied: numpy in ./.venv/lib/python3.12/site-packages
(2.1.3)
Requirement already satisfied: matplotlib in ./.venv/lib/python3.12/site-
packages (3.9.3)
Requirement already satisfied: seaborn in ./.venv/lib/python3.12/site-packages
(0.13.2)
Requirement already satisfied: scikit-learn in ./.venv/lib/python3.12/site-
packages (1.5.2)
Requirement already satisfied: mlxtend in ./.venv/lib/python3.12/site-packages
(0.23.3)
Requirement already satisfied: python-dateutil>=2.8.2 in
./.venv/lib/python3.12/site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in ./.venv/lib/python3.12/site-
```

```
packages (from pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in ./.venv/lib/python3.12/site-
packages (from pandas) (2024.2)
Requirement already satisfied: contourpy>=1.0.1 in ./.venv/lib/python3.12/site-
packages (from matplotlib) (1.3.1)
Requirement already satisfied: cycler>=0.10 in ./.venv/lib/python3.12/site-
packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in ./.venv/lib/python3.12/site-
packages (from matplotlib) (4.55.2)
Requirement already satisfied: kiwisolver>=1.3.1 in ./.venv/lib/python3.12/site-
packages (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in ./.venv/lib/python3.12/site-
packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in ./.venv/lib/python3.12/site-packages
(from matplotlib) (11.0.0)
Requirement already satisfied: pyparsing>=2.3.1 in ./.venv/lib/python3.12/site-
packages (from matplotlib) (3.2.0)
Requirement already satisfied: scipy>=1.6.0 in ./.venv/lib/python3.12/site-
packages (from scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in ./.venv/lib/python3.12/site-
packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
./.venv/lib/python3.12/site-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: six>=1.5 in ./.venv/lib/python3.12/site-packages
(from python-dateutil>=2.8.2->pandas) (1.17.0)

[notice] A new release of pip is
available: 24.2 -> 24.3.1
[notice] To update, run:
pip install --upgrade pip
Note: you may need to restart the kernel to use updated packages.
```

[90]:

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, permutation_test_score,␣
  ↪StratifiedShuffleSplit, GridSearchCV
from sklearn.inspection import permutation_importance
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.metrics import (
    mean_squared_error, mean_absolute_error, r2_score,
    roc_curve, auc,
    classification_report, accuracy_score, confusion_matrix,
    adjusted_rand_score, silhouette_score
)
```

```
from sklearn.mixture import GaussianMixture
from mlxtend.evaluate import bias_variance_decomp

from sklearn.preprocessing import PolynomialFeatures, StandardScaler,␣
 ↪LabelEncoder, LabelBinarizer
from sklearn.pipeline import make_pipeline

from sklearn import tree
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

import torch
import torch.nn as nn
import torch.optim as optim
import lightning as pl
import lightning.pytorch.callbacks as pl_callbacks
from torch.utils.data import DataLoader, Dataset, TensorDataset
from typing import cast

import os
is_linux = os.name == 'posix'
```

[52]:

```
# Reading in the data
spotify = pd.read_csv("dataset.csv")
spotify
```

[52]:

```
        Unnamed: 0                track_id                 artists  \
0                0  5SuOikwiRyPMVoIQDJUgSV             Gen Hoshino
1                1  4qPNDBW1i3p13qLCt0Ki3A            Ben Woodward
2                2  1iJBSr7s7jYXzM8EGcbK5b  Ingrid Michaelson;ZAYN
3                3  6lfxq3CG4xtTiEg7opyCyx            Kina Grannis
4                4  5vjLSffimiIP26QG5WcN2K        Chord Overstreet
…             …                      …                       …
113995      113995  2C3TZjDRiAzdyViavDJ217           Rainy Lullaby
113996      113996  1hIz5L4IB9hN3WRYPOCGPw           Rainy Lullaby
113997      113997  6x8ZfSoqDjuNa5SVP5QjvX           Cesária Evora
113998      113998  2e6sXL2bYv4bSz6VTdnfLs        Michael W. Smith
113999      113999  2hETkH7cOfqmz3LqZDHZf5           Cesária Evora

                                              album_name  \
0                                                  Comedy
1                                        Ghost (Acoustic)
```

```
2                                          To Begin Again
3       Crazy Rich Asians (Original Motion Picture Sou…
4                                                 Hold On
…                                                   …
113995  #mindfulness - Soft Rain for Mindful Meditatio…
113996  #mindfulness - Soft Rain for Mindful Meditatio…
113997                                            Best Of
113998                                  Change Your World
113999                                     Miss Perfumado

                        track_name  popularity  duration_ms  explicit  \
0                           Comedy          73       230666     False
1                 Ghost - Acoustic          55       149610     False
2                   To Begin Again          57       210826     False
3       Can't Help Falling In Love          71       201933     False
4                          Hold On          82       198853     False
…                            …         …          …       …
113995         Sleep My Little Boy          21       384999     False
113996            Water Into Light          22       385000     False
113997              Miss Perfumado          22       271466     False
113998                     Friends          41       283893     False
113999                   Barbincor          22       241826     False

        danceability  energy  …  loudness  mode  speechiness  acousticness  \
0              0.676  0.4610  …    -6.746     0       0.1430        0.0322
1              0.420  0.1660  …   -17.235     1       0.0763        0.9240
2              0.438  0.3590  …    -9.734     1       0.0557        0.2100
3              0.266  0.0596  …   -18.515     1       0.0363        0.9050
4              0.618  0.4430  …    -9.681     1       0.0526        0.4690
…              …     …  …       …   …          …            …
113995         0.172  0.2350  …   -16.393     1       0.0422        0.6400
113996         0.174  0.1170  …   -18.318     0       0.0401        0.9940
113997         0.629  0.3290  …   -10.895     0       0.0420        0.8670
113998         0.587  0.5060  …   -10.889     1       0.0297        0.3810
113999         0.526  0.4870  …   -10.204     0       0.0725        0.6810

        instrumentalness  liveness  valence    tempo  time_signature  \
0               0.000001    0.3580   0.7150   87.917               4
1               0.000006    0.1010   0.2670   77.489               4
2               0.000000    0.1170   0.1200   76.332               4
3               0.000071    0.1320   0.1430  181.740               3
4               0.000000    0.0829   0.1670  119.949               4
…                  …       …      …      …             …
113995          0.928000    0.0863   0.0339  125.995               5
113996          0.976000    0.1050   0.0350   85.239               4
113997          0.000000    0.0839   0.7430  132.378               4
113998          0.000000    0.2700   0.4130  135.960               4
```

```
113999        0.000000    0.0893   0.7080   79.198               4

        track_genre
0          acoustic
1          acoustic
2          acoustic
3          acoustic
4          acoustic
…               …
113995  world-music
113996  world-music
113997  world-music
113998  world-music
113999  world-music

[114000 rows x 21 columns]
```

We decided to remove the “Unnamed: 0” column, since we can uniquely identify songs from their track_id, so the counter values aren’t very useful.

[53]:

```python
spotify_clean = spotify.drop(columns=["Unnamed: 0"])
```

Then we looked into NA values, and found one observation. We decided to drop this row since along with missing values, it also has other unexpected/unreasonable statistics, such as popularity being 0, and a duration of 0.

[54]:

```python
print(spotify_clean.isna().sum())
```

```
track_id            0
artists             1
album_name          1
track_name          1
popularity          0
duration_ms         0
explicit            0
danceability        0
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
tempo               0
time_signature      0
track_genre         0
dtype: int64
```

[55]:

```
# Looking specifically at the row of missing values
spotify_clean[spotify_clean.isna().any(axis=1)]
```

[55]:

```
                     track_id artists album_name track_name  popularity  \
65900  1kR4gIb7nGxHPI3D2ifs59     NaN        NaN        NaN           0

       duration_ms  explicit  danceability  energy  key  loudness  mode  \
65900            0     False         0.501   0.583    7     -9.46     0

       speechiness  acousticness  instrumentalness  liveness  valence  \
65900       0.0605          0.69           0.00396    0.0747    0.734

         tempo  time_signature track_genre
65900  138.391               4       k-pop
```

[56]:

```
# Dropping the row
spotify_clean = spotify_clean.dropna()
```

To investigate any unreasonable/odd values, we decided to visualize each numeric variable with boxplots.

[57]:

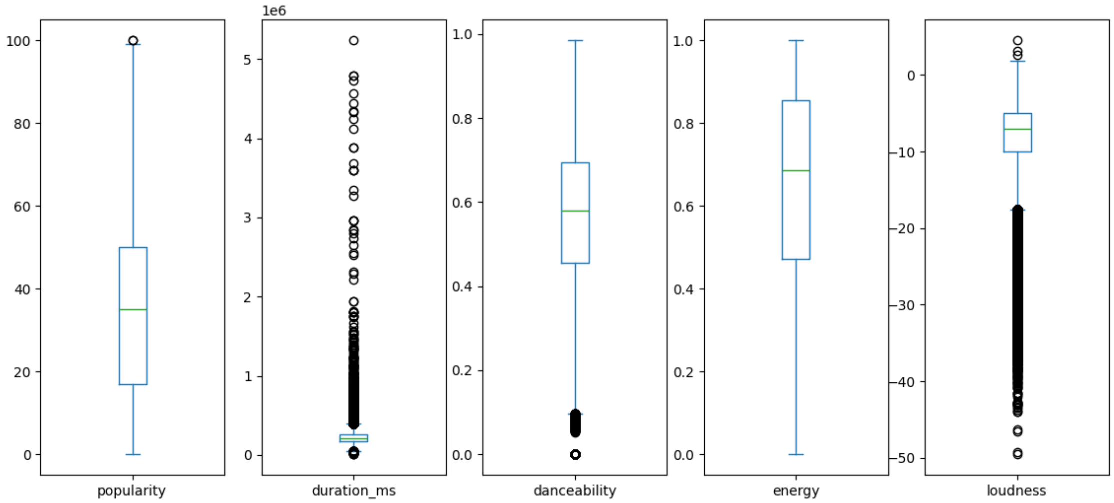
```
# String and categorical columns in the dataset
# these will be dropped or one-hot-encoded depending on the model
string_columns = ['track_id', 'artists', 'album_name', 'track_name']
categorical_columns = ['key', 'mode', 'time_signature', 'track_genre']

# helper function to remove all categorical and string columns
def numeric(df: pd.DataFrame) -> pd.DataFrame:
    df_number = df.select_dtypes(include=[np.number])
    return df_number.loc[:,~df_number.columns.isin(categorical_columns)]
```

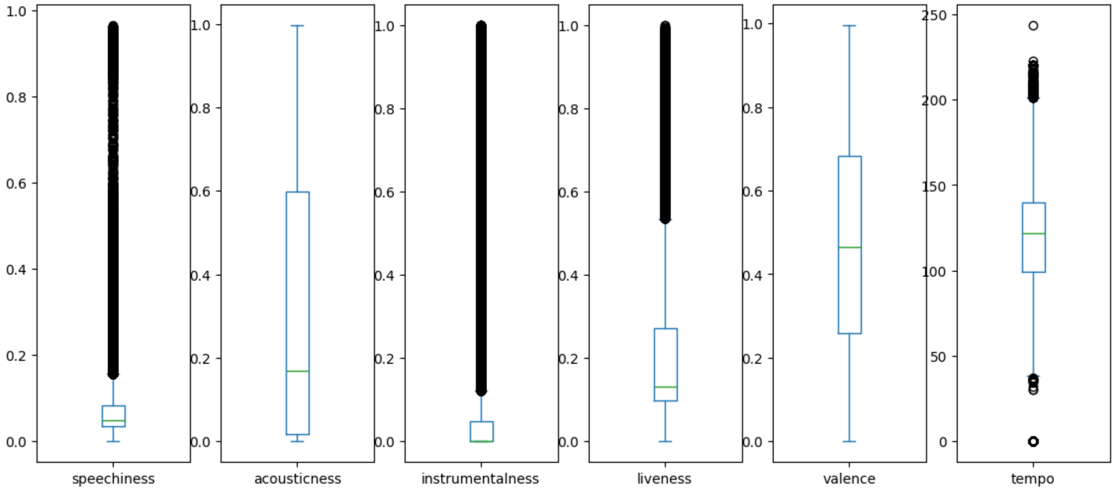
[58]:

```
# Creating boxplots
numeric_spotify = numeric(spotify_clean)
columns = numeric_spotify.columns

numeric_spotify[columns[:len(columns) // 2]].plot.box(figsize = (14, 6),␣
 ↪subplots=True)
numeric_spotify[columns[len(columns) // 2:]].plot.box(figsize = (14, 6),␣
 ↪subplots=True)
```

[58]:

```
speechiness            Axes(0.125,0.11;0.110714x0.77)
acousticness        Axes(0.257857,0.11;0.110714x0.77)
instrumentalness    Axes(0.390714,0.11;0.110714x0.77)
liveness            Axes(0.523571,0.11;0.110714x0.77)
valence             Axes(0.656429,0.11;0.110714x0.77)
tempo               Axes(0.789286,0.11;0.110714x0.77)
dtype: object
```





Based on the boxplots, there seem to be quite a few numeric variables with a significant number of outliers. However, we decided to mainly only focus on the songs in which these outliers would be unreasonable based on domain knowledge, including duration being too low, the tempo being too slow, and the time signature being 0.

First, we addressed the songs with duration being too low (the song is too short). We decided that a threshold for a song to be "too short" as a song that is shorter than 30 seconds.

[59]:
```
short_songs = spotify_clean[spotify_clean['duration_ms'] < 30000]

print(f"Number of tracks with duration less than 30 seconds: {len(short_songs)}")
short_songs
```

```
Number of tracks with duration less than 30 seconds: 16
```

[59]:

```
                      track_id  \
11398   1egJZfc8JBT2blFQ4clPKe
16288   1T5QvLF9l04H030ZQbaX9p
16292   5viwzFJxwRE10EUR7G6hiD
16856   5YKCM3jbJ8lqUXUwfU7KwZ
39233   1T5QvLF9l04H030ZQbaX9p
39236   5viwzFJxwRE10EUR7G6hiD
59306   3qSaeaXmt0uzkqe7DKgoiM
59310   6hsyfegVY5yklJneM40mWi
59434   1AsX7B48DFJZplJEwmhGpl
59458   1sayezH8bWoxHMAQCccCTi
59609   1oVrTBrCsM2eTE1G50yxY9
59711   787rIUDmWWBIfZXwHUeXXQ
59775   1HVjSh7scH1PaPiLjy2LEu
59812   380gh3rsHba83kXx13gbKs
66925   0DVMaexfdXDz19zUv1zKej
101159  6bg9fEHIulR3DYNYbWG0Jz

                                                  artists  \
11398                    Benjamin Britten;Steven Isserlis
16288                    Robert Schumann;Pavel Nersessian
16292                    Robert Schumann;Pavel Nersessian
16856              Wolfgang Amadeus Mozart;Ingrid Haebler
39233                    Robert Schumann;Pavel Nersessian
39236                    Robert Schumann;Pavel Nersessian
59306                                          Leila Bela
59310                                          Leila Bela
59434   Alireza Mashayekhi;Ata Ebtekar;The Iranian Orc…
59458                                          Leila Bela
59609                                          Leila Bela
59711                                          Leila Bela
59775                      Leila Bela;Leila's Opera Class
59812                                          Leila Bela
66925                                   Dora The Explorer
101159  Traditional;Cappella Musicale di Santa Maria i…

                                               album_name  \
11398                          October Classical Playlist
16288   Schumann, Poulenc & Others: Piano Works (Live …
16292   Schumann, Poulenc & Others: Piano Works (Live …
16856                  Mozart: The Complete Piano Sonatas
39233   Schumann, Poulenc & Others: Piano Works (Live …
39236   Schumann, Poulenc & Others: Piano Works (Live …
59306                                         Angra Manyu
59310                                         Angra Manyu
```

```
59434                                          Ornamentalism
59458                                            Angra Manyu
59609                                            Angra Manyu
59711                                            Angra Manyu
59775                                            Angra Manyu
59812                                            Angra Manyu
66925                                      Dora The Explorer
101159       Giovannini: Messa a Quattro Breve Concertata

                                               track_name  popularity  \
11398   Cello Suite No. 3, Op. 87: IX. Passacaglia (Ex…           0
16288   Carnaval, Op. 9: No. 20, Pause (Live in Japan,…           0
16292   Carnaval, Op. 9: No. 13, Estrella (Live in Jap…           0
16856                          Andante in C Major, K. 1a           0
39233   Carnaval, Op. 9: No. 20, Pause (Live in Japan,…           0
39236   Carnaval, Op. 9: No. 13, Estrella (Live in Jap…           0
59306                                                V-7           0
59310                             The Exorsism Begins…           0
59434                                         Aural Blue           0
59458                                                V-3           0
59609                                            Shatter           0
59711                                      Breath Ritual           0
59775   Screams for a Finale! (feat. Leila's Opera Class)           0
59812                                                V-4           0
66925                                Backpack, Backpack!           8
101159                                        Pax Domini           0

        duration_ms  explicit  danceability  energy  key  loudness  mode  \
11398         22266     False         0.335  0.0593   11   -26.365     0
16288         17826     False         0.372  0.2780    8   -16.882     1
16292         23506     False         0.379  0.2370    5   -18.265     1
16856         17453     False         0.467  0.0301    2   -28.518     0
39233         17826     False         0.372  0.2780    8   -16.882     1
39236         23506     False         0.379  0.2370    5   -18.265     1
59306         21120     False         0.229  0.0577    8   -27.960     0
59310          8586     False         0.000  0.0400    8   -29.714     0
59434         24666     False         0.187  0.9750    1    -8.223     1
59458         28026     False         0.612  0.1370    8   -31.953     1
59609         21240     False         0.424  0.8690    9    -8.168     0
59711         28946     False         0.359  0.1430    4   -30.401     1
59775         15800     False         0.251  0.5080    5   -10.564     0
59812         13386     False         0.000  0.2240   11   -22.196     1
66925         24266     False         0.903  0.3940    2    -8.018     1
101159        24000     False         0.358  0.0335    1   -28.683     1

        speechiness  acousticness  instrumentalness  liveness  valence  \
11398        0.0430        0.9920            0.8690    0.1160   0.1950
```

```
16288       0.0370    0.9850           0.9210  0.1640  0.9120
16292       0.0470    0.9930           0.8870  0.1440  0.4770
16856       0.0428    0.9950           0.9000  0.1240  0.0000
39233       0.0370    0.9850           0.9210  0.1640  0.9120
39236       0.0470    0.9930           0.8870  0.1440  0.4770
59306       0.1960    0.6260           0.9310  0.1080  0.2530
59310       0.0000    0.9280           0.9560  0.1150  0.0000
59434       0.2360    0.0431           0.9800  0.3570  0.1360
59458       0.7920    0.8480           0.0000  0.0868  0.3930
59609       0.0728    0.7070           0.0893  0.1170  0.0000
59711       0.4390    0.3930           0.0379  0.3930  0.0366
59775       0.3160    0.9690           0.9990  0.9520  0.0000
59812       0.0000    0.9700           0.0000  0.9070  0.0000
66925       0.1040    0.0047           0.0000  0.0830  0.5430
101159      0.0435    0.9810           0.0000  0.2510  0.2980

          tempo  time_signature track_genre
11398    77.266               5     british
16288    89.032               1   classical
16292   116.093               4   classical
16856    84.375               4   classical
39233    89.032               1      german
39236   116.093               4      german
59306   172.897               4     iranian
59310     0.000               0     iranian
59434    96.548               4     iranian
59458   100.765               4     iranian
59609   135.107               4     iranian
59711   119.207               5     iranian
59775   184.051               3     iranian
59812     0.000               0     iranian
66925   109.974               4        kids
101159   95.684               3       sleep
```

We found that there are only 16 songs that are less than 30 seconds. Since there were so few, we decided to look manually into these songs and investigate whether or not these songs seem to be real songs. Turns out, the majority of them are concert pauses (empty tracks) or sound effects and sound clips. Since we don't want these tracks to affect our investigation of genres, we decided to drop them.

[60]:

```python
spotify_clean = spotify_clean[spotify_clean['duration_ms'] >= 30000]
```

Next we looked at implausible 0 values with time signature and tempo. For context, time signature should be expressed in a fraction, while tempo is in BPM (so 0 BPM doesn't make sense).

[61]:

```python
print("Tempos == 0: ", spotify_clean["tempo"].eq(0).sum())
print("Time signatures == 0: ", spotify_clean["time_signature"].eq(0).sum())
```

```
Tempos == 0:  155
```

```
Time signatures == 0:  161
```

```
[62]: tempo_timesig_0_songs = spotify_clean[(spotify_clean['tempo'] == 0) |␣
       ↪(spotify_clean['time_signature'] == 0)]
      tempo_timesig_0_songs
```

```
[62]:                       track_id  \
2926    0jdfbvSdaWvxfAlD20TtNc
4131    59gg6zQhSKGVnkT3hWAY3l
4379    4acmzQsAeMJa5sGFSog7fu
4664    1Kb2DqjHRv0cT5xeWtz3t5
26910   7HSc2wpHlXKIl8SCZK7zsP
…                        …
101993  6H0kAiSAFB84jX7dgEDWd6
112172  0jdfbvSdaWvxfAlD20TtNc
113428  5EYzrykQ95u0mepteDi9KT
113688  2EnZf7wbFv7ST4CJ3EvNzT
113856  6XsYJ0dwT2hRzp0Qles78F


                                                  artists  \
2926                                           Yaşlı Amca
4131                                Max Richter;Lang Lang
4379     Dario Marianelli;Jack Liebeck;Benjamin Wallfisch
4664                                     Sylvain Chauveau
26910                                        Benny Martin
…                                                   …
101993                                        Rain Sounds
112172                                         Yaşlı Amca
113428  El Ruido Blanco;Soñoliento Juan;Mantra para Do…
113688                                    El Ruido Blanco
113856                                        -


                                               album_name  \
2926                                            Akşamüstü
4131                      Voyager - Essential Max Richter
4379       Jane Eyre - Original Motion Picture Soundtrack
4664                              Des Plumes Dans La Tête
26910             Here Comes the Sun (Piano Instrumental)
…                                                   …
101993                                               Rain
112172                                          Akşamüstü
113428                 Aire Acondicionado de Ruido Blanco
113688  Ruido Blanco para el bebé: sonidos relajantes …
113856              -                …


                                       track_name  popularity  duration_ms  \
2926                              Sanki Yapamadım          44       213198
```

```
4131                                    The Departure         64        151506
4379        The End of Childhood (feat. Jack Liebeck)         55         73266
4664                                   Ferme Les Yeux         53         68493
26910        Here Comes the Sun (Piano Instrumental)          18        203705
…                                           …         …          …
101993                        Rain: Natural Recording         32         84219
112172                                Sanki Yapamadım         44        213198
113428                                 Aire de verano         27        128000
113688           Ruido Rosa Puro - Una Hora Versión           24       3601693
113856                             (      )          22       302185

        explicit  danceability   energy  key  loudness  mode  speechiness  \
2926       False         0.442  0.56700    8    -6.346     0       0.0516
4131       False         0.000  0.03620    0   -22.519     0       0.0000
4379       False         0.000  0.04450    0   -26.440     0       0.0000
4664       False         0.000  0.03230    2   -23.636     0       0.0000
26910      False         0.329  0.06070    9   -28.310     1       0.0507
…           …           …      …  …       …   …          …
101993     False         0.000  0.02540    8   -19.925     1       0.0000
112172     False         0.442  0.56700    8    -6.346     0       0.0516
113428     False         0.000  0.18800    8   -25.837     0       0.0000
113688     False         0.000  0.00002    1   -11.165     1       0.0000
113856     False         0.000  0.22400    8   -10.224     1       0.0000

        acousticness  instrumentalness  liveness  valence    tempo  \
2926        0.238000          0.000325    0.0852    0.639  138.616
4131        0.994000          0.940000    0.0958    0.000    0.000
4379        0.972000          0.972000    0.0873    0.000    0.000
4664        0.994000          0.973000    0.0922    0.000    0.000
26910       0.994000          0.880000    0.0858    0.421   93.948
…              …                …       …       …       …
101993      0.000002          0.838000    0.3390    0.000    0.000
112172      0.238000          0.000325    0.0852    0.639  138.616
113428      0.139000          0.339000    0.1220    0.000    0.000
113688      0.186000          1.000000    0.3620    0.000    0.000
113856      0.142000          0.986000    0.4110    0.000    0.000

        time_signature  track_genre
2926                 0     alt-rock
4131                 0      ambient
4379                 0      ambient
4664                 0      ambient
26910                0       disney
…                …          …
101993               0        sleep
112172               0      turkish
113428               0  world-music
```

```
113688                  0  world-music
113856                  0  world-music

[161 rows x 20 columns]
```

We manually looked through the songs with time signature and tempos of 0, and found that most of them tended to be ambient tracks, such as tracks of rainfall sounds or white noise. We decided that it might be good to remove these rows from our cleaned dataset, as we didn't want to the zero values to skew the rest of our exploration in any way, and also because we hoped to look more a typical songs rather than ambient tracks.

Additionally, the overall count of these suspicious rows wasn't very high compared to size of the entire dataset (163 vs > 114k), so we figured that removing these values wouldn't drastically affect the size and comprehensiveness of our dataset.

We also confirmed this decision by seeing how the means of some of the other variables would change based on if we removed or kept these suspicious rows (see below).

[63]:

```
spotify_clean_temp = spotify_clean[spotify_clean['time_signature']!= 0]
spotify_clean_temp = spotify_clean[spotify_clean['tempo']!= 0]

mean_temp = spotify_clean_temp.mean(numeric_only=True)
mean_clean = spotify_clean.mean(numeric_only=True)

# Calculate the difference
mean_difference = mean_clean - mean_temp
mean_difference
```

[63]:

```
popularity           0.006038
duration_ms        -73.741857
explicit            -0.000116
danceability        -0.000772
energy              -0.000706
key                 -0.000157
loudness            -0.018772
mode                 0.000072
speechiness         -0.000115
acousticness         0.000240
instrumentalness     0.000676
liveness             0.000327
valence             -0.000646
tempo               -0.166333
time_signature      -0.005316
dtype: float64
```

From this, the effects on the means by removing the suspicious rows doesn't seem to be too large, with the largest being duration, which is measured in milliseconds, so would actually be less than a second difference. Thus, we dropped the rows where time signature or tempo were 0, which was a total of 161 rows.

[64]:

```
spotify_clean = spotify_clean_temp
spotify_clean
```

[64]:

```
                      track_id                 artists  \
0       5Su0ikwiRyPMVoIQDJUgSV             Gen Hoshino
1       4qPNDBW1i3p13qLCt0Ki3A            Ben Woodward
2       1iJBSr7s7jYXzM8EGcbK5b  Ingrid Michaelson;ZAYN
3       6lfxq3CG4xtTiEg7opyCyx            Kina Grannis
4       5vjLSffimiIP26QG5WcN2K        Chord Overstreet
…                        …                      …
113995  2C3TZjDRiAzdyViavDJ217           Rainy Lullaby
113996  1hIz5L4IB9hN3WRYPOCGPw           Rainy Lullaby
113997  6x8ZfSoqDjuNa5SVP5QjvX           Cesária Evora
113998  2e6sXL2bYv4bSz6VTdnfLs        Michael W. Smith
113999  2hETkH7c0fqmz3LqZDHZf5           Cesária Evora

                                                album_name  \
0                                                   Comedy
1                                         Ghost (Acoustic)
2                                           To Begin Again
3       Crazy Rich Asians (Original Motion Picture Sou…
4                                                  Hold On
…                                                      …
113995  #mindfulness - Soft Rain for Mindful Meditatio…
113996  #mindfulness - Soft Rain for Mindful Meditatio…
113997                                             Best Of
113998                                   Change Your World
113999                                      Miss Perfumado

                        track_name  popularity  duration_ms  explicit  \
0                           Comedy          73       230666     False
1                 Ghost - Acoustic          55       149610     False
2                   To Begin Again          57       210826     False
3       Can't Help Falling In Love          71       201933     False
4                          Hold On          82       198853     False
…                            …         …          …       …
113995         Sleep My Little Boy          21       384999     False
113996            Water Into Light          22       385000     False
113997              Miss Perfumado          22       271466     False
113998                     Friends          41       283893     False
113999                   Barbincor          22       241826     False

        danceability  energy  key  loudness  mode  speechiness  acousticness  \
0              0.676  0.4610    1    -6.746     0       0.1430        0.0322
1              0.420  0.1660    1   -17.235     1       0.0763        0.9240
2              0.438  0.3590    0    -9.734     1       0.0557        0.2100
3              0.266  0.0596    0   -18.515     1       0.0363        0.9050
```

```
4              0.618  0.4430    2    -9.681     1       0.0526         0.4690
…              …     …  …       …    …          …          …
113995         0.172  0.2350    5   -16.393     1       0.0422         0.6400
113996         0.174  0.1170    0   -18.318     0       0.0401         0.9940
113997         0.629  0.3290    0   -10.895     0       0.0420         0.8670
113998         0.587  0.5060    7   -10.889     1       0.0297         0.3810
113999         0.526  0.4870    1   -10.204     0       0.0725         0.6810

        instrumentalness  liveness  valence    tempo  time_signature  \
0               0.000001    0.3580   0.7150   87.917               4
1               0.000006    0.1010   0.2670   77.489               4
2               0.000000    0.1170   0.1200   76.332               4
3               0.000071    0.1320   0.1430  181.740               3
4               0.000000    0.0829   0.1670  119.949               4
…                    …        …       …       …              …
113995          0.928000    0.0863   0.0339  125.995               5
113996          0.976000    0.1050   0.0350   85.239               4
113997          0.000000    0.0839   0.7430  132.378               4
113998          0.000000    0.2700   0.4130  135.960               4
113999          0.000000    0.0893   0.7080   79.198               4

        track_genre
0          acoustic
1          acoustic
2          acoustic
3          acoustic
4          acoustic
…             …
113995  world-music
113996  world-music
113997  world-music
113998  world-music
113999  world-music

[113828 rows x 20 columns]
```

Since there don't seem to be anymore values in our dataset that are unreasonable or missing, we exported our cleaned dataset to start exploring and visualizing our data.

[65]:
```
# Exporting our cleaned dataset for analysis
spotify_clean.to_csv('spotify.csv', index=False)
```

1.3 Exploratory Data Analysis (EDA)

In order to find out a little more about the general structure and features of our dataset, we did some exploratory data analysis. We started by looking at the shape and structure of the data, and then the correlations between the numeric values, and then also did some visualizations of categorical features.

```
[66]: # Read in the cleaned data
      spotify = pd.read_csv('spotify.csv')
      spotify
```

```
[66]:                   track_id                  artists  \
      0       5SuOikwiRyPMVoIQDJUgSV             Gen Hoshino
      1       4qPNDBW1i3p13qLCt0Ki3A            Ben Woodward
      2       1iJBSr7s7jYXzM8EGcbK5b  Ingrid Michaelson;ZAYN
      3       6lfxq3CG4xtTiEg7opyCyx            Kina Grannis
      4       5vjLSffimiIP26QG5WcN2K        Chord Overstreet
      …                           …                       …
      113823  2C3TZjDRiAzdyViavDJ217           Rainy Lullaby
      113824  1hIz5L4IB9hN3WRYPOCGPw           Rainy Lullaby
      113825  6x8ZfSoqDjuNa5SVP5QjvX           Cesária Evora
      113826  2e6sXL2bYv4bSz6VTdnfLs        Michael W. Smith
      113827  2hETkH7cOfqmz3LqZDHZf5           Cesária Evora

                                                   album_name  \
      0                                                Comedy
      1                                      Ghost (Acoustic)
      2                                        To Begin Again
      3       Crazy Rich Asians (Original Motion Picture Sou…
      4                                               Hold On
      …                                                   …
      113823  #mindfulness - Soft Rain for Mindful Meditatio…
      113824  #mindfulness - Soft Rain for Mindful Meditatio…
      113825                                          Best Of
      113826                                Change Your World
      113827                                   Miss Perfumado

                              track_name  popularity  duration_ms  explicit  \
      0                           Comedy          73       230666     False
      1                 Ghost - Acoustic          55       149610     False
      2                   To Begin Again          57       210826     False
      3       Can't Help Falling In Love          71       201933     False
      4                          Hold On          82       198853     False
      …                            …         …          …       …
      113823         Sleep My Little Boy          21       384999     False
      113824            Water Into Light          22       385000     False
      113825              Miss Perfumado          22       271466     False
      113826                     Friends          41       283893     False
      113827                   Barbincor          22       241826     False

              danceability  energy  key  loudness  mode  speechiness  acousticness  \
      0              0.676  0.4610    1    -6.746     0       0.1430        0.0322
      1              0.420  0.1660    1   -17.235     1       0.0763        0.9240
      2              0.438  0.3590    0    -9.734     1       0.0557        0.2100
```

```
3              0.266  0.0596    0  -18.515     1       0.0363        0.9050
4              0.618  0.4430    2   -9.681     1       0.0526        0.4690
…              …     …  …       …   …          …           …
113823         0.172  0.2350    5  -16.393     1       0.0422        0.6400
113824         0.174  0.1170    0  -18.318     0       0.0401        0.9940
113825         0.629  0.3290    0  -10.895     0       0.0420        0.8670
113826         0.587  0.5060    7  -10.889     1       0.0297        0.3810
113827         0.526  0.4870    1  -10.204     0       0.0725        0.6810

        instrumentalness  liveness  valence    tempo  time_signature  \
0                0.000001    0.3580   0.7150   87.917               4
1                0.000006    0.1010   0.2670   77.489               4
2                0.000000    0.1170   0.1200   76.332               4
3                0.000071    0.1320   0.1430  181.740               3
4                0.000000    0.0829   0.1670  119.949               4
…                  …       …      …      …             …
113823           0.928000    0.0863   0.0339  125.995               5
113824           0.976000    0.1050   0.0350   85.239               4
113825           0.000000    0.0839   0.7430  132.378               4
113826           0.000000    0.2700   0.4130  135.960               4
113827           0.000000    0.0893   0.7080   79.198               4

        track_genre
0          acoustic
1          acoustic
2          acoustic
3          acoustic
4          acoustic
…             …
113823  world-music
113824  world-music
113825  world-music
113826  world-music
113827  world-music

[113828 rows x 20 columns]
```

```
[67]: spotify.describe()
```

```
[67]:
          popularity   duration_ms  danceability         energy  \
count  113828.000000  1.138280e+05  113828.000000  113828.000000
mean       33.237384  2.281340e+05       0.567603       0.642140
std        22.314498  1.062882e+05       0.172371       0.250761
min         0.000000  3.008000e+04       0.051300       0.000020
25%        17.000000  1.742130e+05       0.456000       0.473000
50%        35.000000  2.130000e+05       0.580000       0.685000
75%        50.000000  2.615970e+05       0.695000       0.854000
```

```
max       100.000000  5.237295e+06       0.985000       1.000000

                 key      loudness           mode    speechiness  \
count  113828.000000  113828.000000  113828.000000  113828.000000
mean        5.309186      -8.238433       0.637488       0.084758
std         3.559470       4.991371       0.480728       0.105735
min         0.000000     -46.591000       0.000000       0.022100
25%         2.000000     -10.000250       0.000000       0.035900
50%         5.000000      -6.997000       1.000000       0.049000
75%         8.000000      -5.000000       1.000000       0.084600
max        11.000000       4.532000       1.000000       0.965000

        acousticness  instrumentalness       liveness        valence  \
count  113828.000000     113828.000000  113828.000000  113828.000000
mean        0.314602          0.155314       0.213220       0.474737
std         0.332302          0.308835       0.189925       0.258831
min         0.000000          0.000000       0.009250       0.000000
25%         0.016900          0.000000       0.098000       0.261000
50%         0.168000          0.000041       0.132000       0.464000
75%         0.597000          0.047600       0.273000       0.683000
max         0.996000          1.000000       1.000000       0.995000

               tempo  time_signature
count  113828.000000   113828.000000
mean      122.317259        3.909460
std        29.653245        0.407685
min        30.200000        0.000000
25%        99.432750        4.000000
50%       122.024000        4.000000
75%       140.078000        4.000000
max       243.372000        5.000000
```

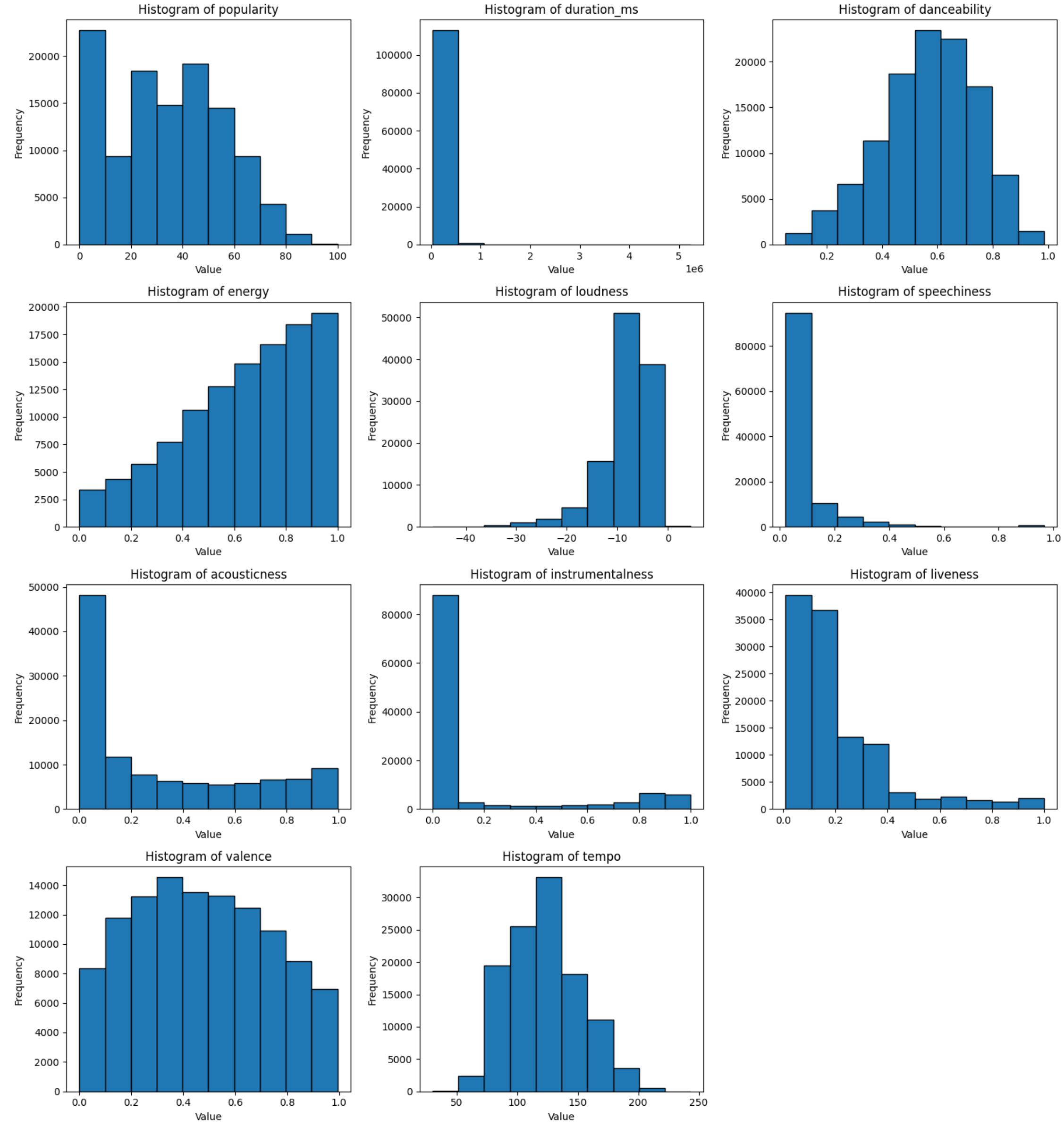
[68]:

```
# Select only numeric columns (remove categorical ones) using numeric() function written in data cleaning section
# Removed categorical columns: key, time signature, mode
numeric_spotify = numeric(spotify)
```

We started by looking at the distributions of all of the numeric variables with a histogram.

[69]:

```
# Create subplots
num_columns = len(numeric_spotify.columns)
num_rows = (num_columns // 3) + (num_columns % 3 > 0)
fig, axes = plt.subplots(num_rows, 3, figsize=(15, num_rows * 4))
axes = axes.flatten()

# Create a histogram for each variable
for i, column in enumerate(numeric_spotify.columns):
    ax = axes[i]
    numeric_spotify[column].hist(bins=10, edgecolor='black', ax=ax)
    ax.set_title(f'Histogram of {column}')
    ax.set_xlabel('Value')
    ax.set_ylabel('Frequency')
    ax.grid(False)

# Hiding unused subplots
for j in range(i + 1, len(axes)):
    axes[j].axis('off')

plt.tight_layout()
plt.show()
```

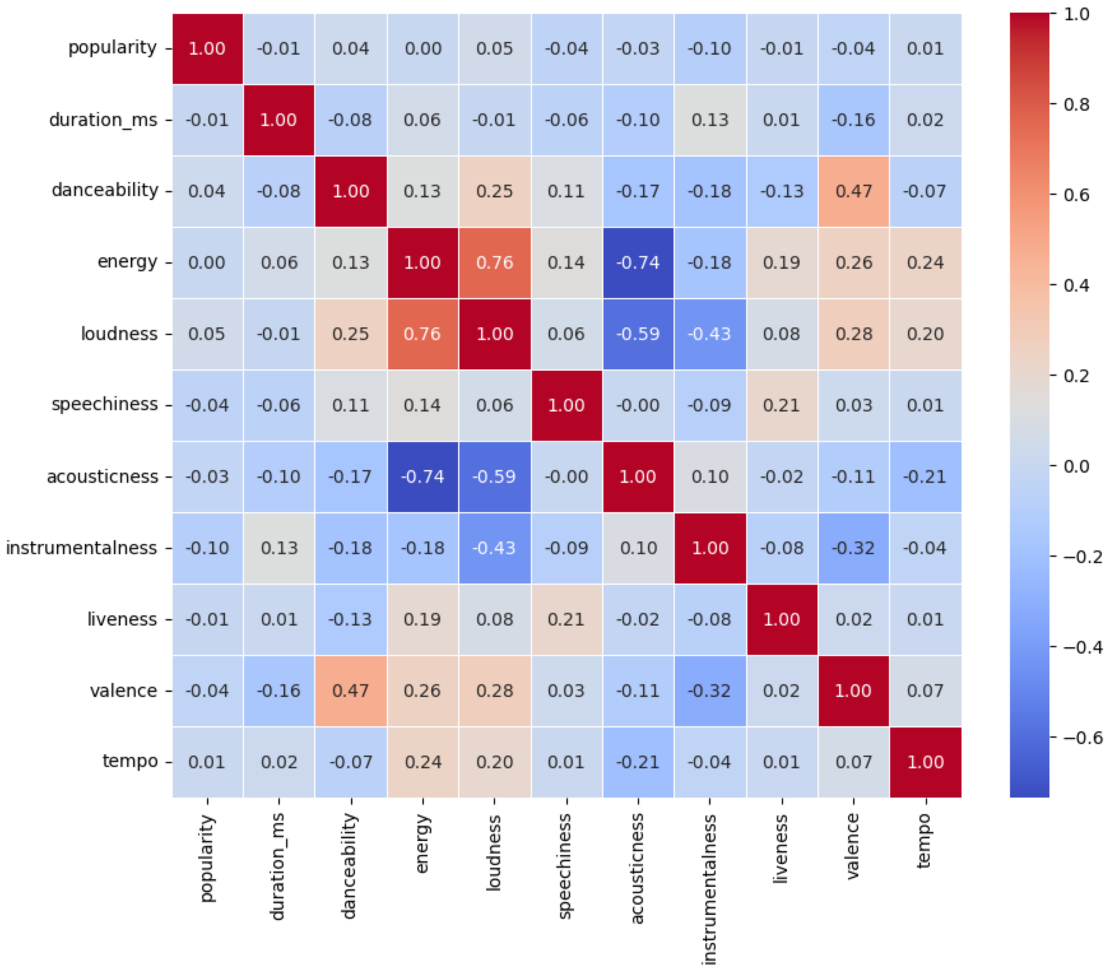


Based on this, we definitely have a few variables that are extremely skewed. However, we decided not to transform the data to make it more normal because the most of the data is already on a scale between 0 and 1, and we didn't want to lose possible meaningful information. For example, in the description of the data, it describes the "speechiness" variable with "Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks", which would be lost if we were to correct the right-skew of the speechiness variable.

We then decided to try to look at some relationships between variables by creating a correlation heatmap of every quantitative variable.

[70]:

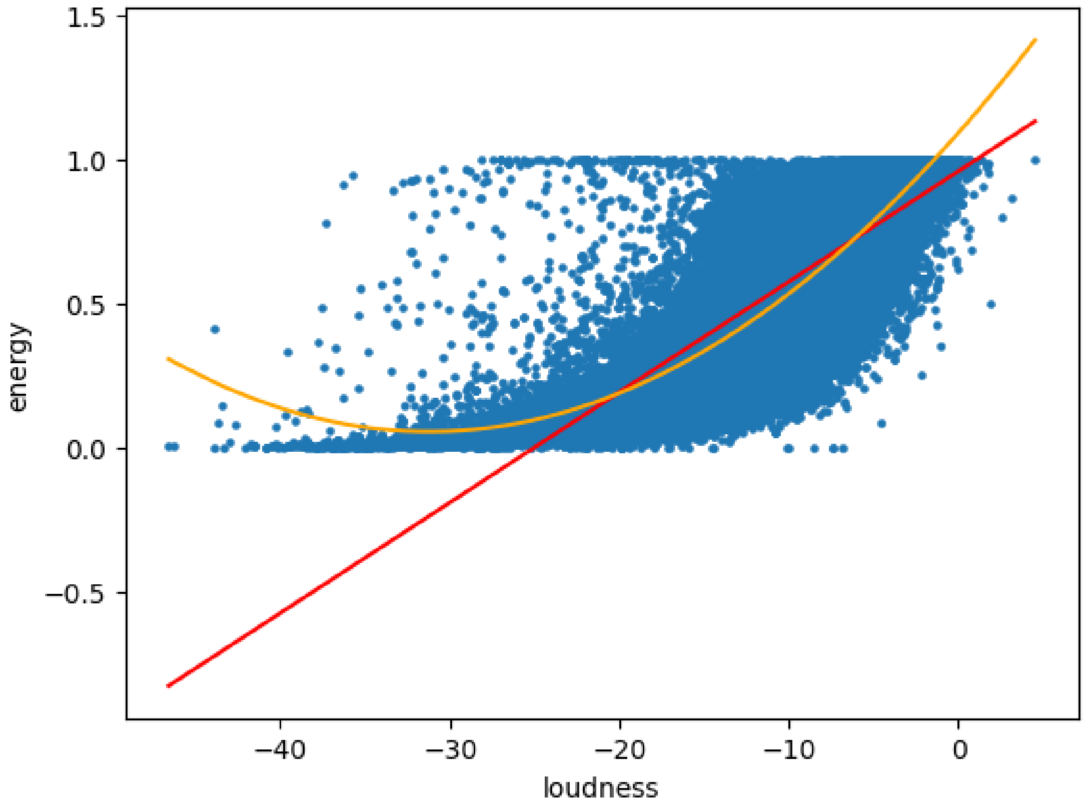
```
# Finding the correlation matrix
spotify_corr = numeric_spotify.corr()
spotify_corr

# Making correlation heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(spotify_corr, annot=True, fmt='.2f', cmap='coolwarm', linewidths=0.
  ↪5)

plt.show()
```

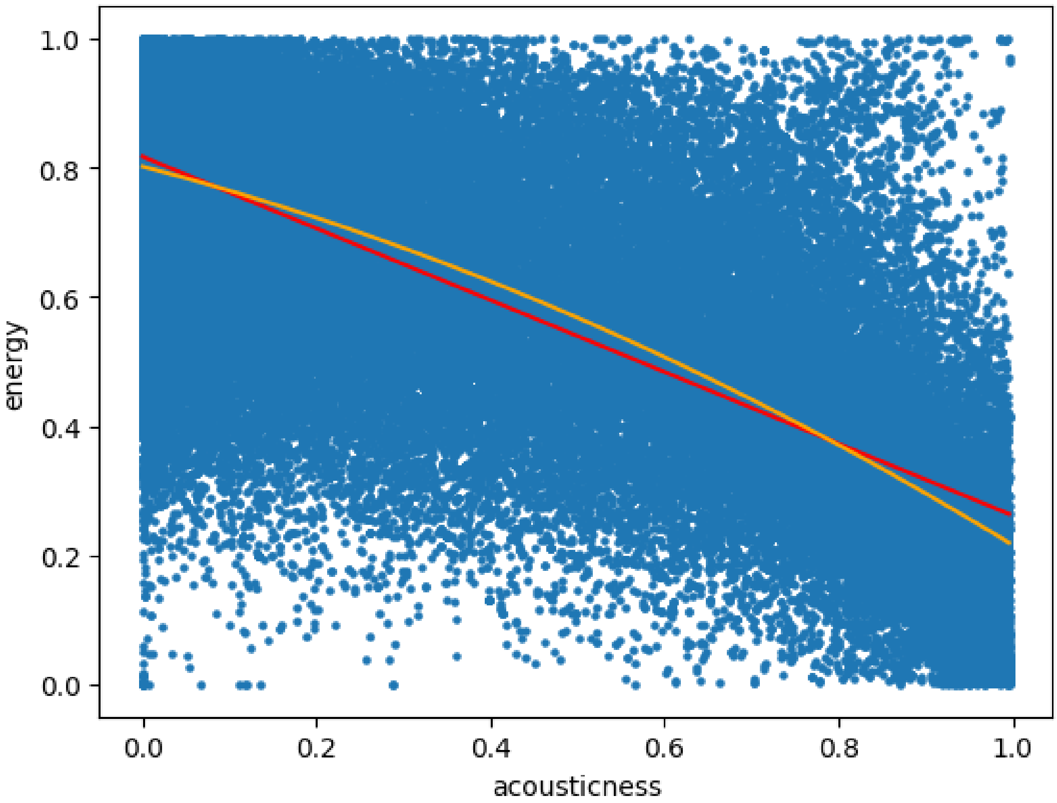


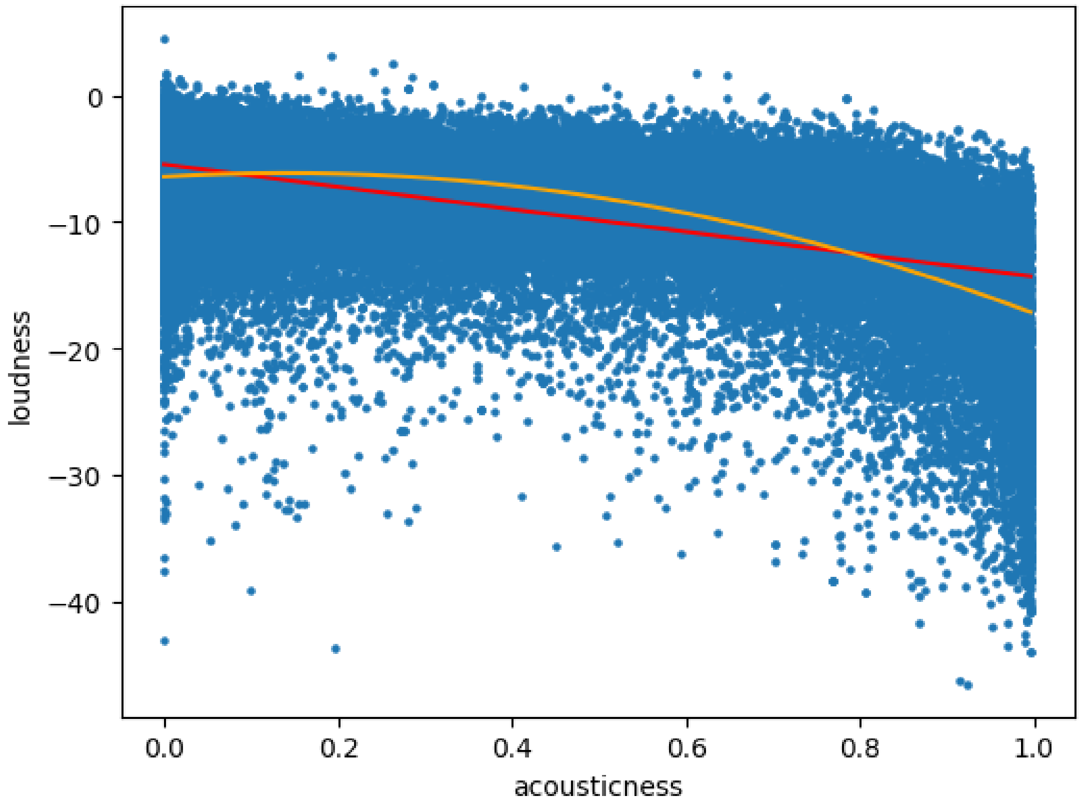
Based on the heatmap of correlations, we wanted to see a more detailed scatterplots of the features that were more correlated. So, we decided to plot more detailed scatterplots of the correlations larger than 0.4 or smaller than -0.4. We then plotted a linear and quadratic regression for each.

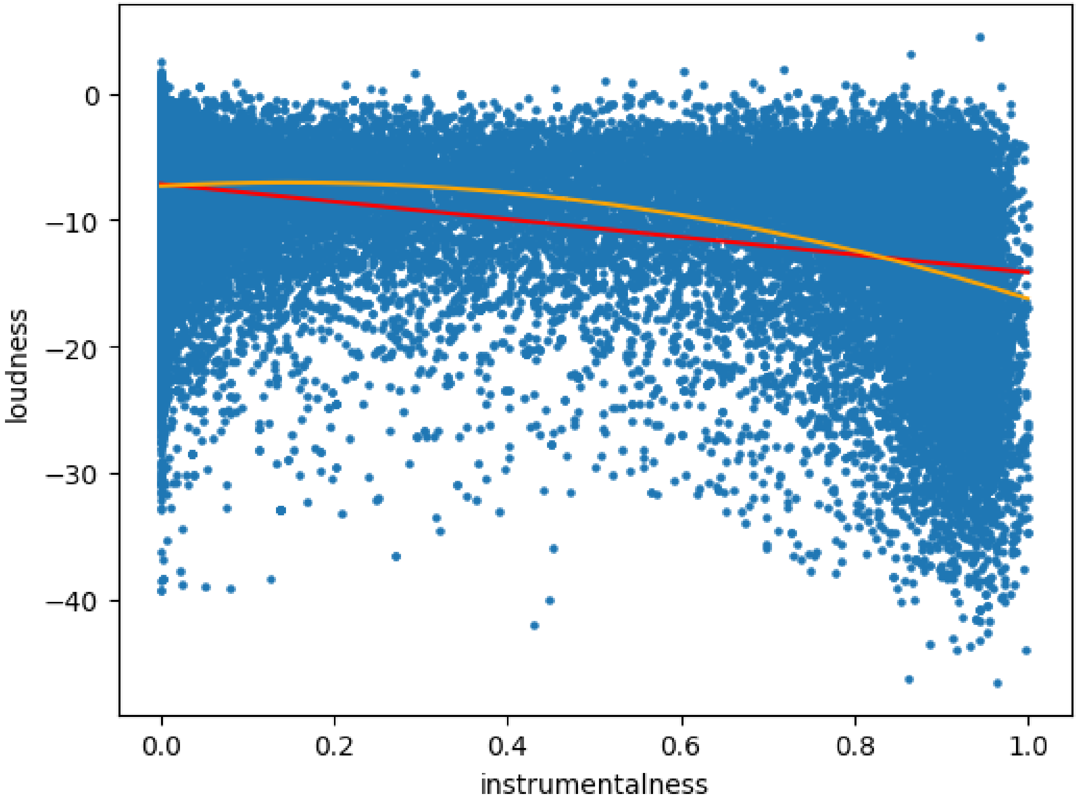
[71]:

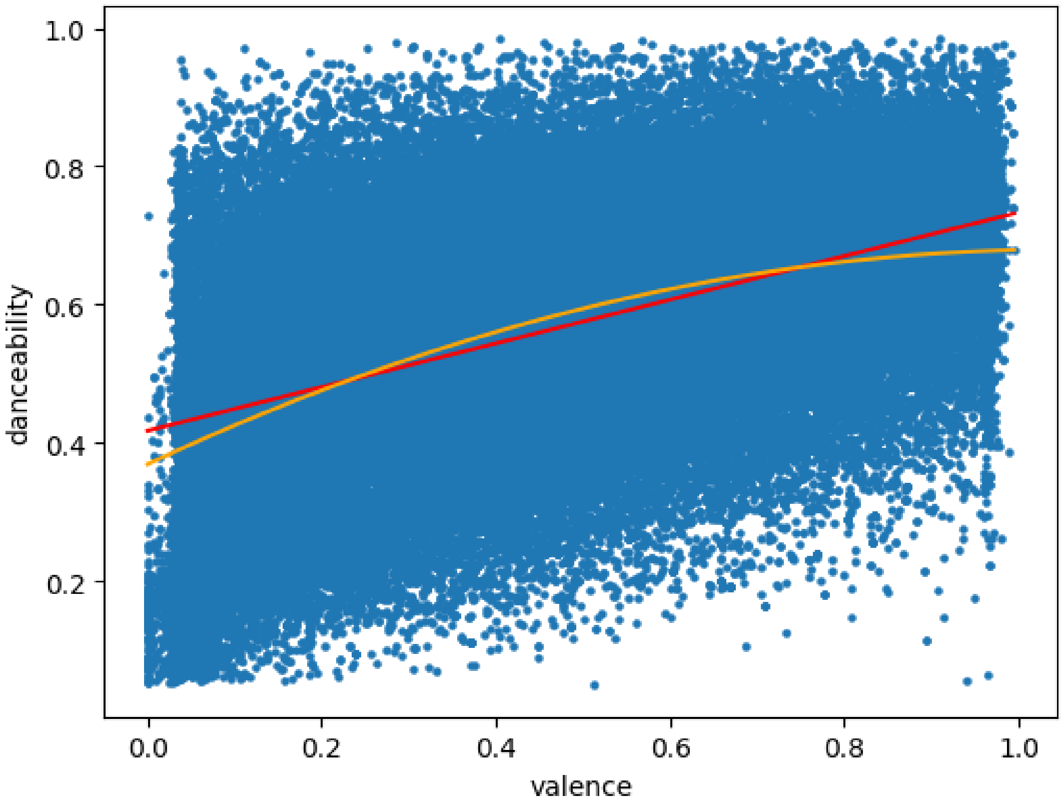
```
# Filtering out the pairs of higher correlated features
correlated_features = [
    ("loudness", "energy"),
    ("acousticness", "energy"),
    ("acousticness", "loudness"),
    ("instrumentalness", "loudness"),
    ("valence", "danceability"),
]

# Making scatterplots for each variable vs popularity
for (i, j) in correlated_features:
    plt.plot(np.unique(numeric_spotify[i]), np.poly1d(np.
↪polyfit(numeric_spotify[i], numeric_spotify[j], 1))(np.
↪unique(numeric_spotify[i])), color='red')
    plt.plot(np.unique(numeric_spotify[i]), np.poly1d(np.
↪polyfit(numeric_spotify[i], numeric_spotify[j], 2))(np.
↪unique(numeric_spotify[i])), color='orange')
    plt.scatter(numeric_spotify[i], numeric_spotify[j], s=5)
    plt.xlabel(i)
    plt.ylabel(j)
    plt.show()
```




1.0
0.8
0.6
0.4
0.2
0.0
energy
0.0
0.2
0.4
0.6
0.8
1.0
acousticness


0
−10
−20
−30
−40
loudness
0.0
0.2
0.4
0.6
0.8
1.0
acousticness


0
−10
−20
−30
−40
loudness
0.0
0.2
0.4
0.6
0.8
1.0
instrumentalness



Though the variability from our fitted lines seemed pretty high on our scatterplots, some of the shapes of the graphs were pretty interesting. In particular, we thought the shapes of the (acousticness vs loudness), (instrumentalness vs loudness), (acousticness vs energy), and (energy vs loudness) graphs seemed to have a pretty distinct shape. The variables may have some sort of relationship with each other, which we noted in case they played some part in later sections of our exploration in our project.

We also looked into the categorical variables (excluding genre, which we will go into a more detailed exploration of later).

[72]:
```
# Selecting the categories: key, mode, explicit, time signature
spotify_categories = spotify[categorical_columns + ['explicit']]
spotify_categories = spotify_categories.drop(columns='track_genre')

key_mapping = {
    0: 'C', 1: 'C /D ', 2: 'D', 3: 'D /E ', 4: 'E', 5: 'F', 6: 'F /G ', 7: 'G',
    8: 'G /A ', 9: 'A', 10: 'A /B ', 11: 'B', -1: 'No Key Detected'
}

# Map the 'key' column to pitch names
spotify_categories['key'] = spotify_categories['key'].map(key_mapping)
```

```
# Mode is 0 or 1 (1 for Major, 0 for Minor)
spotify_categories['mode'] = spotify_categories['mode'].map({0: 'Minor', 1:␣
 ↪'Major'})

# Time signature
spotify_categories['time_signature'] = spotify_categories['time_signature'].
 ↪astype(str)

spotify_categories
```

[72]:

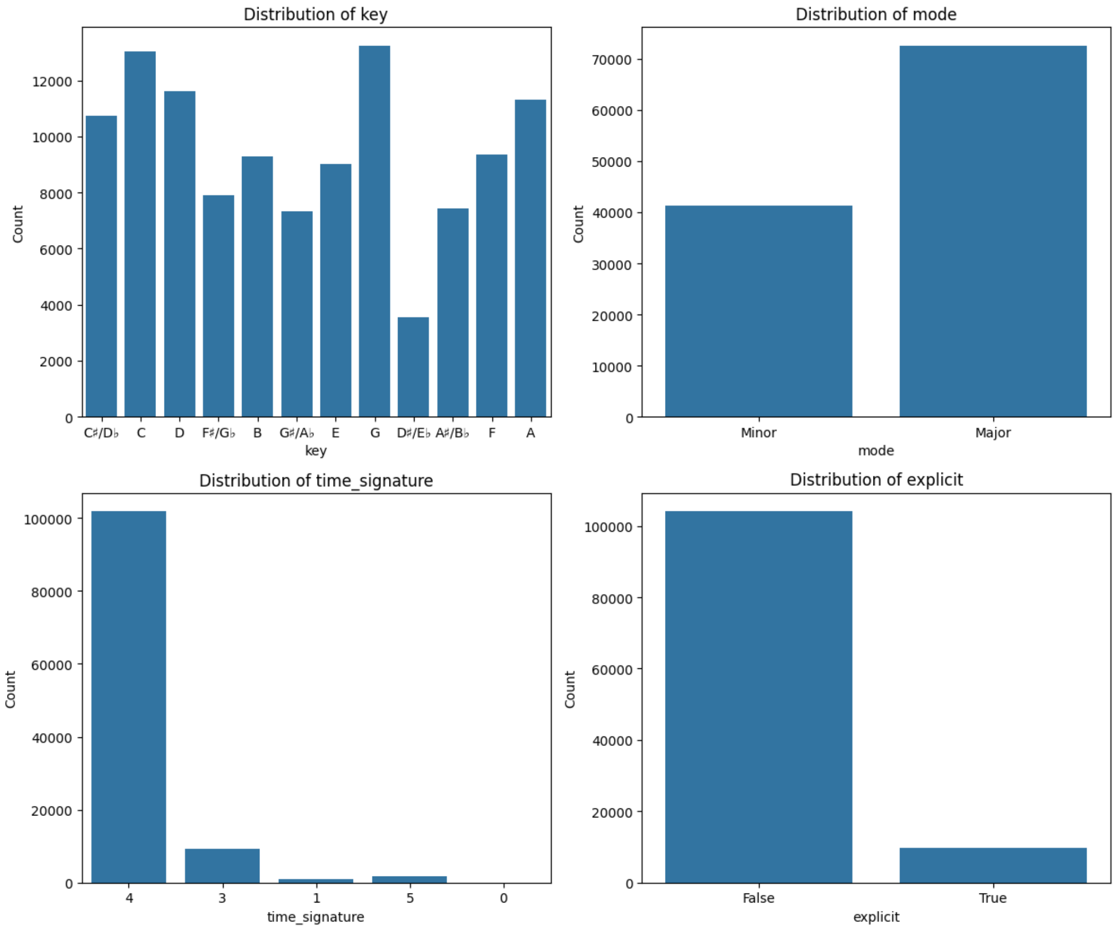
```
          key   mode time_signature  explicit
0       C/D   Minor              4     False
1       C/D   Major              4     False
2           C  Major              4     False
3           C  Major              3     False
4           D  Major              4     False
…       …    …             …      …
113823      F  Major              5     False
113824      C  Minor              4     False
113825      C  Minor              4     False
113826      G  Major              4     False
113827  C/D   Minor              4     False

[113828 rows x 4 columns]
```

[73]:

```
# Making barplots for each categorical value

# Create subplots for each categorical variable
plt.figure(figsize=(12, 10))
num_columns = len(spotify_categories.columns)
num_rows = (num_columns // 2) + (num_columns % 2 > 0)
fig, axes = plt.subplots(num_rows, 2, figsize=(12, num_rows * 5))
axes = axes.flatten()

# Loop through each categorical variable to create a bar plot
for i, column in enumerate(spotify_categories.columns):
    ax = axes[i]
    sns.countplot(x=column, data=spotify_categories, ax=ax)
    ax.set_title(f'Distribution of {column}')
    ax.set_xlabel(column)
    ax.set_ylabel('Count')
    ax.grid(False)

# Hiding unused subplots
for j in range(i + 1, len(axes)):
    axes[j].axis('off')
```

```
plt.tight_layout()
plt.show()
```

```
<Figure size 1200x1000 with 0 Axes>
```



Based on these visualizations it seems like the distributions for the key the song is in is fairly uniformly distributed, with D#/E the least number of tracks. Additionally, most songs seem to be in major, have a 4/4 time signature, or non-explicit.

After a more general exploration of some of the relationships and other features in our dataset, we decided to look closer into genre, the main focus of our project.

```
[74]: genre_counts = spotify['track_genre'].value_counts()
      print(genre_counts)
```

```
track_genre
acoustic       1000
afrobeat       1000
alt-rock       1000
alternative    1000
```

```
anime           1000
               …
classical        997
world-music      997
guitar           996
iranian          990
sleep            861
Name: count, Length: 114, dtype: int64
```

We have 114 different genres, and they all seem fairly split. In fact, our dataset seems to have 1000 samples for each genre, as the genres that have less than 1000 samples are genres that we cleaned data values from. We looked further into the specific genres and names.

[75]:

```
genre_names = spotify['track_genre'].unique()
print(genre_names)
```

```
['acoustic' 'afrobeat' 'alt-rock' 'alternative' 'ambient' 'anime'
 'black-metal' 'bluegrass' 'blues' 'brazil' 'breakbeat' 'british'
 'cantopop' 'chicago-house' 'children' 'chill' 'classical' 'club' 'comedy'
 'country' 'dance' 'dancehall' 'death-metal' 'deep-house' 'detroit-techno'
 'disco' 'disney' 'drum-and-bass' 'dub' 'dubstep' 'edm' 'electro'
 'electronic' 'emo' 'folk' 'forro' 'french' 'funk' 'garage' 'german'
 'gospel' 'goth' 'grindcore' 'groove' 'grunge' 'guitar' 'happy'
 'hard-rock' 'hardcore' 'hardstyle' 'heavy-metal' 'hip-hop' 'honky-tonk'
 'house' 'idm' 'indian' 'indie-pop' 'indie' 'industrial' 'iranian'
 'j-dance' 'j-idol' 'j-pop' 'j-rock' 'jazz' 'k-pop' 'kids' 'latin'
 'latino' 'malay' 'mandopop' 'metal' 'metalcore' 'minimal-techno' 'mpb'
 'new-age' 'opera' 'pagode' 'party' 'piano' 'pop-film' 'pop' 'power-pop'
 'progressive-house' 'psych-rock' 'punk-rock' 'punk' 'r-n-b' 'reggae'
 'reggaeton' 'rock-n-roll' 'rock' 'rockabilly' 'romance' 'sad' 'salsa'
 'samba' 'sertanejo' 'show-tunes' 'singer-songwriter' 'ska' 'sleep'
 'songwriter' 'soul' 'spanish' 'study' 'swedish' 'synth-pop' 'tango'
 'techno' 'trance' 'trip-hop' 'turkish' 'world-music']
```

We saw that some genres were a lot more specific than others, for example, the genre of "pop" versus "disney", so we kept that in mind while doing later investigations and processing that we might want to group certain similar genres together, like grouping rock genres, pop genres, jazz, genres, etc.

We also looked at how some of the other variables were distributed grouped by track genre to see if certain genres had differentiable characteristics.

[76]:

```
temp = spotify['track_genre']
by_genres = numeric(spotify)
by_genres['track_genre'] = temp

by_genres.groupby('track_genre').mean()
```

```
[76]:              popularity   duration_ms  danceability    energy   loudness  \
      track_genre
      acoustic       42.483000  214896.957000      0.549593  0.435368  -9.447843
      afrobeat       24.399000  248412.791000      0.669580  0.702812  -7.789353
      alt-rock       33.943000  235455.907000      0.534493  0.754173  -6.191489
      alternative    24.337000  222016.180000      0.559927  0.720030  -6.078777
      ambient        44.151454  237478.207623      0.368974  0.237762 -18.584524
      …                    …            …           …         …        …
      techno         39.042000  312311.477000      0.684348  0.746413  -8.077874
      trance         37.635000  269007.478000      0.583409  0.845272  -6.329711
      trip-hop       34.460000  274954.026000      0.634695  0.622363  -9.239915
      turkish        40.698000  219529.010000      0.616077  0.609804  -8.224722
      world-music    41.925777  294045.881645      0.415819  0.534177  -9.398517

                   speechiness  acousticness  instrumentalness  liveness   valence  \
      track_genre
      acoustic        0.043247      0.566816          0.038336  0.153244  0.424023
      afrobeat        0.086579      0.270860          0.253483  0.184596  0.698619
      alt-rock        0.055071      0.122162          0.054097  0.210249  0.518260
      alternative     0.070101      0.147820          0.038159  0.201376  0.495570
      ambient         0.041687      0.776158          0.675362  0.129396  0.168002
      …                     …            …               …       …        …
      techno          0.064212      0.081414          0.540038  0.159434  0.321878
      trance          0.079705      0.035870          0.423501  0.234357  0.276881
      trip-hop        0.076303      0.225615          0.383761  0.190342  0.478069
      turkish         0.105087      0.321125          0.035603  0.180750  0.462314
      world-music     0.041894      0.299980          0.089768  0.250248  0.251048

                        tempo
      track_genre
      acoustic     119.010624
      afrobeat     119.213337
      alt-rock     124.634404
      alternative  122.232394
      ambient      111.447471
      …                  …
      techno       128.255482
      trance       133.276726
      trip-hop     118.743616
      turkish      120.367607
      world-music  121.758988

      [114 rows x 11 columns]
```

In order to better visualize these results, we decided to group the genres even further (as visualizing the differences between 114 grouped genres may be unclear). To do so, we manually grouped the genres into 10 more over-arching, general genres:

- **Pop:** cantopop, j-pop, k-pop, mandopop, pop, indie-pop, power-pop, pop-film, synth-pop

- **Rock:** alt-rock, alternative, hard-rock, punk-rock, psych-rock, rock, rock-n-roll, grunge, emo, rockabilly, guitar

- **Metal:** black-metal, death-metal, heavy-metal, metal, metalcore, grindcore

- **Electronic:** edm, electro, electronic, house, garage, techno, trance, dubstep, idm, minimal-techno, progressive-house, chicago-house, deep-house, detroit-techno, disco, drum-and-bass, dub, club, dance, dancehall

- **Hip-Hop:** hip-hop, rap, r-n-b, breakbeat

- **Jazz:** jazz, blues, soul, funk

- **Classical:** classical, opera, piano

- **World:** afrobeat, brazil, british, latin, latino, samba, salsa, reggae, reggaeton, tango, world-music, indian, iranian, turkish, malay, mpb, pagode, forro, french, german, spanish, swedish

- **Folk:** folk, bluegrass, country, singer-songwriter, songwriter, honky-tonk

- **Misc:** acoustic, ambient, anime, children, chill, comedy, disney, happy, party, study, sleep, show-tunes, new-age, kids, industrial, gospel, goth, groove, hardcore, hardstyle, indie, j-dance, j-idol, j-rock, punk, romance, sad, sertanejo, ska, trip-hop

[77]:

```
original_data = pd.read_csv('spotify.csv')

genre_groups = {
    'pop': ['cantopop', 'j-pop', 'j-idol', 'k-pop', 'mandopop', 'pop',␣
 ↪'indie-pop', 'power-pop', 'pop-film', 'synth-pop'],
    'rock': ['alt-rock', 'alternative', 'hard-rock', 'indie', 'punk', 'j-rock',␣
 ↪'punk-rock', 'psych-rock', 'rock', 'rock-n-roll', 'grunge', 'emo',␣
 ↪'rockabilly', 'guitar'],
    'metal': ['black-metal', 'death-metal', 'heavy-metal', 'metal',␣
 ↪'metalcore', 'grindcore'],
    'electronic': ['edm', 'electro', 'electronic', 'house', 'garage',␣
 ↪'j-dance', 'hardcore', 'hardstyle', 'industrial', 'techno', 'trance',␣
 ↪'dubstep', 'idm', 'minimal-techno', 'progressive-house', 'chicago-house',␣
 ↪'deep-house', 'detroit-techno', 'disco', 'drum-and-bass', 'dub', 'club',␣
 ↪'dance', 'dancehall'],
    'hip-hop': ['hip-hop', 'rap', 'r-n-b', 'breakbeat', 'trip-hop'],
    'jazz': ['jazz', 'blues', 'soul', 'funk', 'ska', 'gospel'],
    'classical': ['classical', 'opera', 'piano'],
    'world': ['afrobeat', 'brazil', 'sertanejo', 'british', 'latin', 'latino',␣
  ↪'samba', 'salsa', 'reggae', 'reggaeton', 'tango', 'world-music', 'indian',␣
  ↪'iranian', 'turkish', 'malay', 'mpb', 'pagode', 'forro', 'french', 'german',␣
  ↪'spanish', 'swedish'],
    'folk': ['folk', 'bluegrass', 'country', 'singer-songwriter', 'songwriter',␣
  ↪'honky-tonk'],
    'misc': ['acoustic', 'ambient', 'anime', 'children', 'chill', 'comedy',␣
  ↪'disney', 'happy', 'party', 'study', 'sleep', 'show-tunes', 'new-age',␣
  ↪'kids', 'goth', 'groove', 'romance', 'sad']
}

genre_map = dict()
for genre, l in genre_groups.items():
    for original in l:
        genre_map[original] = genre

data = original_data.copy()
data['track_genre'] = data['track_genre'].map(genre_map)

data.to_csv(
    "grouped_cleaned_spotify.csv",
    index=False
)
```

[78]:

```
grouped_spotify = pd.read_csv("grouped_cleaned_spotify.csv")
grouped_spotify['track_genre'].value_counts()
```

[78]:

```
track_genre
electronic    24000
world         22984
misc          17855
rock          13996
pop            9999
metal          6000
folk           6000
jazz           5999
hip-hop        4000
classical      2995
Name: count, dtype: int64
```

Though now we have some imbalance between the different genres, it is much easier for us to visualize the values. Looking again at the means:

[79]:

```
temp = grouped_spotify['track_genre']
by_grouped_genres = numeric(grouped_spotify)
by_grouped_genres['track_genre'] = temp
```

```python
grouped_genre_means = by_grouped_genres.groupby('track_genre').mean()
grouped_genre_means
```

```
[79]:              popularity    duration_ms  danceability    energy   loudness  \
      track_genre
      classical     27.671452  223765.185309      0.383762  0.275876 -16.901773
      electronic    32.682375  244199.154417      0.628392  0.748102  -6.786162
      folk          28.781833  214844.595833      0.557295  0.484704  -9.592910
      hip-hop       32.257250  255499.212000      0.657858  0.699074  -7.198840
      jazz          28.944157  226728.059177      0.568563  0.578545  -8.072706
      metal         30.441833  238321.365167      0.375544  0.893222  -5.626057
      misc          32.046766  202753.826211      0.544729  0.519480 -11.052483
      pop           41.354135  236116.865087      0.576878  0.647109  -7.206672
      rock          36.582809  216122.028079      0.531166  0.673804  -7.515469
      world         33.082884  231900.404760      0.600875  0.635310  -7.881580

                   speechiness  acousticness  instrumentalness  liveness   valence  \
      track_genre
      classical       0.048077      0.806379          0.432656  0.176999  0.303223
      electronic      0.092085      0.122595          0.249558  0.190737  0.432817
      folk            0.046643      0.528443          0.048824  0.178637  0.517899
      hip-hop         0.095396      0.205441          0.200120  0.216372  0.534306
      jazz            0.074014      0.385527          0.028089  0.215736  0.539197
      metal           0.098494      0.017465          0.241315  0.251464  0.296137
      misc            0.123619      0.488473          0.250852  0.230444  0.411343
      pop             0.061161      0.313732          0.028029  0.185500  0.511655
      rock            0.062589      0.258902          0.072948  0.204043  0.530961
      world           0.082780      0.372472          0.082835  0.243521  0.547976

                        tempo
      track_genre
      classical    110.627554
      electronic   126.276463
      folk         120.840527
      hip-hop      123.145587
      jazz         119.278760
      metal        126.118669
      misc         117.992933
      pop          124.357350
      rock         124.747857
      world        120.740060
```

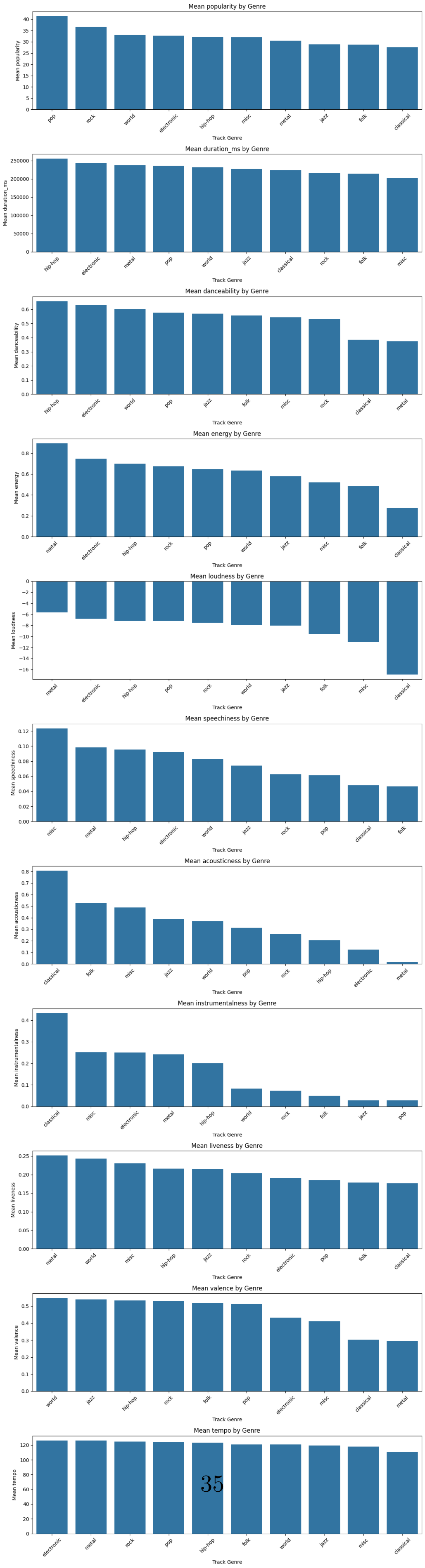
```python
[80]: ranges = grouped_genre_means.max() - grouped_genre_means.min()
      ranges
```

```
[80]: popularity              13.682683
      duration_ms          52745.385789
```

```
danceability           0.282314
energy                 0.617346
loudness              11.275715
speechiness            0.076976
acousticness           0.788914
instrumentalness       0.404627
liveness               0.074465
valence                0.251839
tempo                 15.648908
dtype: float64
```

[81]:

```
num_vars = len(grouped_genre_means.columns)
fig, axes = plt.subplots(nrows=num_vars, ncols=1, figsize=(12, num_vars * 4))

# Plot each variable as a barplot
for i, (column, ax) in enumerate(zip(grouped_genre_means.columns, axes)):
    sorted_data = grouped_genre_means[column].sort_values(ascending=False) #␣
 ↪sort descending

    sns.barplot(
        x=sorted_data.index,
        y=sorted_data.values,
        ax=ax,
    )
    ax.set_title(f'Mean {column} by Genre')
    ax.set_xlabel('Track Genre')
    ax.set_ylabel(f'Mean {column}')
    ax.tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()
```


Mean popularity by Genre
Mean popularity
0
5
10
15
20
25
30
35
40
pop
rock
world
electronic
hip-hop
misc
metal
jazz
folk
classical
Track Genre
Mean duration_ms by Genre
Mean duration_ms
0
50000
100000
150000
200000
250000
hip-hop
electronic
metal
pop
world
jazz
classical
rock
folk
misc
Track Genre
Mean danceability by Genre
Mean danceability
0.0
0.1
0.2
0.3
0.4
0.5
0.6
hip-hop
electronic
world
pop
jazz
folk
misc
rock
classical
metal
Track Genre
Mean energy by Genre
Mean energy
0.0
0.2
0.4
0.6
0.8
metal
electronic
hip-hop
rock
pop
world
jazz
misc
folk
classical
Track Genre
Mean loudness by Genre
Mean loudness
0
−2
−4
−6
−8
−10
−12
−14
−16
metal
electronic
hip-hop
pop
rock
world
jazz
folk
misc
classical
Track Genre
Mean speechiness by Genre
Mean speechiness
0.00
0.02
0.04
0.06
0.08
0.10
0.12
misc
metal
hip-hop
electronic
world
jazz
rock
pop
classical
folk
Track Genre
Mean acousticness by Genre
Mean acousticness
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
classical
folk
misc
jazz
world
pop
rock
hip-hop
electronic
metal
Track Genre
Mean instrumentalness by Genre
Mean instrumentalness
0.0
0.1
0.2
0.3
0.4
classical
misc
electronic
metal
hip-hop
world
rock
folk
jazz
pop
Track Genre
Mean liveness by Genre
Mean liveness
0.00
0.05
0.10
0.15
0.20
0.25
metal
world
misc
hip-hop
jazz
rock
electronic
pop
folk
classical
Track Genre
Mean valence by Genre
Mean valence
0.0
0.1
0.2
0.3
0.4
0.5
world
jazz
hip-hop
rock
folk
pop
electronic
misc
classical
metal
Track Genre
Mean tempo by Genre
Mean tempo
0
20
40
60
80
100
120
electronic
metal
rock
pop
hip-hop
folk
world
jazz
misc
classical
Track Genre

From the above visualizations, we can make a few interesting observations about each variable: - Pop music seems to be the most popular, though not necessarily by very much (around 5 points difference from rock). - Duration doesn't seem to have that much variability across genres when considering the range of the means is about 43000ms, which is about a 42 second difference. However, hip-hop songs seem to be the longest in duration compared to other genres. - Classical and metal tracks seem to score lower on danceability scores compared to other genres, and hip-hop is the highest for danceability. - Metal scores very high for energy levels, while classical seems to score lower. - Similarly, metal scores high for loudness, while classical scores much lower. In this variable, loudness, the difference between classical and the rest of the variables is much more apparent. - For the speechiness variable, folk and classical have the least amount of speechiness, while miscellaneous genres have the most. - For acousticness, classical music scores very high while metal scores extremely low. - With instrumentalness, classical music once again scores high, with pop and jazz scoring low. - There doesn't seem to be too large of a difference in liveness across the variables, though metal does score the highest while classical scores the lowest. - Surprisingly, metal and classical both score low on valence, with jazz, hip-hop, and world tracks scoring higher. - Tempo seems to be fairly uniformly distributed across the genres, with classical and jazz barely scoring lower than the other genres.

In summary, it seems like classical tracks and metal tracks have the largest distinction between their variables, and the variables acousticness and instrumentalness seem to have the most variance across genres.

To investigate our genres in our dataset further, such as which features may play a role in the labelling of genres and if there's a way for us to predict the genre of a song based on its features, we can prepare our data for further model and training. We decided we didn't need to do any feature engineering since several of our variables already ranged from 0 to 1, some with meaningful values (as discussed in the cleaning section). We also didn't add any extra data through data augmentation because we already had over 100k samples, which we felt would be sufficient in our investigation.

In order to prepare our data for more learning models, we split it into training, validation, and testing datasets (60-20-20). an example of how we split our data is in the code below, but we re-split it for each model for the sake of simplicity. We did this both for our original cleaned dataset and also our dataset grouped by our 10 generalized genres.

[82]:
```
random_seed = 42

# encode categorical categories
for column in categorical_columns:
    spotify[column] = pd.Categorical(spotify[column])

# First split: separate out 20% for the test set
spotify_train_val, spotify_test = train_test_split(spotify, test_size=0.2,␣
 ↪random_state=random_seed)
# Second split: separate remaining 80% into 60% training and 20% validation
```

```
spotify_train, spotify_val = train_test_split(spotify_train_val, test_size=0.
↪25, random_state=random_seed)  # 0.25 * 0.8 = 0.2

# Grouped genre dataset, grouped_spotify
# First split: separate out 20% for the test set
grouped_spotify_train_val, grouped_spotify_test =␣
↪train_test_split(grouped_spotify, test_size=0.2, random_state=random_seed)
# Second split: separate remaining 80% into 60% training and 20% validation
grouped_spotify_train, grouped_spotify_val =␣
↪train_test_split(grouped_spotify_train_val, test_size=0.25,␣
↪random_state=random_seed)  # 0.25 * 0.8 = 0.2
```

A summary of the datasets that result from the train-validation-test splitting is below:

Original 114 genre dataset: - `spotify_train` (60% of the total dataset) - `spotify_val` (20% of the total dataset) - `spotify_test` (20% of the total dataset)

Re-grouped 10 genre dataset: - `grouped_spotify_train` (60% of the total dataset) - `grouped_spotify_val` (20% of the total dataset) - `grouped_spotify_test` (20% of the total dataset)

[83]:

```
# This code does OHE and removed genre from grouped_spotify
response_variable = "track_genre"
ohe_column_transformer_wo_genre = ColumnTransformer(
    transformers=[
        ('ohe', OneHotEncoder(sparse_output=False), [col for col in␣
↪categorical_columns if col != response_variable]),
        ('string', 'drop', string_columns),
        ('numeric', 'passthrough', [col for col in spotify.columns if col !=␣
↪response_variable and col not in string_columns])
    ],
    verbose_feature_names_out=False
)
ohe_column_transformer_wo_genre.set_output(transform="pandas")
ohe_column_transformer_wo_genre.fit(grouped_spotify)

ohe_grouped_column_transformer_wo_genre = ColumnTransformer(
    transformers=[
        ('ohe', OneHotEncoder(sparse_output=False), [col for col in␣
↪categorical_columns if col != response_variable]),
        ('string', 'drop', string_columns),
        ('numeric', 'passthrough', [col for col in grouped_spotify.columns if␣
↪col != response_variable and col not in string_columns])
    ],
    verbose_feature_names_out=False
)
ohe_grouped_column_transformer_wo_genre.set_output(transform="pandas")
ohe_grouped_column_transformer_wo_genre.fit(grouped_spotify)
```

```
[83]: ColumnTransformer(transformers=[('ohe', OneHotEncoder(sparse_output=False),
                                  ['key', 'mode', 'time_signature']),
                                 ('string', 'drop',
                                  ['track_id', 'artists', 'album_name',
                                   'track_name']),
                                 ('numeric', 'passthrough',
                                  ['popularity', 'duration_ms', 'explicit',
                                   'danceability', 'energy', 'key', 'loudness',
                                   'mode', 'speechiness', 'acousticness',
                                   'instrumentalness', 'liveness', 'valence',
                                   'tempo', 'time_signature'])],
                   verbose_feature_names_out=False)
```

1.4 Linear + Polynomial Regression

For our linear regression, we chose to use the `energy` variable as our response variable, as it seemed to have the most relationships with other variables based on our correlation heatmap during our EDA, and we were interested in finding out what may contribute to the energy of a song.

To find out our predictor variables, we used forward feature selection to see which predictors may be most correlated with our response variable (energy).

To find out our predictor variables, we used forward feature selection to see which predictors may be most correlated with our response variable (energy).

```
[52]: response = "energy" # this was chosen based on correlation heatmap

      # Making sure only numeric variables are used:
      num_spotify_train = numeric(spotify_train)
      num_spotify_val = numeric(spotify_val)
      num_spotify_test = numeric(spotify_test)

      # Reshape the data to fit the model
      X_train = num_spotify_train.drop(columns=response)
      y = num_spotify_train[response]

      lin_reg = LinearRegression()

      # Select features
      selector = SequentialFeatureSelector(
          lin_reg,
          n_features_to_select='auto',
          direction='forward',
          scoring='r2',
          cv = 5
      )

      selector.fit(X_train, y)
```

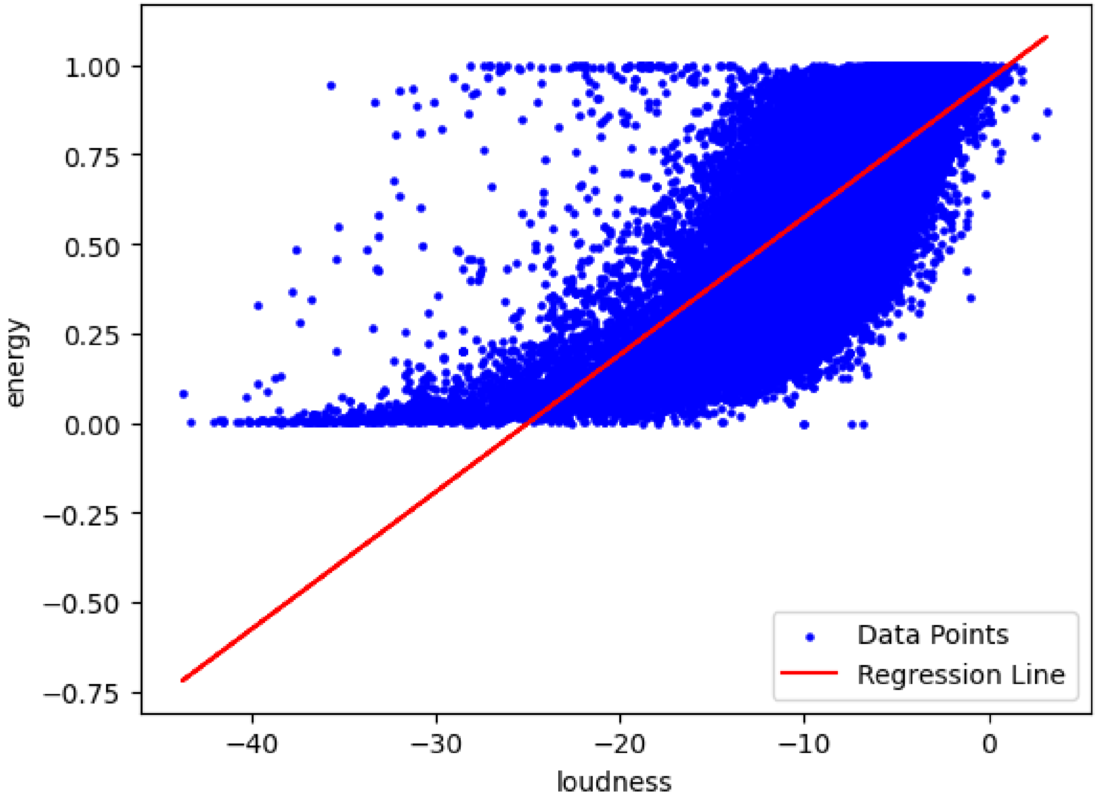
```
selected_features = selector.get_feature_names_out(X_train.columns)
print("Selected Features: ", selected_features)
```

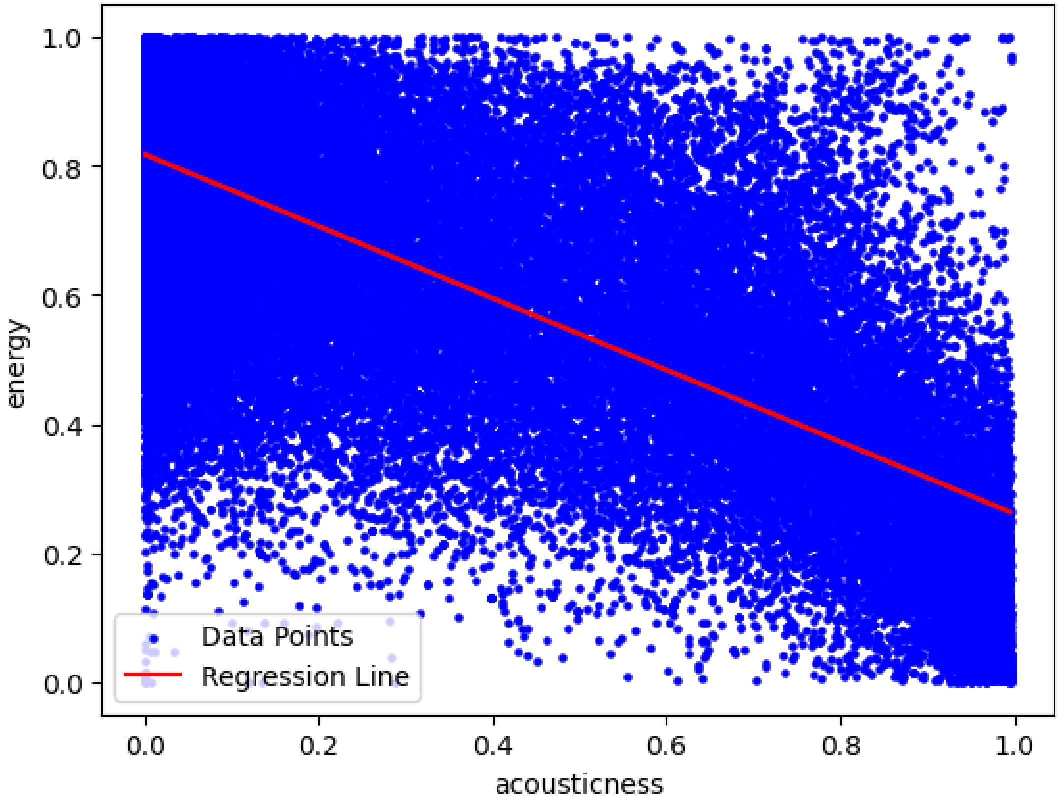
```
Selected Features:  ['loudness' 'acousticness' 'instrumentalness' 'liveness'
'valence']
```

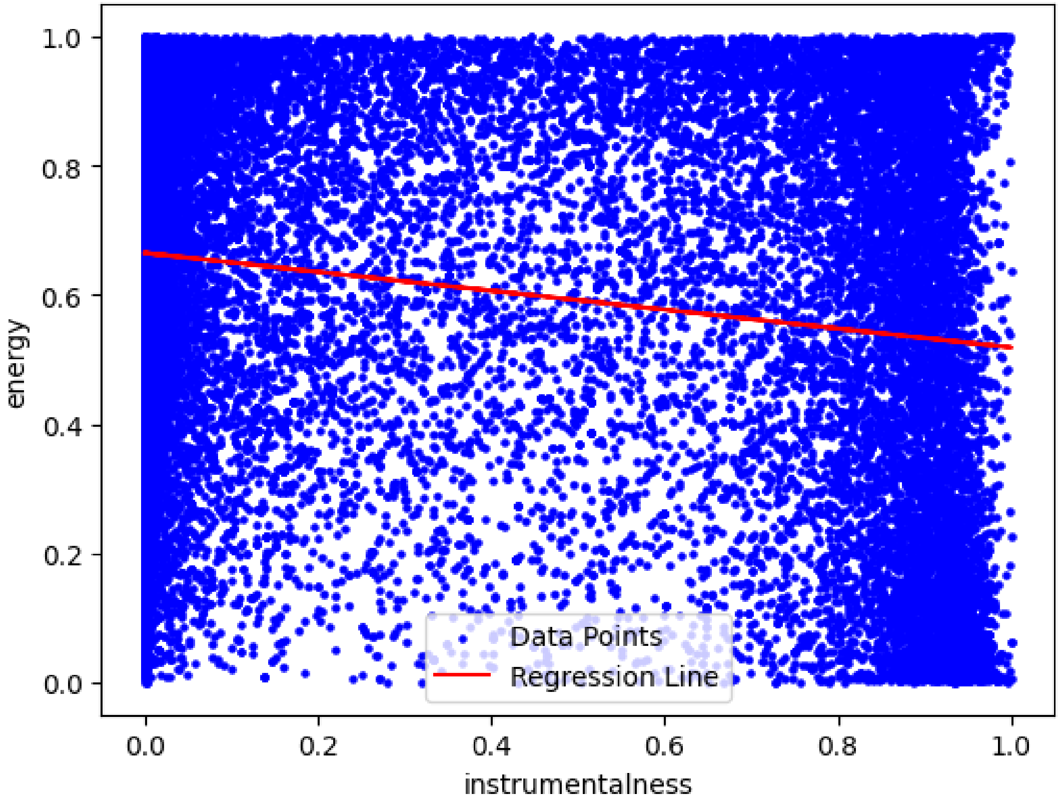
Based on this we found that `'loudness'`, `'acousticness'`, `'instrumentalness'`, `'liveness'`, and `'valence'` were our selected features, and graphed these with energy as the response variable to investigate the relationships.

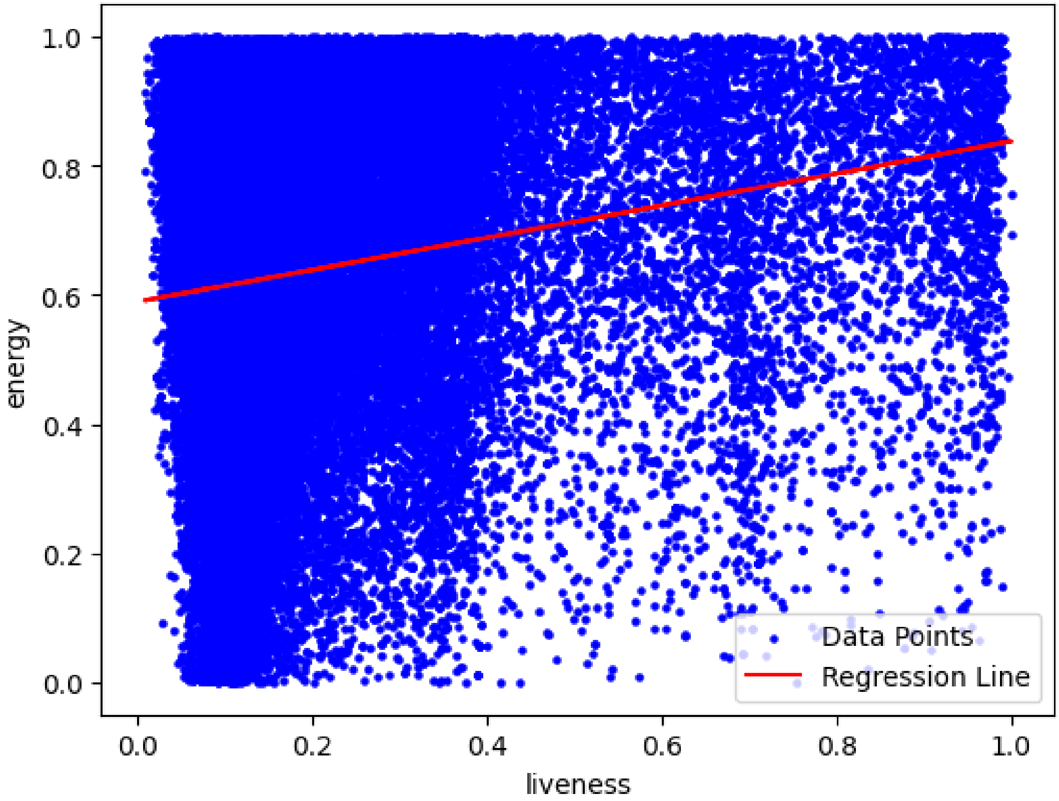
[53]:

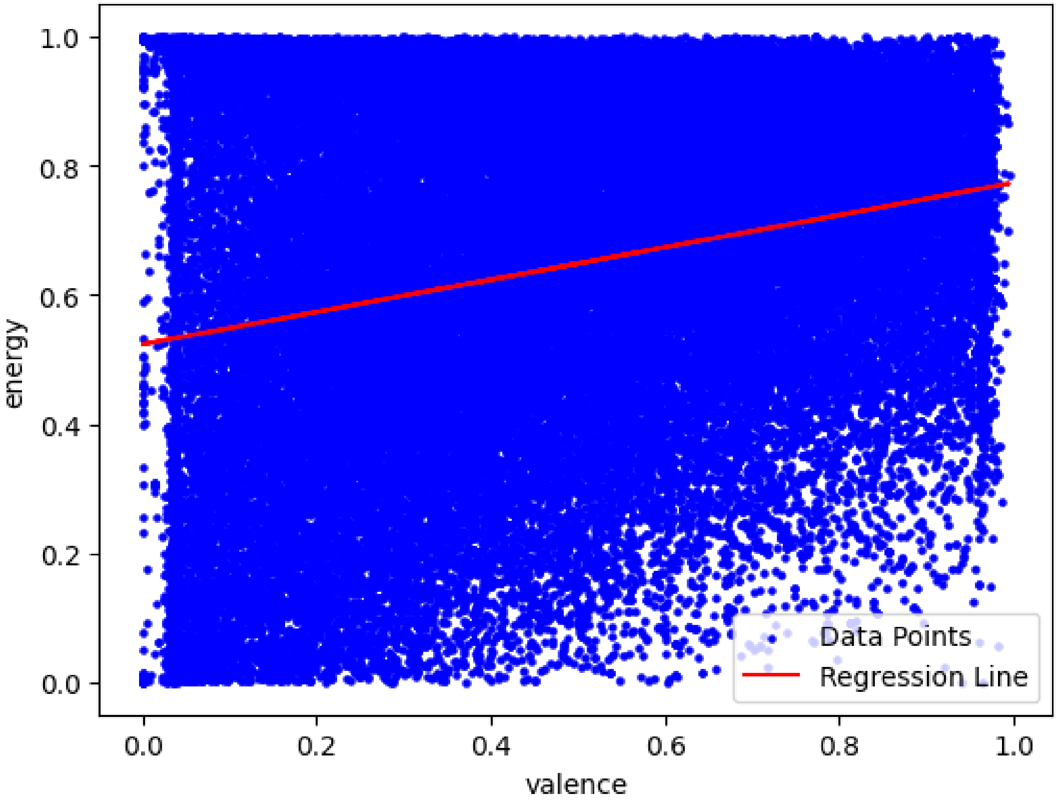
```
X = selector.transform(X_train)

X_test = selector.transform(num_spotify_test.drop(columns=response))
y_test = num_spotify_test[response]

X_val = selector.transform(num_spotify_val.drop(columns=response))
y_val = num_spotify_val[response]

lin_reg.fit(X, y)
y_pred = lin_reg.predict(X)

# Plotting scatter plot with a regression line
for feature in selected_features:
    # Scatter plot of the data points
    plt.scatter(X_train[feature], y, color='blue', s=5, label="Data Points")

    # Calculate the regression line
    feature_values = X_train[feature].values.reshape(-1, 1)
    temp_model = LinearRegression()
    temp_model.fit(feature_values, y)
    y_line = temp_model.predict(feature_values)

    # Plot the regression line
    plt.plot(feature_values, y_line, color='red', label="Regression Line")

    plt.xlabel(feature)
    plt.ylabel(response)
    plt.legend()

    plt.show()
```


1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
energy
−40
−30
−20
−10
0
loudness
Data Points
Regression Line


1.0
0.8
0.6
0.4
0.2
0.0
energy
0.0
0.2
0.4
0.6
0.8
1.0
acousticness
Data Points
Regression Line


1.0
0.8
0.6
0.4
0.2
0.0
energy
0.0
0.2
0.4
0.6
0.8
1.0
instrumentalness
Data Points
Regression Line


1.0
0.8
0.6
0.4
0.2
0.0
energy
0.0
0.2
0.4
0.6
0.8
1.0
liveness
Data Points
Regression Line



Based on these graphs, some of our correlations are likely not linear, and others likely have a large amount of variance. We calculated the evaluation metrics for our linear regression model to see how it was performing.

[54]:

```
# Calculating Evaluation Metrics:
y_val_pred = lin_reg.predict(X_val) # Predict on validation set

# Calculate metrics for the training set
train_mse = mean_squared_error(y, y_pred) # Mean squared error
train_rmse = np.sqrt(train_mse) # Root mean squared error
train_mae = mean_absolute_error(y, y_pred) # Mean average error
train_mad = np.mean(np.abs(y - y_pred))  # Mean absolute deviation
train_r2 = r2_score(y, y_pred) # R^2 (coefficient of determination)

# Calculate metrics for the validation set
val_mse = mean_squared_error(y_val, y_val_pred)
val_rmse = np.sqrt(val_mse)
val_mae = mean_absolute_error(y_val, y_val_pred)
val_mad = np.mean(np.abs(y_val - y_val_pred))
val_r2 = r2_score(y_val, y_val_pred)
```

```
# Print Results:
print(f"Training MSE: {train_mse}, rMSE: {train_rmse}, MAE: {train_mae}, MAD:␣
  ↪{train_mad}, R²: {train_r2}")
print(f"Validation MSE: {val_mse}, rMSE: {val_rmse}, MAE: {val_mae}, MAD:␣
  ↪{val_mad}, R²: {val_r2}")

# bias variance
avg_expected_loss, avg_bias, avg_var = bias_variance_decomp(
    lin_reg,
    X, y.values,
    X_test, y_test.values,
    loss='mse',
    random_seed=123
)

print(f"Loss, variance, and bias: {avg_expected_loss}, {avg_bias}, {avg_var}")
```

```
Training MSE: 0.015919751417806648, rMSE: 0.12617349728768906, MAE:
0.0986015100486982, MAD: 0.0986015100486982, R²: 0.7477655716969742
Validation MSE: 0.016297699800804963, rMSE: 0.1276624447549277, MAE:
0.09952336547066755, MAD: 0.09952336547066755, R²: 0.7385932898496084
Loss, variance, and bias: 0.01592652204991807, 0.015924634631379178,
1.8874185388953818e-06
```

Based on the evaluation metrics we calculated above, our model seems to fit the data decently. Most notably, the MSE is very low and close together for the training and validation sets, 0.016 for both. This suggests there is low error and the model fits the data.

The R^2 values (0.743 and 0.746) are moderately strong, which indicates that the model is explaining a good amount of the variance in the dependent variable (energy). However, we know based on the graphs (that do not look very linear) that we could probably improve our model if we were to use a different model, such as a polynomial regression. However, since the exploration on energy doesn't necessarily contribute to our project goal, we decided to switch directions and look further into genre instead.

Though linear/polynomial regression isn't necessarily a model that aligns with our project goals (which focuses on investigating and predicting the genres, a categorical variable, or different songs), and thus we chose not to include it in our main report, we still did some light explorations of the relationships between our different variables for different genres using regression.

```
[55]: # Make a dictionary for the data for efficiency
genre_groups = {genre: group for genre, group in spotify.groupby('track_genre')}
grouped_genre_groups = {genre: group for genre, group in grouped_spotify.
  ↪groupby('track_genre')}

print(np.unique(spotify["track_genre"]))
print(np.unique(grouped_spotify['track_genre']))
```

```
['acoustic' 'afrobeat' 'alt-rock' 'alternative' 'ambient' 'anime'
```

```
 'black-metal' 'bluegrass' 'blues' 'brazil' 'breakbeat' 'british'
 'cantopop' 'chicago-house' 'children' 'chill' 'classical' 'club' 'comedy'
 'country' 'dance' 'dancehall' 'death-metal' 'deep-house' 'detroit-techno'
 'disco' 'disney' 'drum-and-bass' 'dub' 'dubstep' 'edm' 'electro'
 'electronic' 'emo' 'folk' 'forro' 'french' 'funk' 'garage' 'german'
 'gospel' 'goth' 'grindcore' 'groove' 'grunge' 'guitar' 'happy'
 'hard-rock' 'hardcore' 'hardstyle' 'heavy-metal' 'hip-hop' 'honky-tonk'
 'house' 'idm' 'indian' 'indie' 'indie-pop' 'industrial' 'iranian'
 'j-dance' 'j-idol' 'j-pop' 'j-rock' 'jazz' 'k-pop' 'kids' 'latin'
 'latino' 'malay' 'mandopop' 'metal' 'metalcore' 'minimal-techno' 'mpb'
 'new-age' 'opera' 'pagode' 'party' 'piano' 'pop' 'pop-film' 'power-pop'
 'progressive-house' 'psych-rock' 'punk' 'punk-rock' 'r-n-b' 'reggae'
 'reggaeton' 'rock' 'rock-n-roll' 'rockabilly' 'romance' 'sad' 'salsa'
 'samba' 'sertanejo' 'show-tunes' 'singer-songwriter' 'ska' 'sleep'
 'songwriter' 'soul' 'spanish' 'study' 'swedish' 'synth-pop' 'tango'
 'techno' 'trance' 'trip-hop' 'turkish' 'world-music']
['classical' 'electronic' 'folk' 'hip-hop' 'jazz' 'metal' 'misc' 'pop'
 'rock' 'world']
```

[56]:

```
# Selecting only the numeric features
numeric_spotify = spotify.select_dtypes(include=[np.number])
numeric_spotify = numeric_spotify.loc[:, ~numeric_spotify.columns.isin(["mode",␣
 ↪"key", "time_signature"])]
numeric_spotify
```

[56]:

```
        popularity  duration_ms  danceability  energy  loudness  speechiness  \
0               73       230666         0.676  0.4610    -6.746       0.1430
1               55       149610         0.420  0.1660   -17.235       0.0763
2               57       210826         0.438  0.3590    -9.734       0.0557
3               71       201933         0.266  0.0596   -18.515       0.0363
4               82       198853         0.618  0.4430    -9.681       0.0526
…                …            …            …     …         …          …
113823          21       384999         0.172  0.2350   -16.393       0.0422
113824          22       385000         0.174  0.1170   -18.318       0.0401
113825          22       271466         0.629  0.3290   -10.895       0.0420
113826          41       283893         0.587  0.5060   -10.889       0.0297
113827          22       241826         0.526  0.4870   -10.204       0.0725

        acousticness  instrumentalness  liveness  valence    tempo
0             0.0322          0.000001    0.3580   0.7150   87.917
1             0.9240          0.000006    0.1010   0.2670   77.489
2             0.2100          0.000000    0.1170   0.1200   76.332
3             0.9050          0.000071    0.1320   0.1430  181.740
4             0.4690          0.000000    0.0829   0.1670  119.949
…                  …                 …         …        …        …
113823        0.6400          0.928000    0.0863   0.0339  125.995
113824        0.9940          0.976000    0.1050   0.0350   85.239
```

```
113825         0.8670          0.000000    0.0839    0.7430  132.378
113826         0.3810          0.000000    0.2700    0.4130  135.960
113827         0.6810          0.000000    0.0893    0.7080   79.198

[113828 rows x 11 columns]
```

We'll start with using linear regression. We looked at the linear regression between each of the 114 genres and each other variable to see if there seemed to be any strong relationships. We investigated the R^2, variance, and bias for the fits.

[57]:

```python
numeric_dict = {
    'popularity': 0,
    'duration_ms': 0,
    'danceability': 0,
    'energy': 0,
    'loudness': 0,
    'speechiness': 0,
    'acousticness': 0,
    'instrumentalness': 0,
    'liveness': 0,
    'valence': 0,
    'tempo': 0
}
```

[ ]:

```python
# Modeling linear regression of genres to all other variables

highest_r2 = 0
highest_r2_genre = ''
highest_r2_response = ''

for genre in genre_groups:
    df = genre_groups.get(genre, pd.DataFrame())
    numeric_df = df.select_dtypes(include=[np.number])
    numeric_df = numeric_df.loc[:, ~numeric_df.columns.isin(["mode", "key",␣
 ↪"time_signature"])]

    linear_reg = LinearRegression()

    # Select features
    selector = SequentialFeatureSelector(
            linear_reg,
            n_features_to_select='auto',
            direction='forward',
            scoring='r2',
            cv = 5
        )
    max_train_r2 = 0
    max_validation_r2 = 0
    max_response = ''

    for x in numeric_df.columns:
        random_seed = 42
        response = x
        # Splitting the data
        # First split: separate out 20% for the test set
        train_val, test = train_test_split(numeric_df, test_size=0.2,␣
↪random_state=random_seed)

        # Second split: separate remaining 80% into 60% training and 40%␣
↪validation
        train, val = train_test_split(train_val, test_size=0.25,␣
↪random_state=random_seed)  # 0.25 * 0.8 = 0.2

        # Reshape the data to fit the model
        X_train = train.drop(columns=response)
        y = train[response]


        selector.fit(X_train, y)
        selected_features = selector.get_feature_names_out(X_train.columns)

        # Transform data sets
        X = selector.transform(X_train)

        X_test = selector.transform(test.drop(columns=response))
        y_test = test[response]

        X_val = selector.transform(val.drop(columns=response))
        y_val = val[response]

        linear_reg.fit(X, y)
        y_pred = linear_reg.predict(X)

        # Calculating Evaluation Metrics:
        y_val_pred = linear_reg.predict(X_val)

        # Calculate metrics for the training set
        train_mse = mean_squared_error(y, y_pred) # Mean squared error
        train_rmse = np.sqrt(train_mse) # Root mean squared error
        train_mae = mean_absolute_error(y, y_pred) # Mean average error
        train_mad = np.mean(np.abs(y - y_pred))  # Mean absolute deviation
        train_r2 = r2_score(y, y_pred) # R^2 (coefficient of determination)
        # Calculate metrics for the validation set
        val_mse = mean_squared_error(y_val, y_val_pred)
        val_rmse = np.sqrt(val_mse)
        val_mae = mean_absolute_error(y_val, y_val_pred)
        val_mad = np.mean(np.abs(y_val - y_val_pred))
        val_r2 = r2_score(y_val, y_val_pred)

        # Print Results:
        print("")
        print(f"{genre} x {response} - Training MSE: {train_mse}, rMSE:␣
 ↪{train_rmse}, MAE: {train_mae}, MAD: {train_mad}, R²: {train_r2}")
        print(f"{genre} x {response} - Validation MSE: {val_mse}, rMSE:␣
 ↪{val_rmse}, MAE: {val_mae}, MAD: {val_mad}, R²: {val_r2}")

        if val_r2 > max_validation_r2:
            max_train_r2 = train_r2
            max_validation_r2 = val_r2
            max_response = x

        # bias variance
        avg_expected_loss, avg_bias, avg_var = bias_variance_decomp(
            linear_reg,
            X, y.values,
            X_test, y_test.values,
            loss='mse',
            random_seed=123
        )

        print(f"{genre} x {response} - Loss, Variance, and Bias:␣
 ↪{avg_expected_loss}, {avg_bias}, {avg_var}")
    print("")
    print(f"Response Variable with the Highest Validation R^2 for {genre}:␣
 ↪{max_response}")
    print(f"Train R^2 for {max_response} in {genre}: {max_train_r2}")
    print(f"Validation R^2 for {max_response} in {genre}: {max_validation_r2}")
    numeric_dict[max_response]+=1
    print("")
    print("-----")

    # Storing the variable / genre with the highest R^2 values
    if(max_validation_r2 > highest_r2):
        highest_r2 = max_validation_r2
        highest_r2_genre = genre
        highest_r2_response = response

print(numeric_dict)
print("")
print(f"The highest Validation R^2 was between {genre} and {response}, with a␣
 ↪score of {highest_r2}.")
```

Output: `The highest Validation R^2 was between world-music and tempo, with a score of 0.9132660013292169.`

Based on our linear regression investigation, it seems like energy tended to have the highest validation correlation with various genres, with 101 genres that were correlated the most with energy compared to other features. Following energy, 11 genres were more correlated with loudness, and 1 genre for both speechiness and valence had highest correlations. The relationship that seemed to have the strongest linear correlation was between the world-music genre's variables, with the tempo variable as the response.

We decided to also try a quadratic regression on our data to see if the increase in degree may have any significant effects.

[59]:

```
# Define the degree of the polynomial, in this case, quadratic
degree = 2

# Create a pipeline for Polynomial Regression
poly_reg = make_pipeline(
    PolynomialFeatures(degree=degree),
    LinearRegression()
)
```

[ ]:

```
# Modeling quadratic regression (degree = 2) of genres to all other variables

numeric_dict2 = {
    'popularity' : 0,
    'duration_ms' : 0,
    'danceability' : 0,
    'energy' : 0,
    'loudness' : 0,
    'speechiness' : 0,
    'acousticness' : 0,
    'instrumentalness' : 0,
    'liveness' : 0,
    'valence' : 0,
    'tempo' : 0
}

highest_r2 = 0
highest_r2_genre = ''
highest_r2_response = ''

for genre in genre_groups:
    df = genre_groups.get(genre, pd.DataFrame())
    numeric_df = df.select_dtypes(include=[np.number])
    numeric_df = numeric_df.loc[:, ~numeric_df.columns.isin(["mode", "key",␣
↪"time_signature"])]

    # Select features
    selector = SequentialFeatureSelector(
            linear_reg,
            n_features_to_select='auto',
            direction='forward',
            scoring='r2',
            cv = 5
        )

    max_train_r2 = 0
    max_validation_r2 = 0
    max_response = ''

    for x in numeric_df.columns:
        random_seed = 42
        response = x
        # Splitting the data
        # First split: separate out 20% for the test set
        train_val, test = train_test_split(numeric_df, test_size=0.2,␣
↪random_state=random_seed)

        # Second split: separate remaining 80% into 60% training and 40%␣
↪validation
        train, val = train_test_split(train_val, test_size=0.25,␣
↪random_state=random_seed)  # 0.25 * 0.8 = 0.2

        # Reshape the data to fit the model
        X_train = train.drop(columns=response)
        y = train[response]


        selector.fit(X_train, y)
        selected_features = selector.get_feature_names_out(X_train.columns)

        # Transform data sets
        X = selector.transform(X_train)

        X_test = selector.transform(test.drop(columns=response))
        y_test = test[response]

        X_val = selector.transform(val.drop(columns=response))
        y_val = val[response]

        # Fit the Polynomial Regression model
        poly_reg.fit(X, y)
        y_pred = poly_reg.predict(X)

        # Calculating Evaluation Metrics:
        y_val_pred = poly_reg.predict(X_val)

        # Calculate metrics for the training set
        train_mse = mean_squared_error(y, y_pred) # Mean squared error
        train_rmse = np.sqrt(train_mse) # Root mean squared error
        train_mae = mean_absolute_error(y, y_pred) # Mean average error
        train_mad = np.mean(np.abs(y - y_pred))  # Mean absolute deviation
        train_r2 = r2_score(y, y_pred) # R^2 (coefficient of determination)

        # Calculate metrics for the validation set
        val_mse = mean_squared_error(y_val, y_val_pred)
        val_rmse = np.sqrt(val_mse)
        val_mae = mean_absolute_error(y_val, y_val_pred)
        val_mad = np.mean(np.abs(y_val - y_val_pred))
        val_r2 = r2_score(y_val, y_val_pred)

        # Print Results:
        print("")
        print(f"{genre} x {response} - Training MSE: {train_mse}, rMSE: {train_rmse}, MAE: {train_mae}, MAD: {train_mad}, R²: {train_r2}")
        print(f"{genre} x {response} - Validation MSE: {val_mse}, rMSE: {val_rmse}, MAE: {val_mae}, MAD: {val_mad}, R²: {val_r2}")

        if val_r2 > max_validation_r2:
            max_train_r2 = train_r2
            max_validation_r2 = val_r2
            max_response = x

        # bias variance
        avg_expected_loss, avg_bias, avg_var = bias_variance_decomp(
            linear_reg,
            X, y.values,
            X_test, y_test.values,
            loss='mse',
            random_seed=123
        )

        print(f"{genre} x {response} - Loss, Variance, and Bias: {avg_expected_loss}, {avg_bias}, {avg_var}")
    print("")
    print(f"Response Variable with the Highest Validation R^2 for {genre}: {max_response}")
    print(f"Train R^2 for {max_response} in {genre}: {max_train_r2}")
    print(f"Validation R^2 for {max_response} in {genre}: {max_validation_r2}")
    numeric_dict2[max_response]+=1
    print("")
    print("-----")

    # Storing the variable / genre with the highest R^2 values
    if(max_validation_r2 > highest_r2):
        highest_r2 = max_validation_r2
        highest_r2_genre = genre
        highest_r2_response = response

print(numeric_dict)
print("")
print(f"The highest Validation R^2 was between {genre} and {response}, with a␣
 ↪score of {highest_r2}.")
```

Output: `The highest Validation R^2 was between world-music and tempo, with a score of 0.9293826016602357.`

Compared to the linear regression earlier, the quadratic regression didn't seem to have much of a change at all, other than the highest validation R^2 value between the world-music genre's variables and tempo slightly increasing from 0.913 to 0.929.

We also tried linear regression with our 10 manually grouped genres rather than the original 114 to see if it would make a difference.

```
[ ]: # Modeling linear regression of 10 generalized genres to all other variables

     numeric_dict3 = {
         'popularity' : 0,
         'duration_ms' : 0,
         'danceability' : 0,
         'energy' : 0,
         'loudness' : 0,
         'speechiness' : 0,
         'acousticness' : 0,
         'instrumentalness' : 0,
         'liveness' : 0,
         'valence' : 0,
         'tempo' : 0
     }

     highest_r2 = 0
     highest_r2_genre = ''
     highest_r2_response = ''

     for genre in grouped_genre_groups:
         df = grouped_genre_groups.get(genre, pd.DataFrame())
```

```
    numeric_df = df.select_dtypes(include=[np.number])
    numeric_df = numeric_df.loc[:, ~numeric_df.columns.isin(["mode", "key",␣
↪"time_signature"])]

    linear_reg = LinearRegression()

        # Select features
    selector = SequentialFeatureSelector(
            linear_reg,
            n_features_to_select='auto',
            direction='forward',
            scoring='r2',
            cv = 5
        )

    max_train_r2 = 0
    max_validation_r2 = 0
    max_response = ''

    for x in numeric_df.columns:
        random_seed = 42
        response = x
        # Splitting the data
        # First split: separate out 20% for the test set
        train_val, test = train_test_split(numeric_df, test_size=0.2,␣
↪random_state=random_seed)

        # Second split: separate remaining 80% into 60% training and 40%␣
↪validation
        train, val = train_test_split(train_val, test_size=0.25,␣
↪random_state=random_seed)  # 0.25 * 0.8 = 0.2

        # Reshape the data to fit the model
        X_train = train.drop(columns=response)
        y = train[response]


        selector.fit(X_train, y)
        selected_features = selector.get_feature_names_out(X_train.columns)

        # Transform data sets
        X = selector.transform(X_train)

        X_test = selector.transform(test.drop(columns=response))
        y_test = test[response]

        X_val = selector.transform(val.drop(columns=response))
        y_val = val[response]

        # Fit the Linear Regression model
        linear_reg.fit(X, y)
        y_pred = linear_reg.predict(X)

        # Calculating Evaluation Metrics:
        y_val_pred = linear_reg.predict(X_val)

        # Calculate metrics for the training set
        train_mse = mean_squared_error(y, y_pred) # Mean squared error
        train_rmse = np.sqrt(train_mse) # Root mean squared error
        train_mae = mean_absolute_error(y, y_pred) # Mean average error
        train_mad = np.mean(np.abs(y - y_pred))  # Mean absolute deviation
        train_r2 = r2_score(y, y_pred) # R^2 (coefficient of determination)

        # Calculate metrics for the validation set
        val_mse = mean_squared_error(y_val, y_val_pred)
        val_rmse = np.sqrt(val_mse)
        val_mae = mean_absolute_error(y_val, y_val_pred)
        val_mad = np.mean(np.abs(y_val - y_val_pred))
        val_r2 = r2_score(y_val, y_val_pred)

        # Print Results:
        print("")
        print(f"{genre} x {response} - Training MSE: {train_mse}, rMSE:␣
↪{train_rmse}, MAE: {train_mae}, MAD: {train_mad}, R²: {train_r2}")
        print(f"{genre} x {response} - Validation MSE: {val_mse}, rMSE:␣
↪{val_rmse}, MAE: {val_mae}, MAD: {val_mad}, R²: {val_r2}")

        if val_r2 > max_validation_r2:
            max_train_r2 = train_r2
            max_validation_r2 = val_r2
            max_response = x

        # bias variance
        avg_expected_loss, avg_bias, avg_var = bias_variance_decomp(
            linear_reg,
            X, y.values,
            X_test, y_test.values,
            loss='mse',
            random_seed=123
        )

        print(f"{genre} x {response} - Loss, Variance, and Bias:␣
↪{avg_expected_loss}, {avg_bias}, {avg_var}")
    print("")
```

```
        print(f"Response Variable with the Highest Validation R^2 for {genre}:␣
 ↪{max_response}")
        print(f"Train R^2 for {max_response} in {genre}: {max_train_r2}")
        print(f"Validation R^2 for {max_response} in {genre}: {max_validation_r2}")
        numeric_dict3[max_response]+=1
        print("")
        print("-----")

        # Storing the variable / genre with the highest R^2 values
        if(max_validation_r2 > highest_r2):
            highest_r2 = max_validation_r2
            highest_r2_genre = genre
            highest_r2_response = response

print(numeric_dict)
print("")
print(f"The highest Validation R^2 was between {genre} and {response}, with a␣
 ↪score of {highest_r2}.")
```

Output: `The highest Validation R^2 was between world and tempo, with a score of 0.8921830467528595.`

Compared to the results of our linear regression with the 114 genres, most genres still seemed like energy as the response variable had the highest correlation once again. And similar to before, the highest correlation was within the world genre with tempo as the response variable, though the validation R^2 dropped in comparison to the linear regression with 114 genres (from 0.913 to 0.892).

Because we weren't necessarily thrying to predict anything with our linear and polynomial regression models, and since most of them didn't seem to be doing so well that it suggested overfitting, we didn't think we needed to do regularization on our models. We used these models more for exploration rather than prediction.

However, if interested, we did do lasso and ridge regularization with our exploration of energy as a response variable, which can be found in the week 3 check-in.

1.5 Logistic Regression

For our logistic regression, we wanted to try to see if we could classify a track's genre based on other variables.

[111]:
```
label_encoder = LabelEncoder()
label_encoder.fit(grouped_spotify[response_variable])
Y_train = grouped_spotify_train[response_variable]
Y_train = label_encoder.transform(Y_train)

Y_test = grouped_spotify_test[response_variable]
Y_test = label_encoder.transform(Y_test)
```

```
X_train = ohe_grouped_column_transformer_wo_genre.
 ↪transform(grouped_spotify_train)
X_test = ohe_grouped_column_transformer_wo_genre.transform(grouped_spotify_test)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# logistic regression
logreg = LogisticRegression(solver="lbfgs", max_iter=1000)
logreg.fit(X_train, Y_train)
```

```
[111]: LogisticRegression(max_iter=1000)
```

```
[110]: # Evaluate the model
Y_pred = logreg.predict(X_test)
Y_pred_proba = logreg.predict_proba(X_test)

report = classification_report(
    Y_test,
    Y_pred,
    target_names=label_encoder.classes_,
)
print(report)
```

```
              precision    recall  f1-score   support

   classical       0.36      0.11      0.16       607
  electronic       0.44      0.68      0.54      4839
        folk       0.31      0.18      0.23      1218
     hip-hop       0.50      0.00      0.00       767
        jazz       0.11      0.00      0.00      1242
       metal       0.52      0.57      0.54      1203
        misc       0.43      0.36      0.39      3504
         pop       0.28      0.08      0.13      2020
        rock       0.30      0.28      0.29      2828
       world       0.34      0.52      0.41      4538

    accuracy                           0.39     22766
   macro avg       0.36      0.28      0.27     22766
weighted avg       0.37      0.39      0.35     22766
```

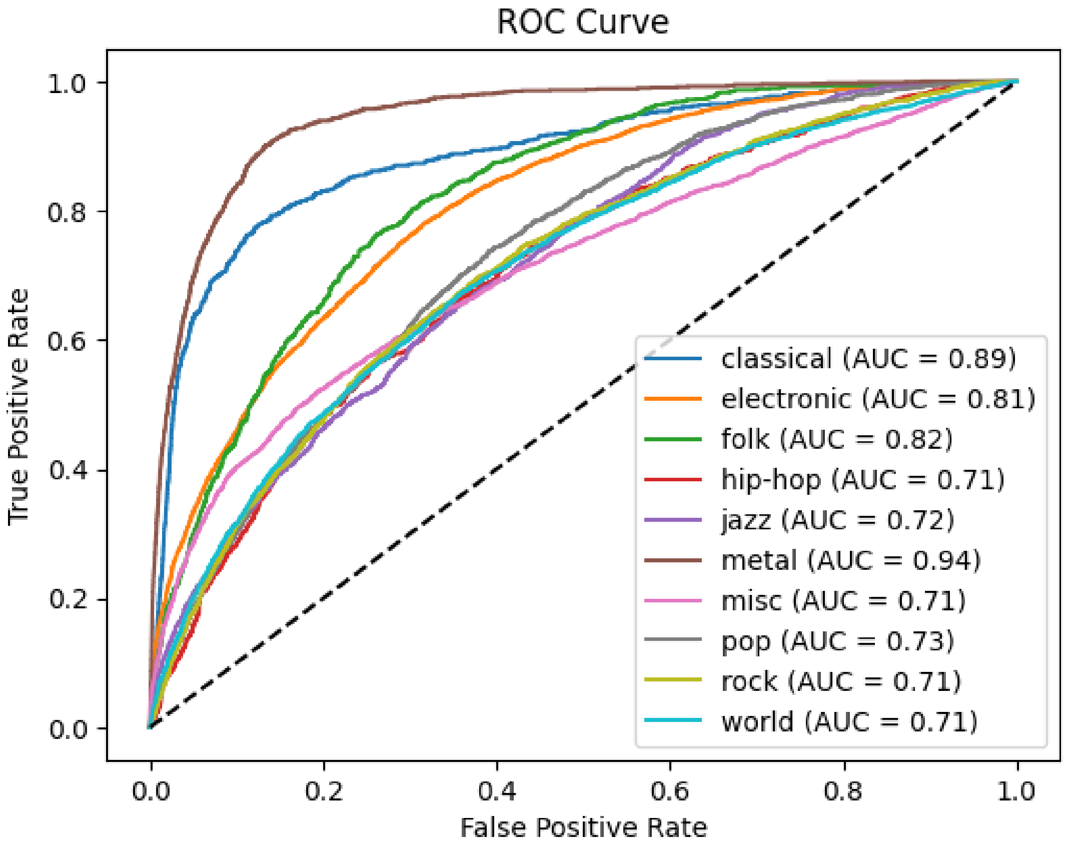
Looking at the evaluation metrics for our logistic regression, it seems like the precision for our predictions is not very high, with the highest being jazz, at 52%.

```
[104]: # ROC and AUC
best_thresholds = np.zeros(Y_pred_proba.shape[1])
```

```
for i, genre in enumerate(label_encoder.classes_):
    fpr, tpr, thesholds = roc_curve(Y_test == i, Y_pred_proba[:, i])
    auc_score = auc(fpr, tpr)
    best_thresholds[i] = thesholds[np.argmax(tpr - fpr)]
    plt.plot(fpr, tpr, label=f"{genre} (AUC = {auc_score:.2f})")

# print best threshold
best_threshold = best_thresholds.mean()
print(f"Best Threshold: {best_threshold}")

plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
```

```
Best Threshold: 0.10861536576803565
```

```
[104]: <matplotlib.legend.Legend at 0x7d7c9c9d4710>
```

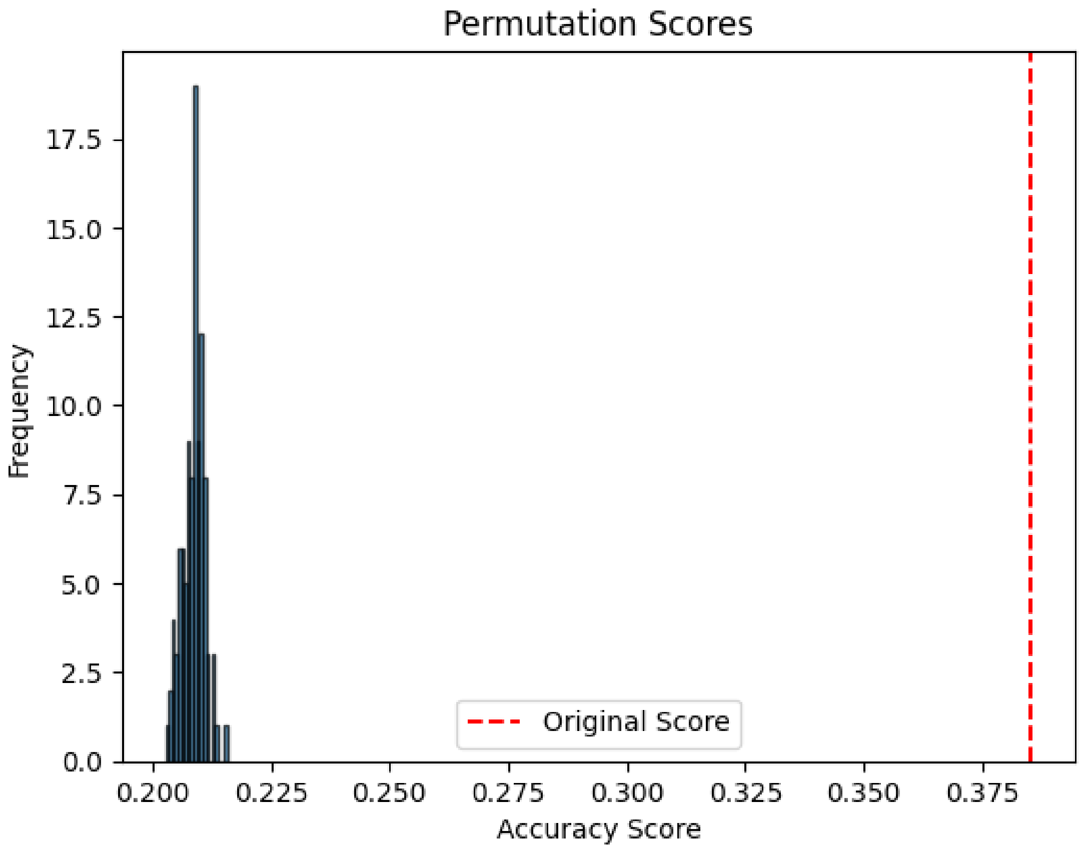


[87]:

```
# permutation importance
perm_importance = permutation_test_score(
    logreg,
    X_test,
    Y_test,
    scoring="accuracy",
    cv=5,
    n_permutations=100,
    n_jobs=1,
    random_state=42
)
score, permutation_scores, p_value = perm_importance
```

[88]:

```
# Plot permutation test scores
plt.hist(permutation_scores, bins=20, edgecolor='k', alpha=0.7)
plt.axvline(score, color='r', linestyle='--', label='Original Score')
plt.xlabel('Accuracy Score')
plt.ylabel('Frequency')
plt.title('Permutation Scores')
plt.legend()
plt.show()
```



[107]:

```
# feature importances
feature_importances = permutation_importance(
    logreg,
    X_test,
    Y_test,
    n_repeats=50,
    n_jobs=1,
    random_state=42
)
pd.DataFrame(
    feature_importances.importances_mean,
    index=ohe_grouped_column_transformer_wo_genre.get_feature_names_out(),
    columns=["Importance"]
)
```

[107]:

```
                    Importance
key_0                -0.000539
key_1                 0.001236
key_2                 0.000697
key_3                 0.000407
key_4                 0.000221
key_5                 0.000479
key_6                -0.000257
key_7                 0.001406
key_8                -0.000363
key_9                 0.000019
key_10                0.000014
key_11                0.000649
mode_0                0.001288
mode_1                0.001288
time_signature_0      0.000000
time_signature_1      0.000172
time_signature_3     -0.000278
time_signature_4     -0.000046
time_signature_5      0.001314
popularity            0.003693
duration_ms           0.010849
explicit              0.002161
danceability          0.058037
energy                0.032968
key                  -0.000184
loudness              0.005119
mode                  0.001288
speechiness           0.013135
acousticness          0.066806
```

```
instrumentalness    0.020670
liveness            0.005648
valence             0.034678
tempo               0.003171
time_signature     -0.000537
```

1.6 KNN/Decision Trees/Random Forest

Since one of our main goals with the project was to see if we can classify or predict genres, KNN, decision trees, and random forests were good models for exploring this question. We decided to start by building a simple decision tree, using a grid search to tune the hyperparameters.

Decision trees are a good model for the data, since it is likely that a classification is not a simple function in any of the features, and cases overlap heavily.

[35]:

```
response_variable = "track_genre"
Y_train = grouped_spotify_train[response_variable]
Y_test = grouped_spotify_test[response_variable]

X_train = grouped_spotify_train.drop(columns=[response_variable,␣
 ↪*string_columns])
X_test = grouped_spotify_test.drop(columns=[response_variable, *string_columns])
```

[ ]:

```
# tuning decision tree hyperparameters
dt_parameters = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 10, 20, 30, 40, 50],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': [None, 'sqrt', 'log2']
}

dt_classifier = DecisionTreeClassifier(
    max_depth=50,
    random_state=42
)

grid_search = GridSearchCV(
    dt_classifier,
    param_grid=dt_parameters,
    cv=5,
    n_jobs=3,
    verbose=2
)

grid_search.fit(X_train, Y_train)
```

```
[ ]: GridSearchCV(cv=5,
                  estimator=DecisionTreeClassifier(max_depth=50, random_state=42),
                  n_jobs=3,
                  param_grid={'criterion': ['gini', 'entropy'],
                              'max_depth': [None, 10, 20, 30, 40, 50],
                              'max_features': [None, 'sqrt', 'log2'],
                              'min_samples_leaf': [1, 2, 4],
                              'min_samples_split': [2, 5, 10]})
```

```
[64]: dt_classifier = grid_search.best_estimator_

      # predictions for testing
      Y_pred = dt_classifier.predict(X_test)

      # Evaluation metrics
      dt_class_report = classification_report(Y_test, Y_pred, zero_division=1)
      dt_conf_matrix = confusion_matrix(Y_test, Y_pred)

      print(f'Classification Report: \n {dt_class_report}')
      print(f'Confusion Matrix: \n {dt_conf_matrix}')
```

```
Classification Report:
               precision    recall  f1-score   support

   classical       0.58      0.34      0.43       607
  electronic       0.49      0.62      0.55      4026
        folk       0.37      0.27      0.31      1218
     hip-hop       0.35      0.09      0.14       578
        jazz       0.38      0.27      0.32       830
       metal       0.63      0.54      0.58      1203
        misc       0.48      0.53      0.51      5931
         pop       0.38      0.25      0.30      1825
        rock       0.38      0.25      0.30      2227
       world       0.44      0.56      0.49      4321

    accuracy                           0.46     22766
   macro avg       0.45      0.37      0.39     22766
weighted avg       0.46      0.46      0.45     22766

Confusion Matrix:
 [[ 206   26   13    0   18    0  208   29   24   83]
 [   2 2506   71   46   32   69  655  114  109  422]
 [   2  114  327   10   71    0  267   71   76  280]
 [   0  156    8   52   10   11  105   54   31  151]
 [   2   87   86    2  227    1  101   38   76  210]
 [   0   93    6    5    0  651  283    9  133   23]
 [  89  803  116   17   88  171 3172  170  263 1042]
 [   7  337   74    4   51   37  400  458   79  378]
 [   6  355  113    6   39   78  582   70  554  424]
 [  39  595   80    5   61   22  821  198  101 2399]]
```

Our decision tree seems to have about 46% accuracy, meaning it classified about 46% of the data correctly. This is better than chance, but could still be improved. In particular, it seems our decision tree was best at calculating electronic tracks, with a precision of 62%, while it was very bad at classifying hip-hop tracks, with a precision score of only 9%.

Based on the confusion matrix, it seems like electronic tracks, when misclassified, tended to be mislabeled as pop (276 instances) or rock (265 instances), which may be some indicator towards the similarities or overlaps with these genres. We also noticed that hip-hop tends to be mislabelled as electronic, as with hip-hop tracks only 160 were correctly labelled while 283 were labelled as electronic.

However, it is important to note that when we combined the genres into 10 more generalized genres, we caused an imbalance in samples. For example, electronic tracks have several more samples than hip-hop ones (20000 vs 3000) which may influence our decision tree's balance.

To learn more about which features in particular were contributing to our classification, we looked at the feature importances of our decision tree.

[66]:

```python
# Get feature importances
feature_importances = dt_classifier.feature_importances_
for i, importance in enumerate(feature_importances):
    print(f'{X_train.columns[i]}: {importance}')
```

```
popularity: 0.2200472160153845
duration_ms: 0.0852801213153109
explicit: 0.006176993344808496
danceability: 0.11891001330395011
energy: 0.046392682641900049
key: 0.0010495388111708972
loudness: 0.041288584589974 59
mode: 0.0065006817367100 05
speechiness: 0.06524558872054981
acousticness: 0.18262725408120783
instrumentalness: 0.09890842233853107
liveness: 0.014775753707866195
valence: 0.05226490886822944
tempo: 0.05978402867389046
time_signature: 0.0007482118505152 86
```

[68]:

```python
# permutation importance
perm_importance = permutation_importance(
    dt_classifier,
    X_test,
    Y_test,
    n_repeats=20,
    random_state=42
)
```

```
perm_importance_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance Mean': perm_importance.importances_mean,
    'Importance Std': perm_importance.importances_std
})

perm_importance_df
```

```
[68]:              Feature  Importance Mean  Importance Std
      0         popularity         0.153321        0.002175
      1        duration_ms         0.038263        0.001421
      2           explicit         0.002715        0.000277
      3       danceability         0.070403        0.001225
      4             energy         0.026368        0.001298
      5                key         0.000020        0.000083
      6           loudness         0.021769        0.001009
      7               mode         0.002462        0.000285
      8        speechiness         0.024363        0.000918
      9       acousticness         0.119643        0.002600
      10  instrumentalness         0.058062        0.001181
      11          liveness         0.004871        0.000420
      12           valence         0.028775        0.001081
      13             tempo         0.024633        0.000823
      14    time_signature         0.000198        0.000110
```

Out of this, it seems like acousticness, popularity, and danceability have the highest importance when it comes to our decision tree. On the other hand, some of the time signatures, keys, and modes didn't really seem to be as key in feature importance.

To add more complexity to our model in hopes of improving its accuracy, we decided to try to train a random forest model on our data as well. We used a grid search again, but this time, we reduced the number of features in the search due to the higher complexity of the model requiring much longer time to do tuning.

```
[38]: rf_parameters = {
          'n_estimators': [100, 200],
          'max_depth': [10, 20, 30],
      }

      # Random forest
      rf_classifier = RandomForestClassifier(
          n_estimators=100,
          max_depth=20,
          random_state=42,
      )

      grid_search = GridSearchCV(
          estimator=rf_classifier,
          param_grid=rf_parameters,
          cv=5,
          n_jobs=1,
          verbose=2
      )
      grid_search.fit(X_train, Y_train)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
[CV] END …max_depth=10, n_estimators=100; total time=   6.3s
[CV] END …max_depth=10, n_estimators=100; total time=   6.3s
[CV] END …max_depth=10, n_estimators=100; total time=   6.3s
[CV] END …max_depth=10, n_estimators=100; total time=   6.3s
[CV] END …max_depth=10, n_estimators=100; total time=   6.2s
[CV] END …max_depth=10, n_estimators=200; total time=  12.4s
[CV] END …max_depth=10, n_estimators=200; total time=  12.6s
[CV] END …max_depth=10, n_estimators=200; total time=  12.5s
[CV] END …max_depth=10, n_estimators=200; total time=  12.5s
[CV] END …max_depth=10, n_estimators=200; total time=  12.4s
[CV] END …max_depth=20, n_estimators=100; total time=  10.8s
[CV] END …max_depth=20, n_estimators=100; total time=  10.8s
[CV] END …max_depth=20, n_estimators=100; total time=  10.9s
[CV] END …max_depth=20, n_estimators=100; total time=  10.8s
[CV] END …max_depth=20, n_estimators=100; total time=  10.9s
[CV] END …max_depth=20, n_estimators=200; total time=  21.8s
[CV] END …max_depth=20, n_estimators=200; total time=  21.1s
[CV] END …max_depth=20, n_estimators=200; total time=  21.0s
[CV] END …max_depth=20, n_estimators=200; total time=  20.9s
[CV] END …max_depth=20, n_estimators=200; total time=  20.7s
[CV] END …max_depth=30, n_estimators=100; total time=  11.0s
[CV] END …max_depth=30, n_estimators=100; total time=  11.1s
[CV] END …max_depth=30, n_estimators=100; total time=  11.4s
[CV] END …max_depth=30, n_estimators=100; total time=  11.5s
[CV] END …max_depth=30, n_estimators=100; total time=  11.2s
[CV] END …max_depth=30, n_estimators=200; total time=  22.3s
[CV] END …max_depth=30, n_estimators=200; total time=  21.9s
[CV] END …max_depth=30, n_estimators=200; total time=  22.0s
[CV] END …max_depth=30, n_estimators=200; total time=  22.3s
[CV] END …max_depth=30, n_estimators=200; total time=  22.5s
```

```
[38]: GridSearchCV(cv=5,
                   estimator=RandomForestClassifier(max_depth=20, random_state=42),
                   n_jobs=1,
                   param_grid={'max_depth': [10, 20, 30], 'n_estimators': [100, 200]},
                   verbose=2)
```

[41]:

```
print(grid_search.best_params_)
rf_classifier = grid_search.best_estimator_
Y_pred_rf = rf_classifier.predict(X_test)
```

```
{'max_depth': 20, 'n_estimators': 200}
```

[46]:

```
# Evaluation metrics
rf_train_accuracy = accuracy_score(Y_train, rf_classifier.predict(X_train))
rf_accuracy = accuracy_score(Y_test, Y_pred_rf)
rf_class_report = classification_report(Y_test, Y_pred_rf, zero_division=1)
rf_conf_matrix = confusion_matrix(Y_test, Y_pred_rf)

print(f'Train accuracy: {rf_train_accuracy}')
print(f'Accuracy: {rf_accuracy}')
print(f'Classification Report: \n {rf_class_report}')
print(f'Confusion Matrix:')
rf_conf_matrix
```

```
Train accuracy: 0.9188239428370621
Accuracy: 0.5578054994289731
Classification Report:
               precision    recall  f1-score   support

   classical       0.60      0.36      0.45       607
  electronic       0.66      0.70      0.68      4026
        folk       0.68      0.55      0.61      1218
     hip-hop       0.30      0.08      0.12       578
        jazz       0.60      0.35      0.45       830
       metal       0.65      0.62      0.63      1203
        misc       0.50      0.65      0.57      5931
         pop       0.48      0.34      0.40      1825
        rock       0.48      0.33      0.39      2227
       world       0.55      0.62      0.59      4321

    accuracy                           0.56     22766
   macro avg       0.55      0.46      0.49     22766
weighted avg       0.55      0.56      0.55     22766

Confusion Matrix:
```

[46]:

```
array([[ 219,   11,   10,    0,    5,    4,  249,   18,   14,   77],
       [   6, 2802,   12,   13,   27,   43,  677,   83,   63,  300],
       [   1,   34,  672,    6,   10,    1,  224,   55,   48,  167],
       [   0,  158,    7,   45,    9,    5,   96,   51,   39,  168],
       [   2,   66,   21,    6,  294,    2,  147,   48,   73,  171],
       [   1,   46,    3,    0,    3,  746,  267,    8,  109,   20],
       [  84,  522,   74,    1,   40,  178, 3884,  195,  282,  671],
       [   1,  200,   49,   31,   26,   27,  515,  613,   78,  285],
       [  16,  119,   68,   16,   36,  119,  751,   59,  746,  297],
       [  32,  286,   79,   30,   36,   28,  901,  136,  115, 2678]])
```

Our random forest model does seem to do much better than just one decision tree, with an increase of accuracy from ~45% to ~56%. Additionally, the individual genres' precisions for the most part seemed to get better. This time, classical and metal genres had the highest precision, which, when thinking back to our EDA where the two variables seemed to stand out, makes sense. Similar with decision trees, the model was not as good at classifying hip-hop tracks.

Looking again at feature importance for our random forest:

[ ]:

```
# permutation importance
perm_importance_rf = permutation_importance(
    rf_classifier,
    X_test,
    Y_test,
    n_repeats=20,
    random_state=42,
)
```

[44]:

```
perm_importance_rf_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance Mean': perm_importance_rf.importances_mean,
    'Importance Std': perm_importance_rf.importances_std
})

perm_importance_rf_df
```

[44]:

```
             Feature  Importance Mean  Importance Std
0         popularity         0.119450        0.002112
1        duration_ms         0.034292        0.001582
2           explicit         0.002846        0.000426
3       danceability         0.053180        0.001849
4             energy         0.030636        0.001262
5                key        -0.000356        0.000504
6           loudness         0.016490        0.001054
7               mode         0.004507        0.000626
8        speechiness         0.027034        0.001284
9       acousticness         0.079966        0.001813
10  instrumentalness         0.055049        0.001748
11          liveness         0.004076        0.000793
12           valence         0.031598        0.001160
13             tempo         0.014998        0.001157
14    time_signature         0.000283        0.000386
```

With our random forest, the importance of specific variables changed slightly from our decision tree, but the most important features, popularity, danceability, and acousticness, stayed about the same.

We also looked into training a KNN model for classification as well, to see how it may do against our decision tree and random forest.

[132]:
```
# KNN
knn_classifier = KNeighborsClassifier(n_neighbors=5)
knn_classifier.fit(X_train, Y_train)

# Make predictions
Y_pred_knn = knn_classifier.predict(X_test)

# Evaluate
knn_accuracy = accuracy_score(Y_test, Y_pred_knn)
knn_class_report = classification_report(Y_test, Y_pred_knn, zero_division=1)
knn_conf_matrix = confusion_matrix(Y_test, Y_pred_knn)

print(f'Accuracy: {knn_accuracy}')
print(f'Classification Report: {knn_class_report}')
print(f'Confusion Matrix:')
knn_conf_matrix
```

```
Accuracy: 0.29438636563296144
Classification Report:               precision    recall  f1-score   support

   classical       0.09      0.10      0.10       607
  electronic       0.31      0.47      0.37      4026
        folk       0.25      0.24      0.25      1218
     hip-hop       0.11      0.06      0.08       578
        jazz       0.41      0.29      0.34       830
       metal       0.13      0.08      0.10      1203
        misc       0.32      0.39      0.35      5931
         pop       0.19      0.11      0.14      1825
        rock       0.27      0.17      0.21      2227
       world       0.33      0.28      0.31      4321

    accuracy                           0.29     22766
   macro avg       0.24      0.22      0.22     22766
weighted avg       0.28      0.29      0.28     22766

Confusion Matrix:
```

[132]:
```
array([[  59,  143,   29,    9,    6,   26,  221,   14,   24,   76],
       [  79, 1875,  119,   47,   48,   84,  973,  160,  150,  491],
       [  33,  252,  290,   21,   26,   32,  338,   33,   45,  148],
       [  11,  150,   24,   35,   17,   21,  162,   34,   31,   93],
       [  13,  159,   26,   14,  242,   18,  164,   44,   52,   98],
       [  41,  268,   44,   22,   16,   95,  416,   46,   87,  168],
       [ 178, 1431,  238,   62,   95,  213, 2309,  248,  346,  811],
       [  50,  421,   96,   28,   35,   59,  578,  193,   98,  267],
       [  56,  440,  107,   23,   59,   84,  715,   87,  386,  270],
       [ 104, 1004,  173,   53,   43,  115, 1274,  139,  198, 1218]])
```

Unfortunately, our KNN model seems to be a lot worse than both our decision tree and random forest, with an accuracy of only ~29%. Classical, hip-hop, and metal do the worst on this, likely because of the class (genre) imbalance we have from our groupings. KNN doesn't seem to be a very good model for our data.

1.7 PCA/Clustering

We tried to conduct PCA and clustering on our data to see if dimensionality reduction or investigation into underlying structures like clusters may relate or help us investigate genre. We tried dimensionality reduction with PCA first.

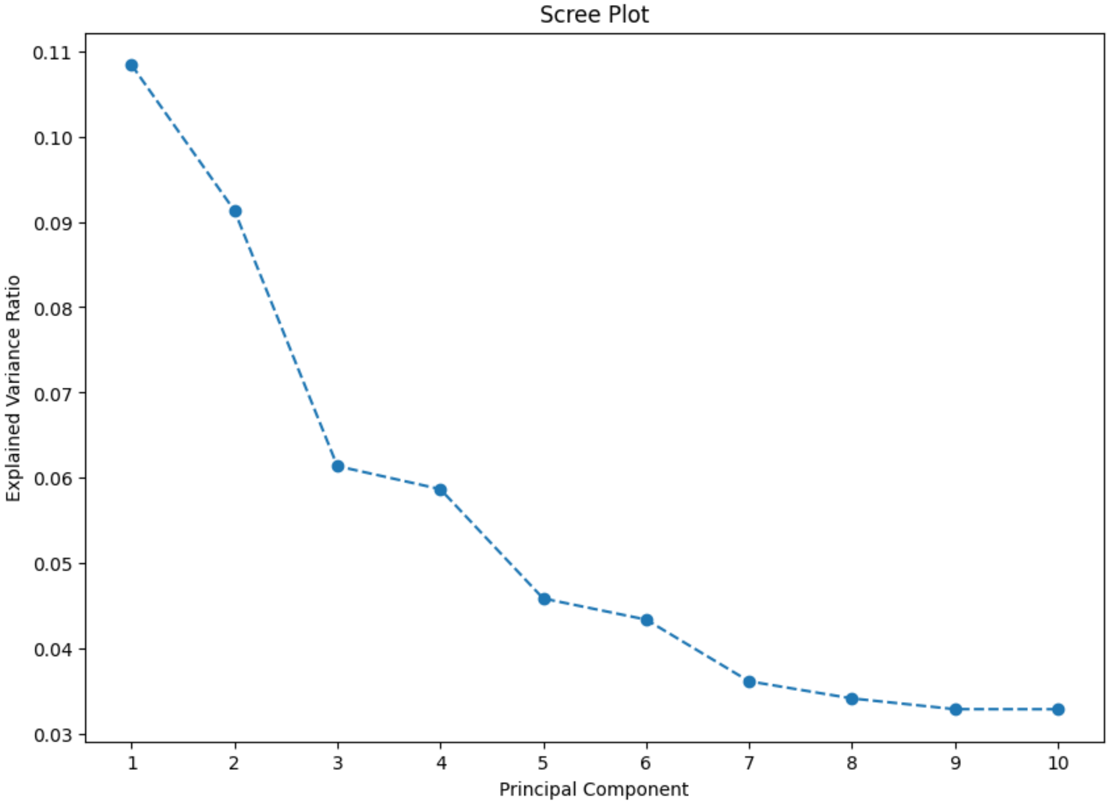
[155]:

```python
# data pre-processing
response_variable = 'track_genre'
categorical_columns = [x for x in categorical_columns if x != response_variable]

# drop string columns and response variable
X_train = ohe_grouped_column_transformer_wo_genre.
 ↪transform(grouped_spotify_train)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
Y_train = grouped_spotify_train[response_variable]
```

[156]:

```python
# do PCA on X
n_components = 10
pca = PCA(n_components=n_components)
X_pca = pca.fit_transform(X_train)
X_pca_df = pd.DataFrame(X_pca, columns=[f'PC{i}' for i in range(n_components)])

explained_variance = pca.explained_variance_ratio_

# Check explained variance ratio for each component
explained_variance = pca.explained_variance_ratio_
print(f"Explained variance ratio for each component: \n {explained_variance}␣
 ↪\n")
print(f"Cumulative explained variance: \n {np.cumsum(explained_variance)}")

plt.figure(figsize=(10, 7))
plt.plot(range(1, len(explained_variance) + 1), explained_variance, marker='o',␣
 ↪linestyle='--')
plt.title('Scree Plot')
plt.xlabel('Principal Component')
plt.ylabel('Explained Variance Ratio')
plt.xticks(range(1, len(explained_variance) + 1))
plt.show()
```

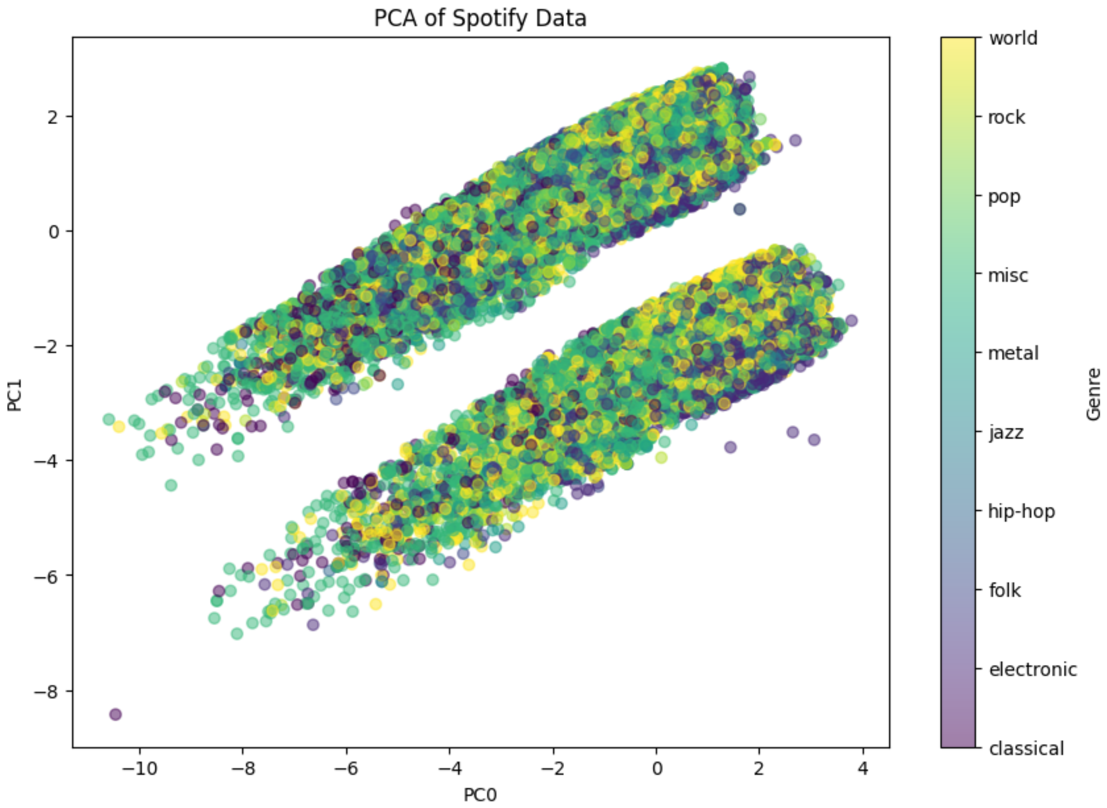
```
Explained variance ratio for each component:
 [0.10836837 0.09131586 0.06138773 0.05869306 0.04588949 0.0434164
 0.0361926  0.03418232 0.03292623 0.03291811]

Cumulative explained variance:
 [0.10836837 0.19968423 0.26107196 0.31976503 0.36565451 0.40907091
 0.44526351 0.47944583 0.51237206 0.54529017]
```



Based on the Scree Plot, it seems like taking the first 3 or 4 principal components would be best for still covering a good amount of variance (~0.18 cumulative) and also keeping it simple for easier visualizations. We plotted the first two PCs and colored them by genre to see if there were any interesting relationships.

[157]:

```
label_encoder = LabelEncoder()
Y_encoded = label_encoder.fit_transform(Y_train)

# plot the first two principal components
plt.figure(figsize=(10, 7))
scatter = plt.scatter(
    X_pca_df['PC0'],
    X_pca_df['PC1'],
    c=Y_encoded,
    cmap='viridis',
    alpha=0.5
)
# label by Y_encoded
cbar = plt.colorbar(scatter)
cbar.set_label('Genre')
cbar.set_ticks(range(len(label_encoder.classes_)))
cbar.set_ticklabels(label_encoder.classes_)

plt.xlabel('PC0')
plt.ylabel('PC1')
plt.title('PCA of Spotify Data')
plt.show()
```



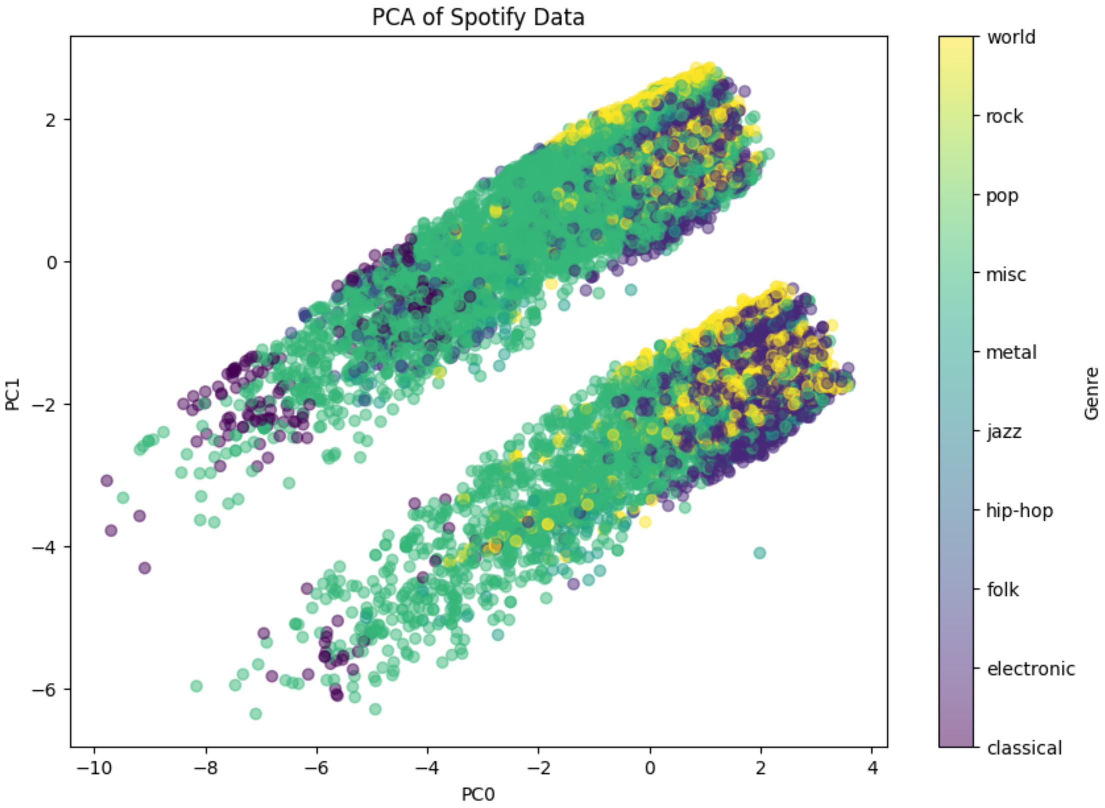
The points do seem like they're getting clustered and colored in some way on the PCA graph which is interesting, but it also looks like there are a lot of overlapping dots, so we may be losing some important dimensions.

We decided to do a regression on the PCA transformed data to see if the PCA improved the fit at all.

[159]:

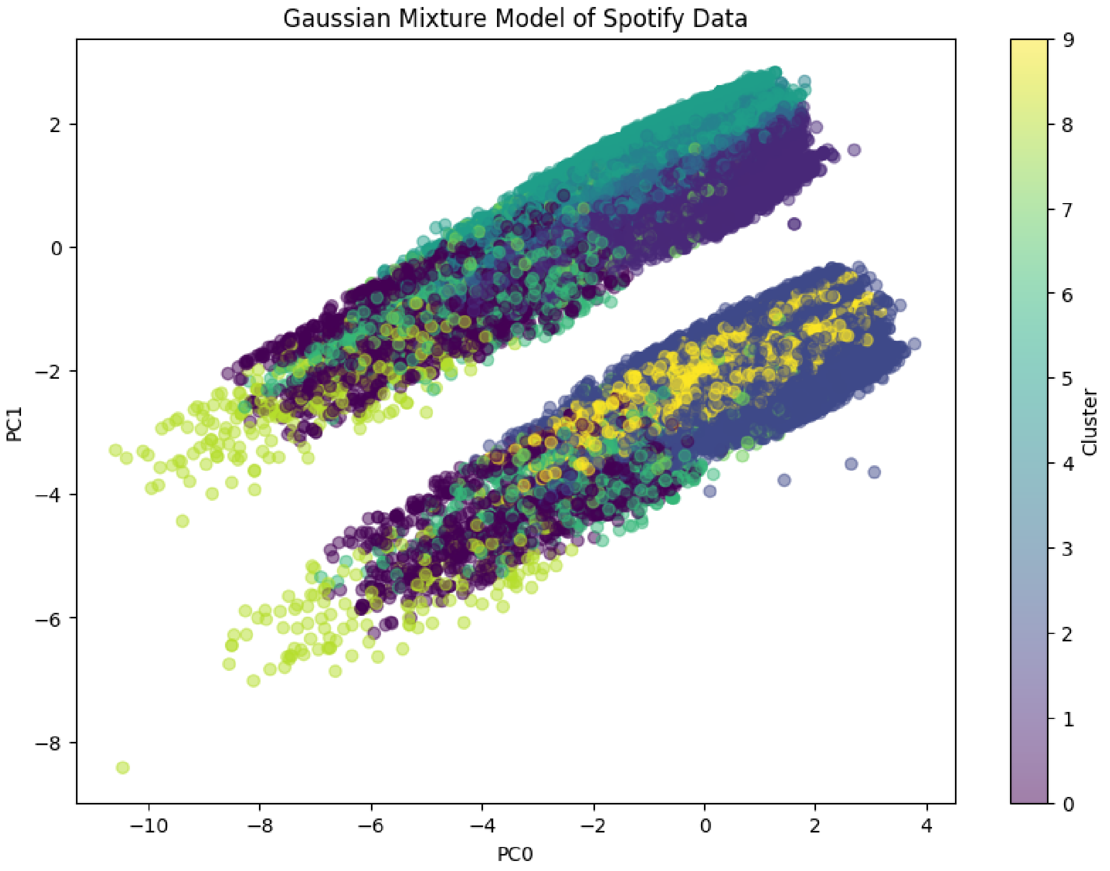
```python
# do a regression using PCA transformed data
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

X_test = ohe_grouped_column_transformer_wo_genre.transform(grouped_spotify_test)
X_test = scaler.transform(X_test)
X_test = pca.transform(X_test)
X_test = pd.DataFrame(X_test, columns=[f'PC{i}' for i in range(n_components)])
Y_test = grouped_spotify_test[response_variable]

model = LogisticRegression(max_iter=1000)
model.fit(X_pca_df, Y_train)
Y_pred = model.predict(X_test)
Y_pred_encoded = label_encoder.transform(Y_pred)

accuracy = accuracy_score(Y_test, Y_pred)
print(f'Accuracy: {accuracy}')

# plot it
plt.figure(figsize=(10, 7))
scatter = plt.scatter(
    X_test['PC0'],
    X_test['PC1'],
    c=Y_pred_encoded,
    cmap='viridis',
    alpha=0.5
)
# label by Y_encoded
cbar = plt.colorbar(scatter)
cbar.set_label('Genre')
cbar.set_ticks(range(len(label_encoder.classes_)))
cbar.set_ticklabels(label_encoder.classes_)
plt.xlabel('PC0')
plt.ylabel('PC1')
plt.title('PCA of Spotify Data')
plt.show()
```

```
Accuracy: 0.3139769832205921
```



Though the accuracy isn't very high with our logistic regression fit, the graph reminded us of what Gaussian Mixture Models tend to look like, so we attempted applying a GMM to the PCA transformed data as well.

[161]:
```
# gaussian mixture model
n_components = 10
gmm = GaussianMixture(n_components=n_components)
gmm.fit(X_pca_df)
Y_pred = gmm.predict(X_pca_df)

plt.figure(figsize=(10, 7))
scatter = plt.scatter(
    X_pca_df['PC0'],
    X_pca_df['PC1'],
    c=Y_pred,
    cmap='viridis',
    alpha=0.5
)
cbar = plt.colorbar(scatter)
cbar.set_label('Cluster')
cbar.set_ticks(range(n_components))
cbar.set_ticklabels(range(n_components))

plt.xlabel('PC0')
plt.ylabel('PC1')
plt.title('Gaussian Mixture Model of Spotify Data')
plt.show()
```



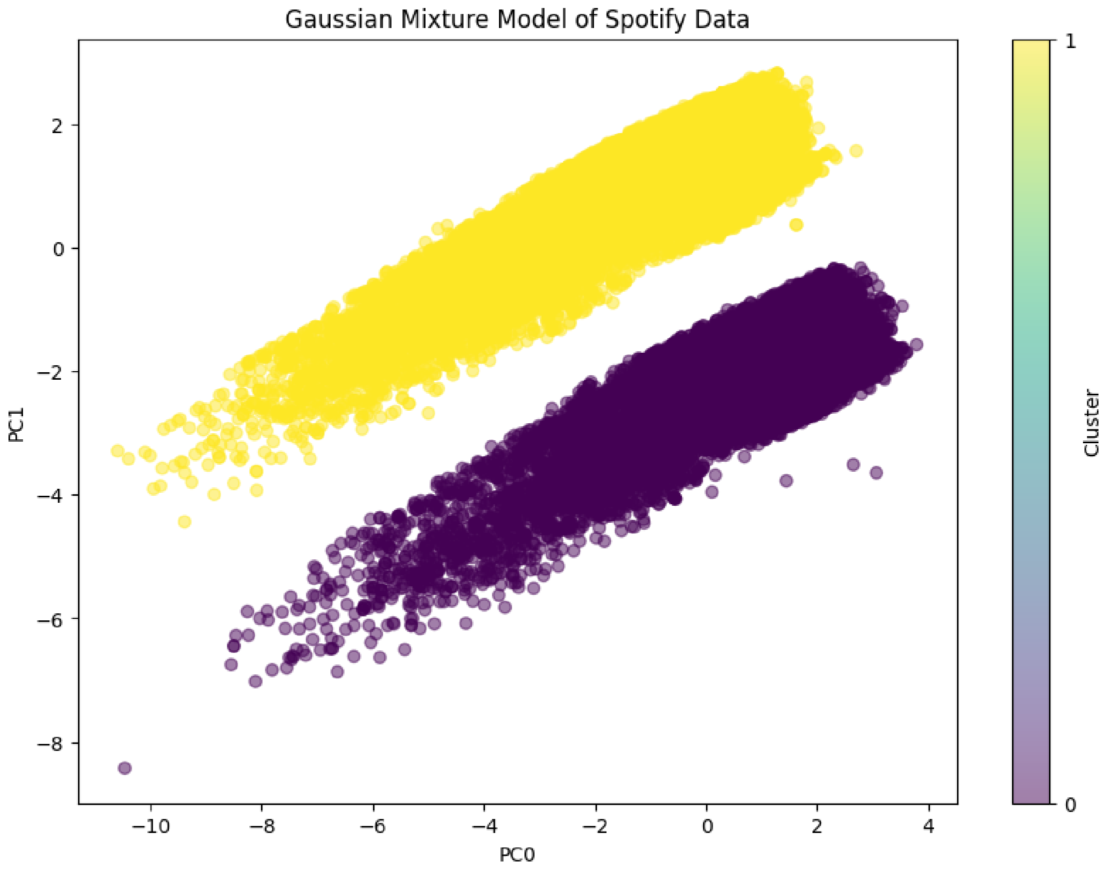
[162]:
```
# evaluate the model
sil_score = silhouette_score(X_pca_df, Y_pred)
print(sil_score)
```

```
0.18532988287647995
```

While the GMM has a pretty nice graph that almost looks right, the silhouette score is not good at all. We decided to try it again with just two genres, pop and not pop (other) to see if it might improve the score.

[163]:
```
# Trying the data but with 2 classes: pop and other
Y_binary = Y_train.apply(lambda x: 'pop' if x == 'pop' else 'misc')
```

```python
# do GMM
n_components = 2
gmm = GaussianMixture(n_components=n_components)
gmm.fit(X_pca_df)
Y_pred = gmm.predict(X_pca_df)


plt.figure(figsize=(10, 7))
scatter = plt.scatter(
    X_pca_df['PC0'],
    X_pca_df['PC1'],
    c=Y_pred,
    cmap='viridis',
    alpha=0.5
)
cbar = plt.colorbar(scatter)
cbar.set_label('Cluster')
cbar.set_ticks(range(n_components))
cbar.set_ticklabels(range(n_components))

plt.xlabel('PC0')
plt.ylabel('PC1')
plt.title('Gaussian Mixture Model of Spotify Data')
plt.show()
```



[164]:

```
# Evaluate
Y_binary_encoded = label_encoder.transform(Y_binary).reshape(-1, 1)
sil_score = silhouette_score(Y_binary_encoded, Y_pred)

print(sil_score)
```

```
-0.030537843090037743
```

Unfortunately, our silhouette score is still less than zero, indicating that our clustering with the GMM is not very good. We decided to try other methods of clustering, K-means and agglomerative, as well to see if they would be better.

Note that when working with the original data that has 114 genres, it's very evenly distributed (1000 samples per genre). This may imply that the sampling was not random, and was stratified via the genre subpopulations. This is likely not proportional to the actual song population, which may lead to bias since underrepresented genres are now equally represented with overrepresented genres. Since we have no way to recover original proportions without using external data, we will simply have to be weary of the results.

Our goal with clustering is to be able to see if it might be able to help us in classifying or predicting the genre of the song. We first start to see if there is any obvious clustering using both agglomerative (hierarchial) and k-means clustering.

[175]:
```
X_train = ohe_grouped_column_transformer_wo_genre.
 ↪transform(grouped_spotify_train)
X_test = ohe_grouped_column_transformer_wo_genre.transform(grouped_spotify_test)

scaler = StandardScaler()
X_train = pd.DataFrame(
    scaler.fit_transform(X_train),
    index=X_train.index,
    columns=X_train.columns
)
X_test = pd.DataFrame(
    scaler.transform(X_test),
    index=X_test.index,
    columns=X_test.columns
)

Y_train = grouped_spotify_train[response_variable]
Y_test = grouped_spotify_test[response_variable]
```

[172]:
```
# sample the training set to speed up hierarchical clustering
sample_size = 0.3
hierarchical_sample_split = StratifiedShuffleSplit(
    n_splits=1,
    test_size=1 - sample_size,
    random_state=42
)
gmm_sample_size = 0.8

for train_index, _ in hierarchical_sample_split.split(X_train, Y_train):
    X_sample = X_train.iloc[train_index].copy()
    Y_sample = Y_train.iloc[train_index].copy()
```

[173]:
```
n_clusters = 10

kmeans = KMeans(
    n_clusters=n_clusters,
    random_state=0
)
hierarchical = AgglomerativeClustering(
    n_clusters=n_clusters,
    metric='euclidean',
    linkage='ward'
)
gmm = GaussianMixture(
    n_components=n_clusters,
    random_state=0
)

hierarchical.fit(X_sample)
kmeans.fit(X_sample)
gmm.fit(X_train)
```

```
[173]: GaussianMixture(n_components=10, random_state=0)
```

```
[176]: X_sample["hcluster"] = hierarchical.labels_
       X_sample["kcluster"] = kmeans.labels_
       Y_pred_gmm = gmm.predict(X_test)

       # encode Y_test_gmm labels using LabelEncoder
       label_encoder = LabelEncoder()
       label_encoder.fit(Y_train)
       Y_train_encoded = label_encoder.transform(Y_train)
```

```
[ ]: # Analyze
     hclust_kclust_ari = adjusted_rand_score(X_sample["hcluster"],␣
      ↪X_sample["kcluster"])

     hclust_y_ari = adjusted_rand_score(X_sample["hcluster"], Y_sample)
     kclust_y_ari = adjusted_rand_score(X_sample["kcluster"], Y_sample)
     kclust_y_ari = adjusted_rand_score(Y_test, Y_pred_gmm)

     hclust_silhouette = silhouette_score(X_sample, X_sample["hcluster"])
     kclust_silhouette = silhouette_score(X_sample, X_sample["kcluster"])
     gmm_silhouette = silhouette_score(X_test, Y_pred_gmm)

     print(f'''
     Hierarchical clustering vs KMeans clustering ARI: {hclust_kclust_ari}

     Hierarchical clustering vs true labels ARI: {hclust_y_ari}
     KMeans clustering vs true labels ARI: {kclust_y_ari}
     GMM clustering vs true labels ARI: {kclust_y_ari}

     Hierarchical clustering silhouette score: {hclust_silhouette}
     KMeans clustering silhouette score: {kclust_silhouette}
     GMM clustering silhouette score: {gmm_silhouette}
     ''')
```

```
Hierarchical clustering vs KMeans clustering ARI: 0.4500737924478871

Hierarchical clustering vs true labels ARI: 0.0019950842701675522
KMeans clustering vs true labels ARI: 0.0022420916160579103
GMM clustering vs true labels ARI: 0.0022420916160579103
```

```
Hierarchical clustering silhouette score: 0.16310140621490865
KMeans clustering silhouette score: 0.22201717965090853
GMM clustering silhouette score: 0.1694012135651898
```

[180]:

```python
pd.set_option('display.max_columns', None)
X_sample.groupby("hcluster").count()
```

[180]:

```
          key_0  key_1  key_2  key_3  key_4  key_5  key_6  key_7  key_8  \
hcluster
0          4098   4098   4098   4098   4098   4098   4098   4098   4098
1          4902   4902   4902   4902   4902   4902   4902   4902   4902
2          4188   4188   4188   4188   4188   4188   4188   4188   4188
3          1190   1190   1190   1190   1190   1190   1190   1190   1190
4          1983   1983   1983   1983   1983   1983   1983   1983   1983
5          1515   1515   1515   1515   1515   1515   1515   1515   1515
6          1497   1497   1497   1497   1497   1497   1497   1497   1497
7           334    334    334    334    334    334    334    334    334
8           614    614    614    614    614    614    614    614    614
9           167    167    167    167    167    167    167    167    167

          key_9  key_10  key_11  mode_0  mode_1  time_signature_0  \
hcluster
0          4098    4098    4098    4098    4098              4098
1          4902    4902    4902    4902    4902              4902
2          4188    4188    4188    4188    4188              4188
3          1190    1190    1190    1190    1190              1190
4          1983    1983    1983    1983    1983              1983
5          1515    1515    1515    1515    1515              1515
6          1497    1497    1497    1497    1497              1497
7           334     334     334     334     334               334
8           614     614     614     614     614               614
9           167     167     167     167     167               167

          time_signature_1  time_signature_3  time_signature_4  \
hcluster
0                     4098              4098              4098
1                     4902              4902              4902
2                     4188              4188              4188
3                     1190              1190              1190
4                     1983              1983              1983
5                     1515              1515              1515
6                     1497              1497              1497
7                      334               334               334
8                      614               614               614
9                      167               167               167
```

```
          time_signature_5  popularity  duration_ms  explicit  danceability  \
hcluster
0                     4098        4098         4098      4098          4098
1                     4902        4902         4902      4902          4902
2                     4188        4188         4188      4188          4188
3                     1190        1190         1190      1190          1190
4                     1983        1983         1983      1983          1983
5                     1515        1515         1515      1515          1515
6                     1497        1497         1497      1497          1497
7                      334         334          334       334           334
8                      614         614          614       614           614
9                      167         167          167       167           167

          energy   key  loudness  mode  speechiness  acousticness  \
hcluster
0           4098  4098      4098  4098         4098          4098
1           4902  4902      4902  4902         4902          4902
2           4188  4188      4188  4188         4188          4188
3           1190  1190      1190  1190         1190          1190
4           1983  1983      1983  1983         1983          1983
5           1515  1515      1515  1515         1515          1515
6           1497  1497      1497  1497         1497          1497
7            334   334       334   334          334           334
8            614   614       614   614          614           614
9            167   167       167   167          167           167

          instrumentalness  liveness  valence  tempo  time_signature  kcluster
hcluster
0                     4098      4098     4098   4098            4098      4098
1                     4902      4902     4902   4902            4902      4902
2                     4188      4188     4188   4188            4188      4188
3                     1190      1190     1190   1190            1190      1190
4                     1983      1983     1983   1983            1983      1983
5                     1515      1515     1515   1515            1515      1515
6                     1497      1497     1497   1497            1497      1497
7                      334       334      334    334             334       334
8                      614       614      614    614             614       614
9                      167       167      167    167             167       167
```

Based on our investigations, the K-means and Agglomerative clustering did ok, with silhouette scores for both methods being ~0.5. However, like before, GMM did terribly. However, the adjusted rand index when compared with track genre was negligible, meaning that the clusters formed do not at all correspond to genre, so clustering will probably not help us with our classification problem.

1.8 Neural Networks

We then applied neural networks to see if they could approximate the genre as a function of the other features.

We first put one-hot-encoded the data, scaled it, and put it onto the GPU (if available). We used a batch size of 64 for data loading.

[185]:

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

```
/home/ketexon/programming/csm148-spotiflies/.venv/lib/python3.12/site-
packages/torch/cuda/__init__.py:716: UserWarning: Can't initialize NVML
  warnings.warn("Can't initialize NVML")
/home/ketexon/programming/csm148-spotiflies/.venv/lib/python3.12/site-
packages/torch/cuda/__init__.py:905: UserWarning: CUDA initialization:
Unexpected error from cudaGetDeviceCount(). Did you run some cuda functions
before calling NumCudaDevices() that might have already set an error? Error 803:
system has unsupported display driver / cuda driver combination (Triggered
internally at ../c10/cuda/CUDAFunctions.cpp:108.)
  r = torch._C._cuda_getDeviceCount() if nvml_count < 0 else nvml_count
```

[186]:

```
response_variable = "track_genre"

# remove string columns and one-hot encode
Y_train = grouped_spotify_train[response_variable]
Y_val = grouped_spotify_val[response_variable]

X_train = ohe_grouped_column_transformer_wo_genre.
  ↪transform(grouped_spotify_train)
X_val = ohe_grouped_column_transformer_wo_genre.transform(grouped_spotify_val)

label_encoder = LabelEncoder()
label_encoder.fit(grouped_spotify[response_variable])
Y_train = label_encoder.transform(Y_train)
Y_val = label_encoder.transform(Y_val)

# create class weights
Y_train_unique = np.unique(Y_train, return_counts=True)
class_weights = len(Y_train) / (Y_train_unique[1] * len(Y_train_unique[1]))
for i, w in enumerate(class_weights):
    label_encoded = Y_train_unique[0][i]
    label_decoded = label_encoder.inverse_transform([label_encoded])[0]
    w_str = f"{w:.3f}"
    count_str = f"{Y_train_unique[1][i]:,}"
    print(f"{label_decoded + ':': <16}{w_str: <16}{count_str}")

# scale
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
```

```
X_val = scaler.transform(X_val)

# convert to tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float32).to(device)
X_val_tensor = torch.tensor(X_val, dtype=torch.float32).to(device)
Y_train_tensor = torch.tensor(Y_train, dtype=torch.long).to(device)
Y_val_tensor = torch.tensor(Y_val, dtype=torch.long).to(device)

class_weights_tensor = torch.tensor(class_weights, dtype=torch.float32).
 ↪to(device)


# create dataset
train_dataset = TensorDataset(X_train_tensor, Y_train_tensor)
validation_dataset = TensorDataset(X_val_tensor, Y_val_tensor)

# create dataloaders
batch_size = 64
num_workers = 12 if is_linux else 0
train_loader = DataLoader(
    train_dataset,
    batch_size=batch_size,
    shuffle=True,
    num_workers=num_workers,
)
validation_loader = DataLoader(
    validation_dataset,
    batch_size=batch_size,
    shuffle=False,
    num_workers=num_workers,
)
```

```
classical:      3.820           1,788
electronic:     0.569           12,002
folk:           1.895           3,604
hip-hop:        3.744           1,824
jazz:           2.854           2,393
metal:          1.876           3,640
misc:           0.380           17,962
pop:            1.268           5,386
rock:           1.040           6,569
world:          0.520           13,128
```

Then we defined our model. Via trial and error, we found that using ReLU caused slow training (since the gradient is 0 if the value is negative), and including dropout added to much variation to the training loss. In addition, switching from softmax to log softmax helped the early stopping algorithm from stopping too early. Thus, we kept a simple model, with 2 fully connected hidden layers, with sigmoid activation for the hidden layers and log softmax for the output.

We used the Adam optimizer with weigth decay for regularization using cross entropy loss. We also used a learning rate scheduler which reduced learning rate by 90% every 10 epochs.

[187]:

```
# Create model
class SpotifyModel(pl.LightningModule):
    def __init__(
        self,
        input_dim: int,
        output_dim: int,
        lr: float = 0.01,
        class_weights: torch.tensor = None,
        hidden_dim1: int = 64,
        hidden_dim2: int = 64,
        weight_decay: float = 0.01,
    ):
        super().__init__()
        self.lr = lr
        self.model = nn.Sequential(
            nn.Linear(input_dim, hidden_dim1),
            nn.Sigmoid(),
            nn.Linear(hidden_dim1, hidden_dim2),
            nn.Sigmoid(),
            nn.Linear(hidden_dim2, output_dim),
            nn.LogSoftmax(dim=1),
        )
        self.n_classes = output_dim
        self.weight_decay = weight_decay
        self.epoch_metrics = []
        self.train_metrics_stack = []
        self.validation_metrics_stack = []
        self.loss = nn.CrossEntropyLoss(weight=class_weights)

    def forward(self, x):
        return self.model(x)

    def training_step(self, batch, batch_idx):
        x, y = batch
        y_hat = self(x)
        loss = self.loss(y_hat, y)
        self.log("train_loss", loss)
        self.train_metrics_stack.append({
            'train_loss': loss,
        })
        return loss

    def validation_step(self, batch, batch_idx):
        x, y = batch
        y_hat = self(x)
        loss = self.loss(y_hat, y)
        preds = torch.argmax(y_hat, dim=1)
        acc = (preds == y).float().mean()
        self.validation_metrics_stack.append({
            'val_loss': loss,
            'val_acc': acc
        })
        self.log("val_loss", loss)
        return loss

    def on_validation_epoch_end(self):
        # sum in validation stack
        if len(self.validation_metrics_stack) == 0:
            return
        if len(self.train_metrics_stack) == 0:
            return
        val_loss = torch.stack([x['val_loss'] for x in self.
↪validation_metrics_stack]).mean()
        val_acc = torch.stack([x['val_acc'] for x in self.
↪validation_metrics_stack]).mean()
        train_loss = torch.stack([x['train_loss'] for x in self.
↪train_metrics_stack]).mean()
        self.epoch_metrics.append({
            'val_loss': val_loss.cpu(),
            'val_acc': val_acc.cpu(),
            'train_loss': train_loss.cpu(),
        })
        # clear stack
        self.validation_metrics_stack = []
        self.train_metrics_stack = []


    def configure_optimizers(self):
        optimizer = optim.Adam(self.parameters(), lr=self.lr, weight_decay=self.
↪weight_decay)
        scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=10, gamma=0.
↪1)
        return [optimizer], [scheduler]
```

To pick an initial learning rate, we used PyTorch's `lr_find` function, which gave us an initial learning rate of about 0.002. We then trained the model, which stopped early at 27 epochs.

[ ]:

```
input_dim = X_train.shape[1]
output_dim = len(
    label_encoder.classes_
)
```

```
lr = 0.001

model = SpotifyModel(
    input_dim,
    output_dim,
    lr=lr,
    class_weights=class_weights_tensor
).to(device)

# train model
early_stopping = pl_callbacks.EarlyStopping(
    monitor='val_loss',
    patience=10,
    min_delta=0.0001,
    mode='min'
)

use_checkpoint = False
ckpt_path="epoch=12-step=18499.ckpt" if use_checkpoint else None
trainer = pl.Trainer(
    max_epochs=100,
    callbacks=[
        early_stopping
    ]
)

# tune the model
from lightning.pytorch.tuner.tuning import Tuner
tuner = Tuner(trainer)

lr_finder = tuner.lr_find(
    model,
    train_dataloaders=train_loader,
    val_dataloaders=validation_loader,
    min_lr=1e-10,
    max_lr=1e-1,
    num_training=100,
)

model.lr = lr_finder.suggestion()
print(f"Learning rate: {model.lr}")

trainer.fit(
    model,
    train_loader,
    validation_loader,
    ckpt_path=ckpt_path
)
```

```
/home/ketexon/programming/csm148-spotiflies/.venv/lib/python3.12/site-
packages/torch/cuda/__init__.py:716: UserWarning: Can't initialize NVML
  warnings.warn("Can't initialize NVML")
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
HPU available: False, using: 0 HPUs
Finding best initial lr:  96%|      | 96/100 [00:00<00:00,
138.32it/s]`Trainer.fit` stopped: `max_steps=100` reached.
Finding best initial lr: 100%|      | 100/100 [00:00<00:00, 132.55it/s]
Learning rate set to 0.0019498445997580478
Restoring states from the checkpoint path at /home/ketexon/programming/csm148-
spotiflies/.lr_find_71f92498-ffbf-4528-aab4-a052b2bdc14c.ckpt
Restored all states from the checkpoint at /home/ketexon/programming/csm148-
spotiflies/.lr_find_71f92498-ffbf-4528-aab4-a052b2bdc14c.ckpt

  | Name  | Type             | Params | Mode
---------------------------------------------------
0 | model | Sequential       | 6.7 K  | train
1 | loss  | CrossEntropyLoss | 0      | train
---------------------------------------------------
6.7 K     Trainable params
0         Non-trainable params
6.7 K     Total params
0.027     Total estimated model params size (MB)
8         Modules in train mode
0         Modules in eval mode

Learning rate: 0.0019498445997580478
Epoch 27: 100%|      | 1423/1423 [00:14<00:00, 100.88it/s, v_num=55]
```

We then plotted a classification report on the model.

[ ]:

```python
# evaluate model
model.eval()
with torch.no_grad():
    outputs = model.to(device)(X_val_tensor.to(device)).cpu()
    _, predicted = torch.max(outputs.data, 1)
    value_counts = pd.DataFrame(predicted).value_counts()
    for label in label_encoder.classes_:
        class_encoded = label_encoder.transform([label])[0]
        count = value_counts.get(class_encoded, 0)
        print(f"{label}: {count}")
    class_report = classification_report(
        Y_val,
        predicted,
        labels=range(len(label_encoder.classes_)),
        target_names=label_encoder.classes_,
        zero_division=1
    )
model.train()

print(class_report)
```

```
classical: 4629
electronic: 4627
folk: 2029
hip-hop: 0
jazz: 890
metal: 6415
misc: 3462
pop: 0
rock: 609
world: 105
              precision    recall  f1-score   support

   classical       0.10      0.77      0.18       607
  electronic       0.26      0.30      0.28      4026
        folk       0.09      0.15      0.11      1218
     hip-hop       1.00      0.00      0.00       578
        jazz       0.07      0.07      0.07       830
       metal       0.17      0.90      0.28      1203
        misc       0.25      0.15      0.19      5931
         pop       1.00      0.00      0.00      1825
        rock       0.09      0.03      0.04      2227
       world       0.30      0.01      0.01      4321

    accuracy                           0.17     22766
   macro avg       0.33      0.24      0.12     22766
weighted avg       0.30      0.17      0.13     22766
```

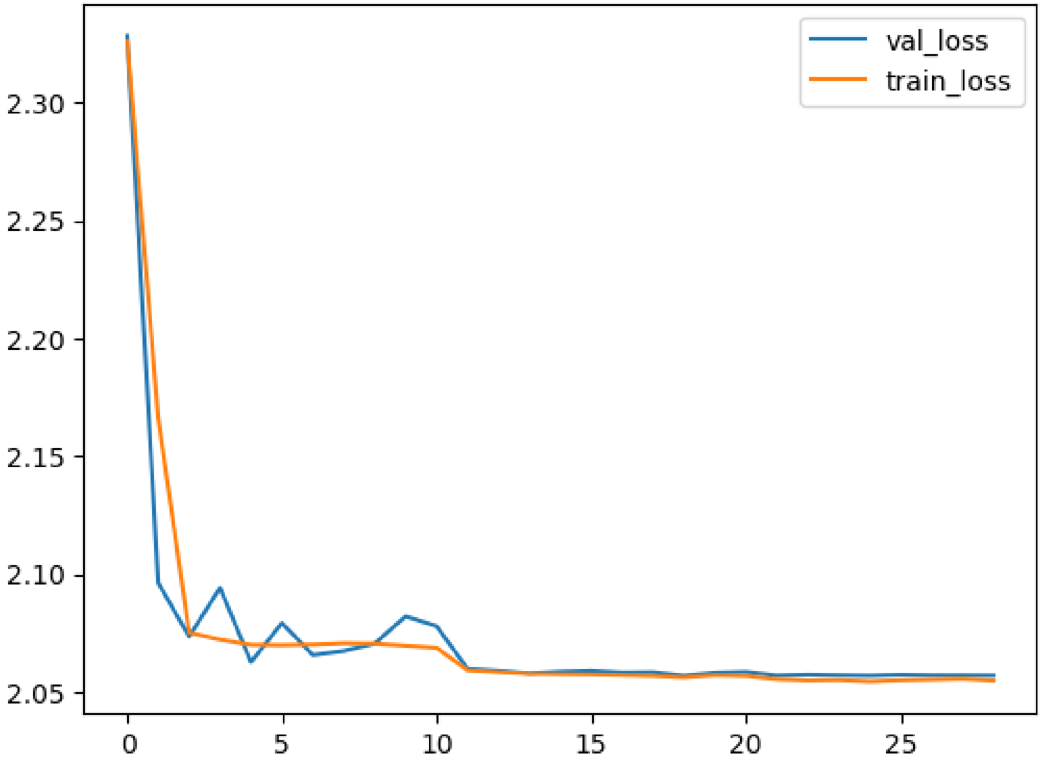
The classification shows pretty bad results, with overall 17% accuracy (which is hardly better than uniform, at 10%).

However, something interesting of note is that the recall for classical and metal was significantly high. This means that if the model predicted that a song was metal or classical, it was likely correct. Something else of note was that pop and hip hop, the most and least represented classes, had 0 predictions. This was stranger, but through othe models, we saw that the class imbalance disproportionately made more represented classes be predicted. When we added class weights, this might have overcompensated for pop, leading to pop having poor predictions, and undercompensated for hip-hop.

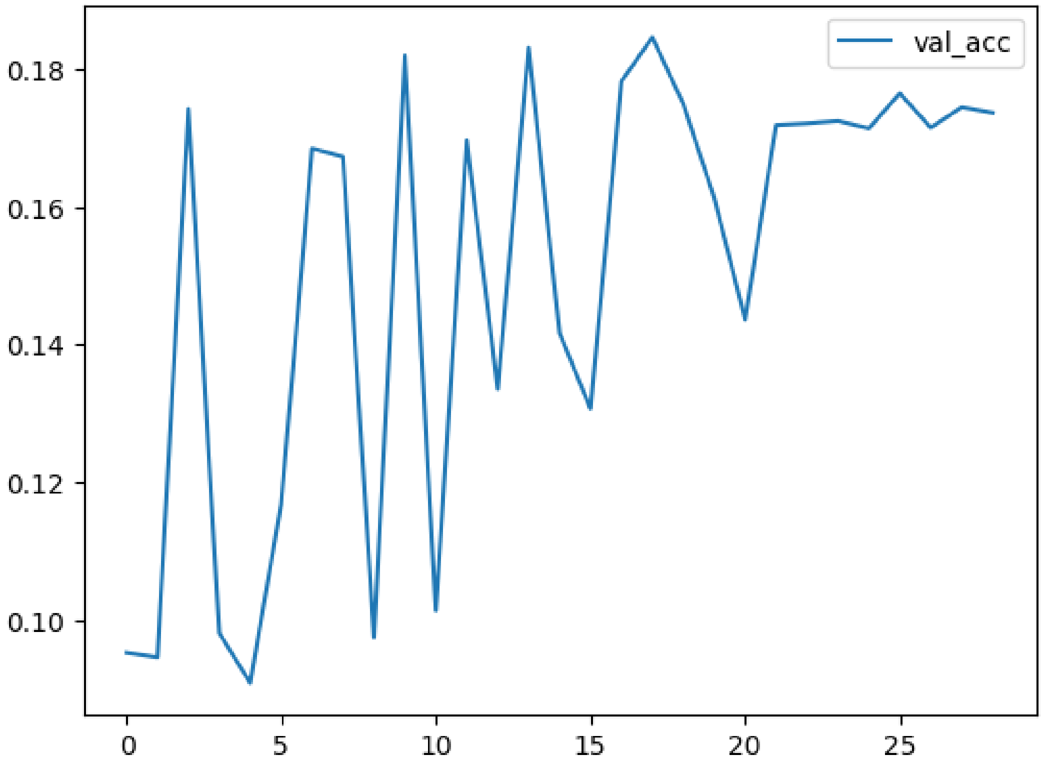
[ ]:

```
# Graph epoch metrics
import matplotlib.pyplot as plt
```

```
# plot epoch to val loss and train loss
plt.plot([x['val_loss'].cpu() for x in model.epoch_metrics], label='val_loss')
plt.plot([x['train_loss'].cpu() for x in model.epoch_metrics],␣
 ↪label='train_loss')
plt.legend()
plt.show()
```



[ ]:
```
# plot accuracy per epoch
plt.plot([x['val_acc'].cpu() for x in model.epoch_metrics], label='val_acc')
plt.legend()
plt.show()
```



Plotting the validation and training loss, as well as the model accuracy over epochs, we can see that thte loss did shrink over time, with accuracy never really increasing. This could be an indicator that cross entropy was not a good loss function.