Introduction to Data Science
Capstone Project
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Data Preprocessing Overview

1. Dimension Reduction:

For dimension reduction, we utilized Principal Component Analysis (PCA). Initially, our dataset contained 10 feature variables, making it complex and computationally intensive to analyze. By applying PCA, we reduced the dimensionality to 3 principal components, capturing approximately 57.36% of the total variance in the dataset. This step simplified our models and reduced the risk of overfitting.

2. Data Cleaning:

Handling Missing Values: We first scrutinized the missing values in the spotify52kData dataset and identified zero missing data. For the starRatings dataset, we filled the missing value with 0 which means that there is no interaction between user and song. We choose this approach to construct the popular base model for simplicity and avoiding potential bias that could mislead the final result.

Duplicate Removal: When calculating the top 10 songs with the greatest hits, we handle duplicates by dropping rows with the same combination of 'track name' and 'artists'. We drop the duplicate for data consistency since duplicate entries for the same song could arise from different sources or errors in data aggregation.

3. Data Transformations:

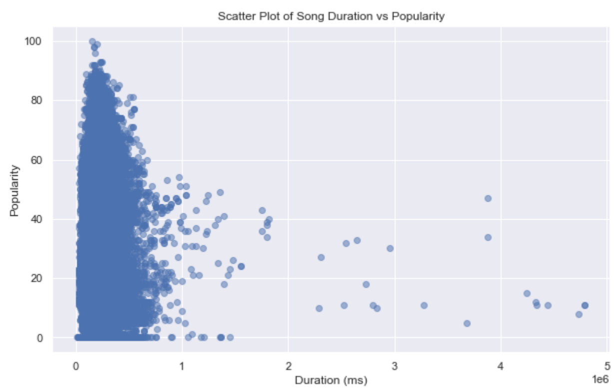
When building neural network models like a Multilayer Perceptron (MLP), we encode categorical variables (52 unique track genres) using LabelEncoder() and scale the feature data using StandardScaler() to make the data suitable for analysis.

4. RNG seeding

We seed our random number generator at 19329713 (N-number of Maggie Xu).

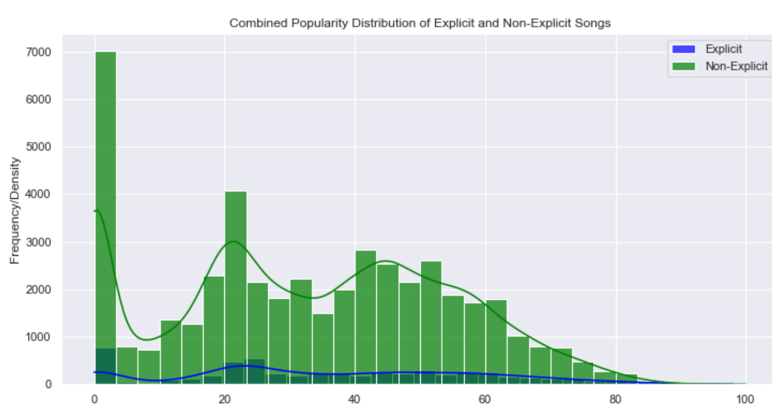
1) Is there a relationship between song length and popularity of a song? If so, is it positive or negative?

To conclusively determine if there is a significant relationship and whether it is positive or negative, a statistical analysis Pearson correlation test is conducted. This test would quantify the strength and direction of the relationship between song length and popularity. The Pearson correlation coefficient between song length and popularity is approximately -0.055, with a highly significant p-value 1.07e-35 (far less than alpha = 0.05). This suggests that there is a very weak negative correlation between song length and popularity. In other words, as the length of a song slightly increases, its popularity tends to decrease marginally.



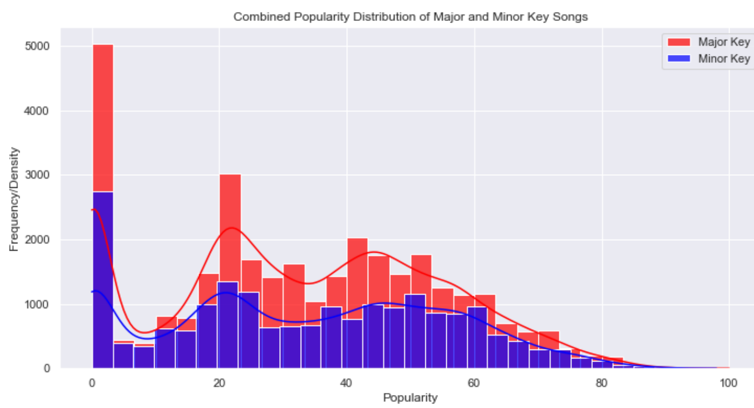
2) Are explicitly rated songs more popular than songs that are not explicit?

We first extracted explicit and not explicit rated songs and put them in the separate dataset. And then, we conducted the one tail t-test comparing the popularity of explicitly rated songs to non-explicit songs. With H0: explicit rated popularity = not explicit popularity and H1: explicit rated popularity > not explicit popularity. The test yields a t-statistic of approximately 9.83, with a highly significant p-value 4.25 e-23(far less than alpha = 0.05). This result indicates that we would reject the Null hypothesis and conclude that explicit rated songs are more popular than songs that are not explicitly rated.



3) Are songs in the major key more popular than songs in the minor key?

We first extracted the major(mode = 1)and minor(mode=0) key songs and put them in the separate dataset. The one tail t-test comparing the popularity of songs in major keys to those in minor keys. With H0: major popularity = minor popularity and H1: major popularity > minor popularity. The test yields a t-statistic of approximately -4.82, with a insignificant p-value 0.99 > alpha = 0.05. This result indicates that we fail to reject the Null hypothesis and conclude that there is no significant difference in popularity between major and minor key songs.



4) Which of the following 10 song features: duration, danceability, energy, loudness, speechiness, acousticness, instrumentalness, liveness, valence and tempo predicts popularity best? How good is this model?

We prepared the data used to fit the model by extracting these 10 song features and popularity from our original spotify data. We first tried to use the linear regression models to make the prediction. By creating a for loop, we use each feature in the 10 song features as a single predictor to fit the model and make a prediction on the value of popularity. By calculating the R^2 score between actual popularity value and predicted popularity value with each feature to evaluate the linear regression models, we got a relatively small R^2 for all 10 features. As shown in the left table below, feature "instrumentalness" has the largest R^2 score of 0.021017, which predicts popularity best. This means that for the 10 features here, they may not have a linear relationship with popularity and the linear regression models do not have a good performance here to make predictions.

Based on this, we then tried to use the random forest regression models for predictions. By creating a for loop, we still use each feature in the 10 song features as a single predictor to fit the model and make a prediction on the value of popularity. To evaluate the random forest models, we calculated the R^2 score between actual popularity value and predicted popularity value with each feature and found out that feature "duration" has the largest R^2 score of 0.643402 as shown in the right table below, which predicts popularity best. For the random forest models here, we have much higher R^2 scores for all features, which means that they have a much better performance than the linear regression models on predictions and better capture the relationship between each feature and popularity.

	Feature	R^2 Score
6	instrumentalness	0.021017
3	loudness	0.003625
2	energy	0.003128
0	duration	0.002987
4	speechiness	0.002355
7	liveness	0.001922
1	danceability	0.001381
8	valence	0.001279
5	acousticness	0.000688
9	tempo	0.000007

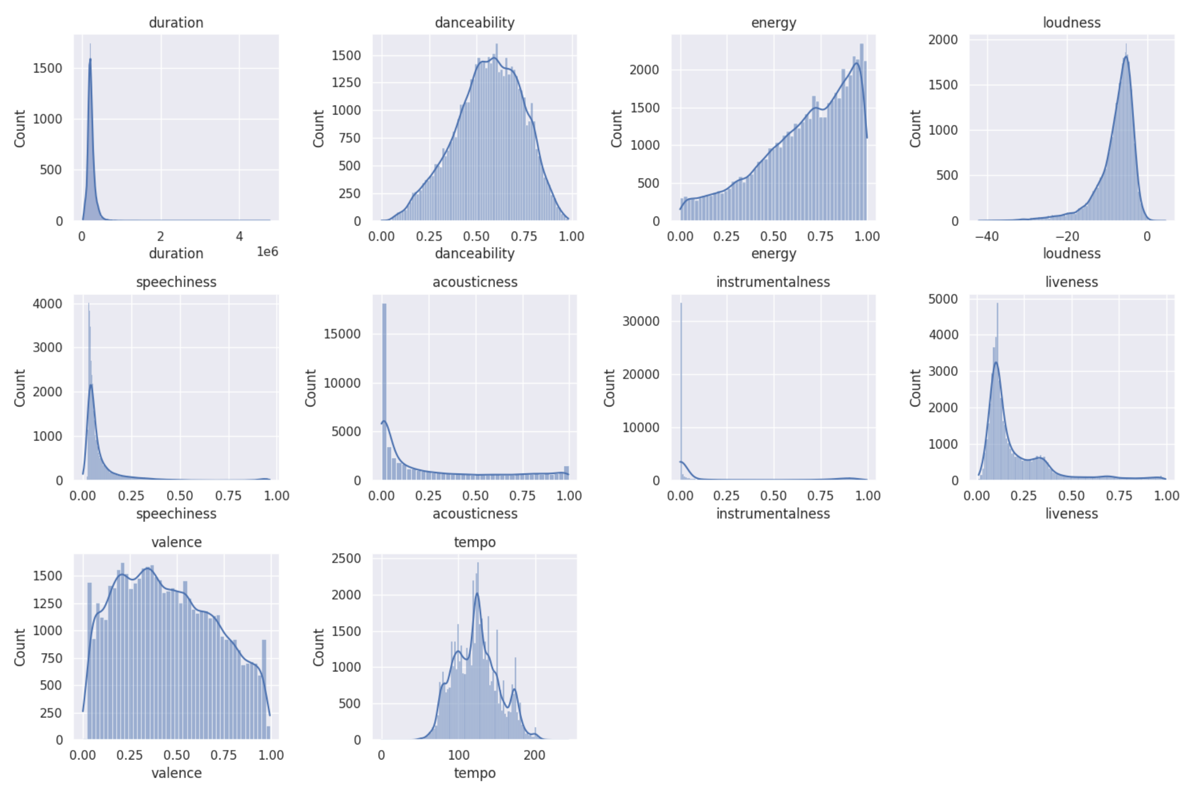
R^2 table for Linear Regression Model

	Feature	R^2 Score
0	duration	0.643402
9	tempo	0.606115
3	loudness	0.376893
5	acousticness	0.159760
6	instrumentalness	0.123671
2	energy	0.075572
8	valence	0.066103
7	liveness	0.062653
4	speechiness	0.059608
1	danceability	0.049276

R^2 table for Random Forest Model

5) Building a model that uses all of the song features mentioned in question 4, how well can you predict popularity? How much (if at all) is this model improved compared to the model in question 4). How do you account for this? What happens if you regularize your model?

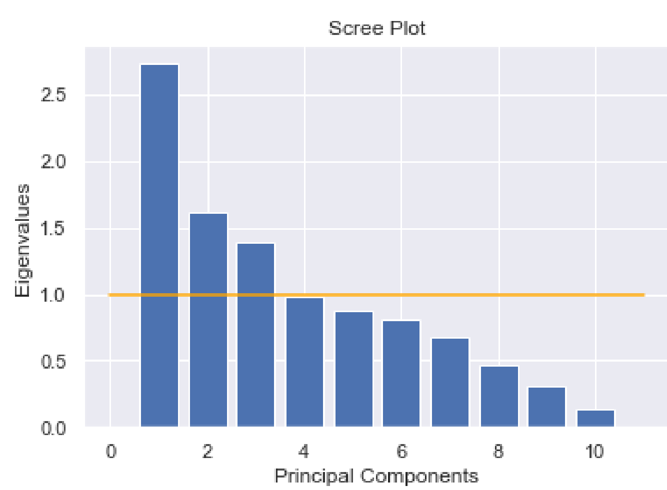
Below are the distribution plots of each feature.



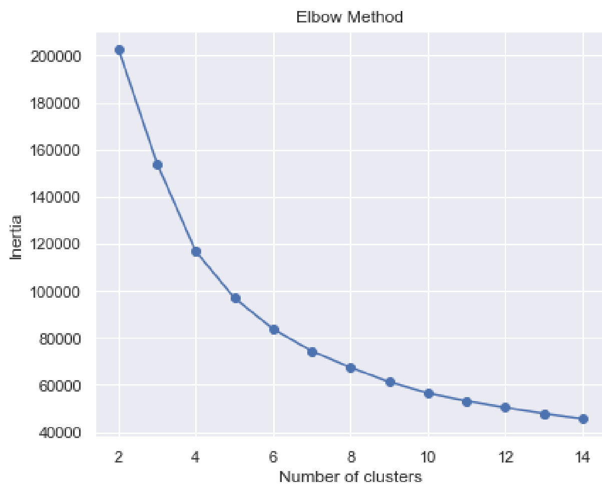
We build two models, multiple linear Ridge regression and Random Forest, and assess the performance of the models using COD and RMSE. We prepared the data by doing a 20-80 test split to train the model. For the linear model, without regularization, we got a R^2 of 0.0463 and RMSE of 21.1632315. Then we decided to use ridge regression because we want to avoid problems of multicollinearity, overfitting since the dataset has 10 features. The performance of the model can be summarized with a R^2=0.046 and RMSE = 21.1632. The performance doesn't improve much compared with the previous question (highest R^2=0.021 for the linear model), which might indicate that the relationship is nonlinear, so we decided to build a Random Forest model again. The R^2 for our Random Forest model is around 0.4, and the RMSE is 16.781. This model has a lower R^2 than the random forest model with duration as the predictor variable in question 4, and it is also lower than the R^2 for tempo as the predictor variable. We think that the reason might be that adding more variables increases the model's complexity. Since according to question 4's results, some of these additional variables are not strongly predictive, they might not contribute to, or could even detract from, the model's ability to explain the variability. Thus, we have a lower R^2 in this question.

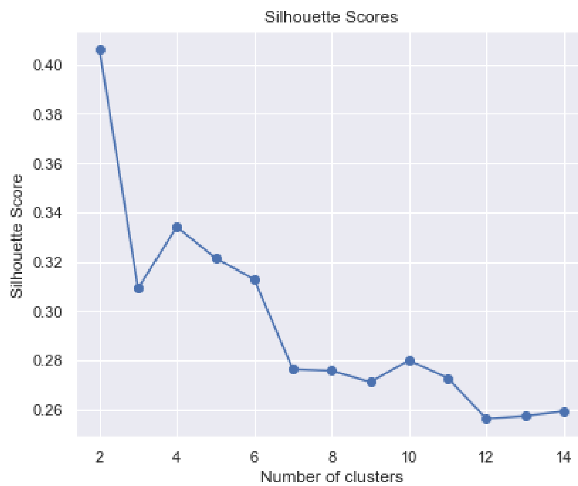
6) When considering the 10 song features in the previous question, how many meaningful principal components can you extract? What proportion of the variance do these principal components account for? Using these principal components, how many clusters can you identify? Do these clusters reasonably correspond to the genre labels in column 20 of the data?

We conducted PCA for the 10 song features in the previous question. According to the outcome Scree Plot below, the orange line is the Kaiser criterion line where eigenvalue = 1, and we can see that there are three principal components with eigenvalues greater than 1. We decided to extract these three PCs for computations and found that these three components accounted for 57.36% of the total variance in the dataset.

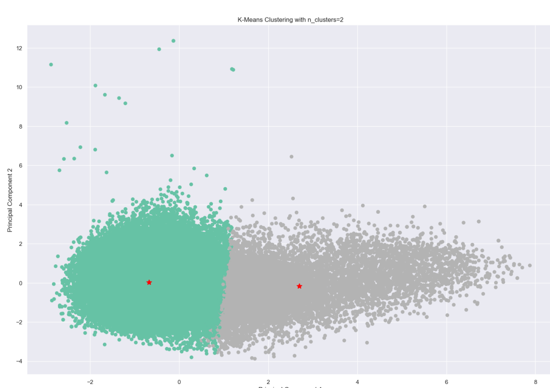


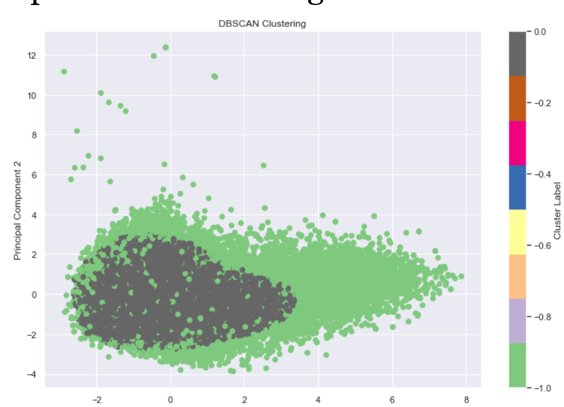
We then find the number of clusters using the Elbow method by setting the range of possible number of clusters from [2,14]. To make sure our estimation is more accurate, we also computed the Silhouette Scores to determine the optimal number of clusters. According to the two plots below, we can see that when cluster = 2, the Silhouette score is the highest (greater than 0.4), and the scores show a decreasing trend for the larger numbers.





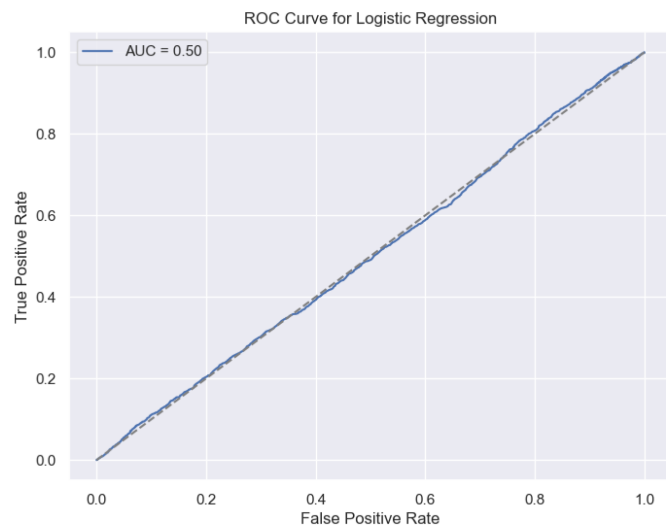
With 52 unique genres in the dataset, neither method suggests a close correspondence to this number of clusters. The high number of genres indicates that the genre classification may be too fine-grained or that the features may not capture all the nuances that distinguish 52 separate genres. We also visualized the clusters in the below scatter plot on the left, and we think that it is reasonable that the dataset does not have an inherent cluster. We then use DBSCAN to confirm our belief that 1 is the optimal number of clusters for our dataset, just as the plot shows on the right.



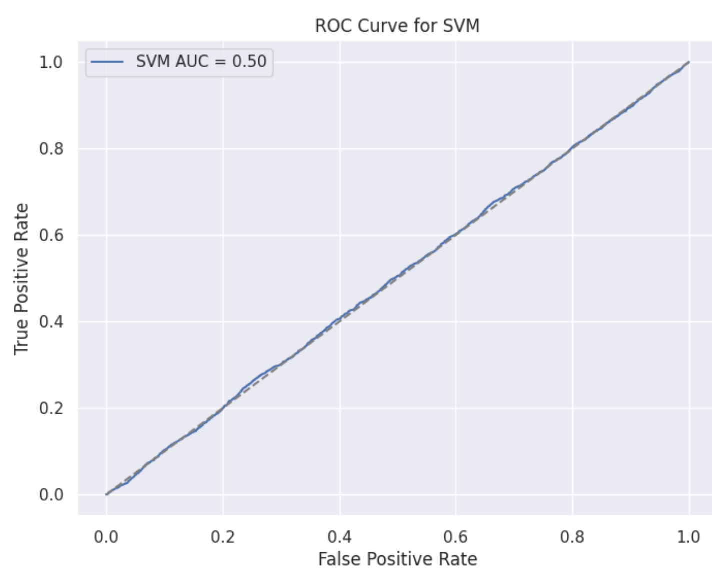


7) Can you predict whether a song is in major or minor key from valence using logistic regression or a support vector machine? If so, how good is this prediction? If not, is there a better one?

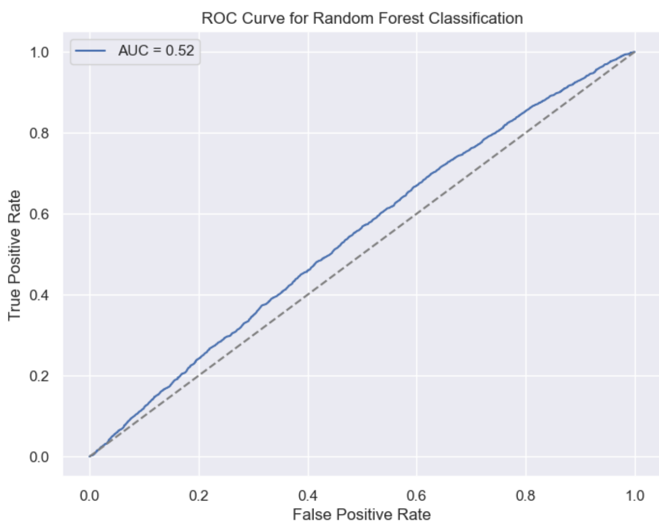
We prepared the data by extracting the valence column from the original spotify dataset our predictor X and extracting mode column as target y. After doing an 80/20 training and testing split on X and y, we first fit the training data with a logistic regression model (*LogisticRegression()*). After making predictions with test data, we calculate the AUC score to evaluate the model and plot out the ROC curve for this logistic model. We got an AUC Score of 0.5 here, which is very low and means that the logistic regression model is not doing a good performance in this case as the plot shown.

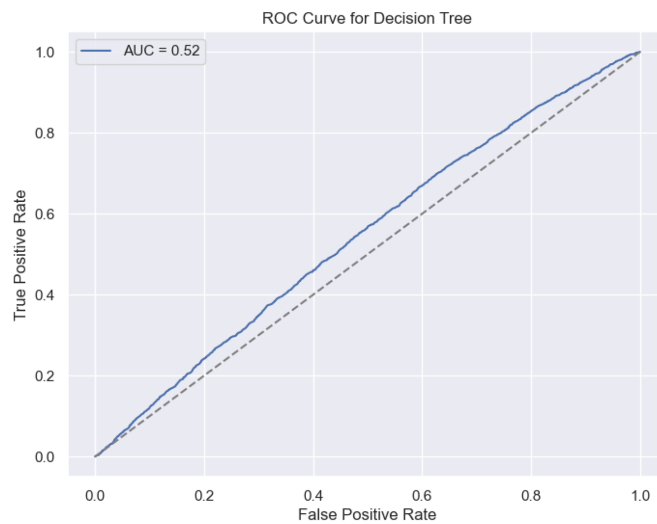


We then fit the training data with a support vector machine. By making predictions with test data, we also calculate the AUC score to evaluate the model and plot out the ROC curve for SVM. With an AUC score of 0.50, the SVM model also got a relatively very low AUC score. By plotting the ROC curves as below, we can see that SVM does not perform well in this case either.



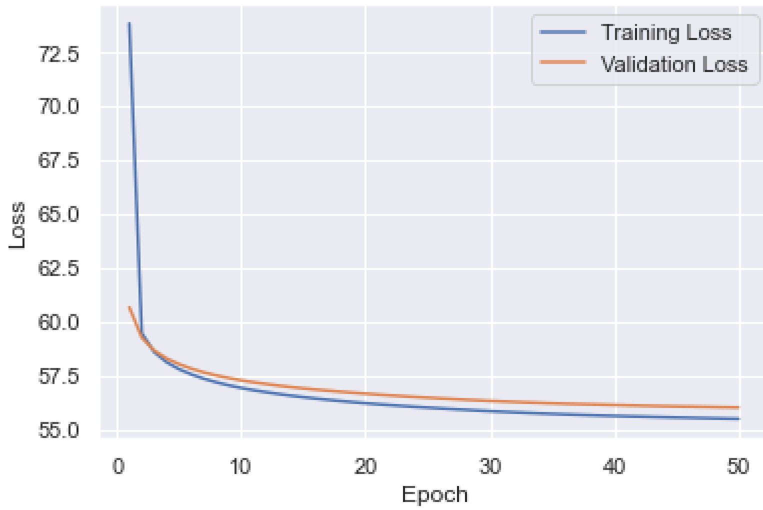
Since the logistic regression model and support vector machine are not doing good for predictions, we also try to fit the training data to a Random forest model and a Decision tree model. After making predictions, By making predictions with test data, we calculate the AUC score to evaluate these two models and plot out the ROC curve for both of them. Both of the models got an AUC score of 0.52, which is better than the logistic regression model and SVM. According to the ROC Curves below, the ROC curve for both models also includes more area than the logistic regression model and SVM. As a result, they are having better performance than logistic regression models and SVM in this case.





8) Can you predict genre by using the 10 song features from question 4 directly or the principal components you extracted in question 6 with a neural network? How well does this work?

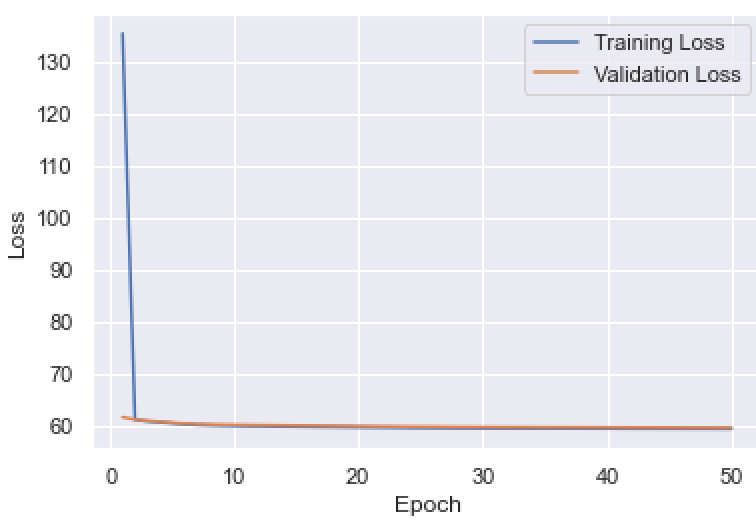
We first develop a set of functions to build the neural network. ‘Module’ function is a base class for neural network modules, with abstract methods forward and backward. The ‘LeastSquareCriterion' is a loss function, assuming one-hot encoded targets, computes mean squared error between predictions and labels. The ‘Linear’ function is a linear (fully connected) layer, implementing forward and backward propagation. The ‘ReLU’ function is an activation function (Rectified Linear Unit) layer, implementing forward and backward propagation. The ‘MLP’ function is a Multi-Layer Perceptron class representing the neural network. It contains two linear layers separated by a ReLU activation function. Then, we develop a training function ‘train_model’, which trains the neural network model using a given training dataset, labels, and validation data. It implements the training loop with forward and backward passes and updates the model weights.



Feature Graph

After building all the necessary functions, we first predict the genre by using 10 song features from question 4. Scale the feature and encode the 52 unique track genre and split the dataset into training and test set. Then, we created instances of MLP and LeastSquareCriterion using feature and encoded track genres and trained using the train_model function. After training, the model's accuracy: 0.2456 is evaluated on the test set.

We then use the principal components you extracted in question 6 (which are 3 components) as a predictor to predict the genre. And have the model's accuracy:0.1352 in the test set. By comparing two model's accuracy, it concludes that the predicted genre by using the 10 song features from question 4 directly with a neural network has higher accuracy than using the PCA.

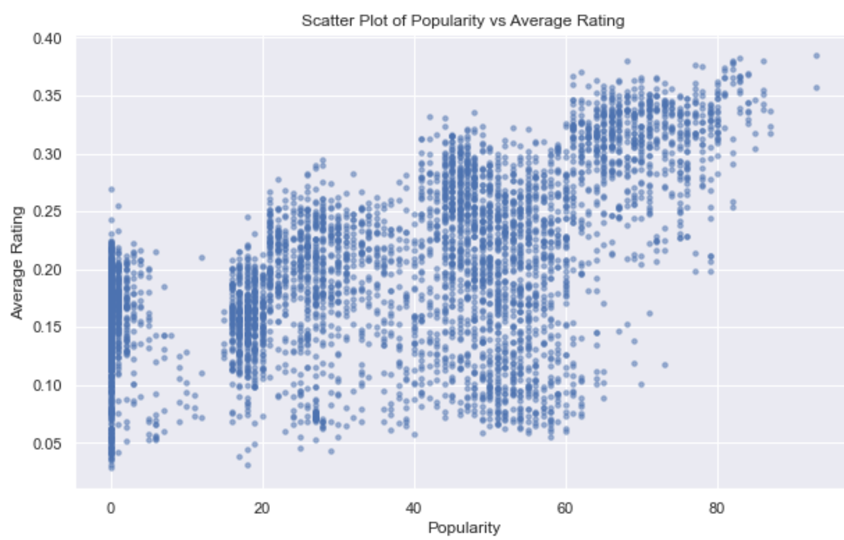


PCA Graph

9) In recommender systems, the popularity based model is an important baseline. We have a two part question in this regard: a) Is there a relationship between popularity and average star rating for the 5k songs we have explicit feedback for? b) Which 10 songs are in the "greatest hits" (out of the 5k songs), on the basis of the popularity based model?

To use the popularity based model, we prepare our data by first filling the missing value in the star rating dataset with 0, which means that there is no interaction between user and song, and calculating the average star rating for each song (mean value of each column). Then, we extract the first 5000 rows with columns of 'album_name', 'songNumber', 'track_name', 'popularity', 'artists'. By adding a new column 'average_star_rating' with values of average star rating for each song to the current dataframe, we are ready for the following questions.

a) We first use a simple correlation function to calculate the correlation between popularity and average_star_rating and get a correlation of 0.566, which means that there is a relatively moderate positive correlation between these two variables. As the plot shown below, we can also see an obvious positive trend from the points.



b) Since we find out that there is duplication in 'track_name' and 'artists', to find the top 10 songs with greatest hits, we first further handle our data by drop rows with duplicate combination of 'track_name' and 'artists' (drop_duplicates(subset=['track_name', 'artists'])). Then, we sort the data frame by popularity with descending order to have the top 10 songs. As a result, our 10 songs with greatest hits on the basis of popularity based model are songNumer of 2003, 2000, 3004, 2002, 2053, 3006, 4002, 3255, 2057 and 2367 with specific song information shown in the table below.

	album_name	songNumber	track_name	popularity	artists	average_star_rating
2003	I Love You.	2003	Sweater Weather	93	The Neighbourhood	0.3849
2000	Wiped Out!	2000	Daddy Issues	87	The Neighbourhood	0.3233
3004	abcdefu	3004	abcdefu	86	GAYLE	0.3802
2002	Hard To Imagine The Neighbourhood Ever Changing	2002	Softcore	86	The Neighbourhood	0.3380
2053	Pablo Honey	2053	Creep	85	Radiohead	0.3179
3006	Hybrid Theory (Bonus Edition)	3006	In the End	85	Linkin Park	0.3468
4002	Cigarettes After Sex	4002	Apocalypse	84	Cigarettes After Sex	0.3296
3255	Demon Days	3255	Feel Good Inc.	84	Gorillaz	0.3352
2057	Elephant	2057	Seven Nation Army	84	The White Stripes	0.3439
2367	The Colour And The Shape	2367	Everlong	84	Foo Fighters	0.3372

10) You want to create a "personal mixtape" for all 10k users we have explicit feedback for. This mixtape contains individualized recommendations as to which 10 songs (out of the 5k) a given user will enjoy most. How do these recommendations compare to the "greatest hits" from the previous question and how good is your recommender system in making recommendations?

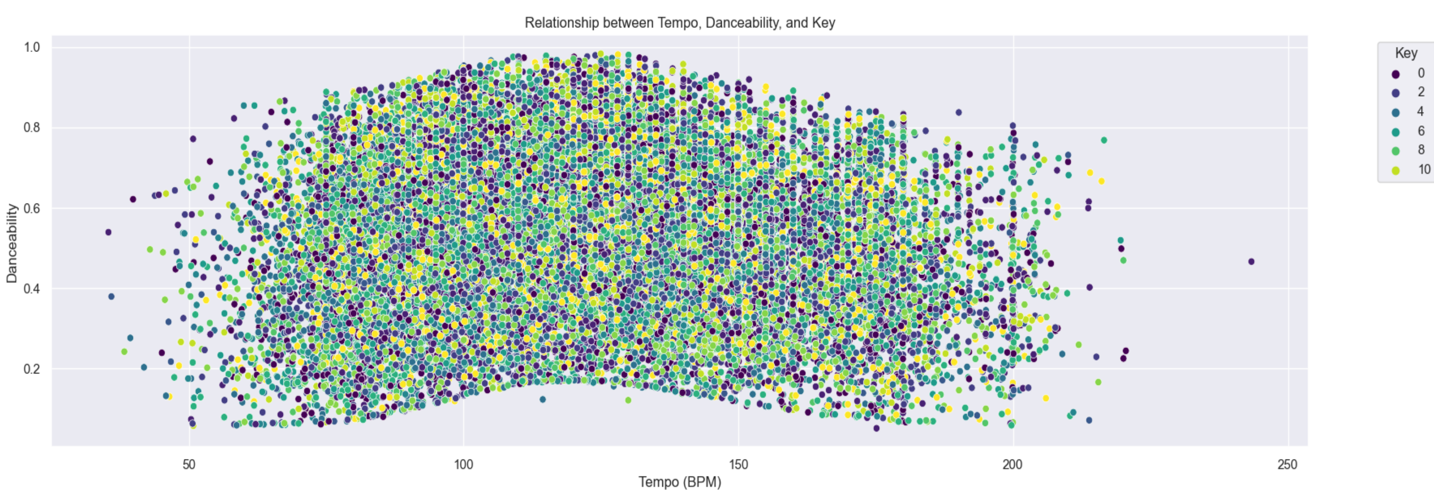
We created a recommender system using collaborative filtering to predict the preferences of a user. We removed the duplicates from the spotify data and aligned each song with the ratings from the star ratings dataset. We then built a user similarity matrix and used it to find the top 10 song recommendations for each given user.

	songNumber	track_name	artists	popularity	Average Rating
1897	1897	Bienvenida	Jorge Drexler	18	1.55
2293	2293	Dragula	Rob Zombie	0	1.55
1895	1895	Sincronia	Samuca e a Selva	16	1.40
2460	2460	Are You Gonna Be My Girl	Jet	76	1.30
2480	2480	Miss World	Hole	0	1.20
991	991	Little Life	Frank Turner	25	1.15
565	565	Sappy - Early Demo	Kurt Cobain	50	1.05
2346	2346	Corazones Rojos	Los Prisioneros	0	1.00
37	37	Throwing Good After Bad	Brandi Carlile	0	1.00
2613	2613	Cough Syrup	Young the Giant	71	1.00

Above is an example of the recommendations for the user with index 0. We can see that the songs are very different from the top hits songs in the previous question, which might suggest that song preference is personal and subjective if the system performs well. To evaluate the performance, we extracted the actual ratings and compared them with the predicted data. We calculated average precision and recall as the metrics for evaluation, and we set a threshold=4 (starts) as the indicator of whether the individual liked or disliked the recommended song. The result is precision = 0.999 and recall = 0.55, which indicates that there's a 99.94% chance that the user would like the recommended song (rate it 4 stars) and that the system correctly identifies about 55.1% of the actual songs.

Extra Credit: Can we use the number of beats per measure and the key to predict danceability of the songs?

We first prepared the data by extracting the 'tempo' and 'key' column from the original spotify dataset as our predictor X and extracting 'danceability' column as target y. Then, we do a 80/20 training and testing split on X and y for further model fitting. By plotting out the relationship between temp, key and danceability as the figure shown below, we are able to know that they are not in a linear relationship. Since danceability is a continuous variable, we use the random forest regression model to make the predictions. After doing the above steps, we evaluate our model by R^2 score and RMSE. Here, we got a R^2 score of 0.198 and RMSE of 0.158. As a result, we can make the conclusion that we can use the number of beats per measure and the key to predict danceability of the songs via the random forest regression model, where the model can also have a relatively good performance on this prediction.



capstone

December 21, 2023

[1]:
```
import pandas as pd
import numpy as np
from scipy.stats import pearsonr
import matplotlib.pyplot as plt
from scipy import stats
import seaborn as sns
sns.set()
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn.svm import SVC
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score, accuracy_score,␣
↪classification_report, roc_curve
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.linear_model import LinearRegression
from scipy.stats import zscore
```

[2]:
```
import random
#Seed with N-number of Maggie Xu
random.seed(19329713)
```

0.0.1 Data Preparation

[3]:
```
df = pd.read_csv('spotify52kData.csv')
df.head()
```

[3]:
```
   songNumber                  artists  \
0           0              Gen Hoshino
1           1             Ben Woodward
```

```
2           2  Ingrid Michaelson;ZAYN
3           3             Kina Grannis
4           4         Chord Overstreet

                                           album_name  \
0                                              Comedy
1                                    Ghost (Acoustic)
2                                      To Begin Again
3  Crazy Rich Asians (Original Motion Picture Sou…
4                                             Hold On

                   track_name  popularity  duration  explicit  danceability  \
0                      Comedy          73    230666     False         0.676
1            Ghost - Acoustic          55    149610     False         0.420
2              To Begin Again          57    210826     False         0.438
3  Can't Help Falling In Love          71    201933     False         0.266
4                     Hold On          82    198853     False         0.618

   energy  key  loudness  mode  speechiness  acousticness  instrumentalness  \
0  0.4610    1    -6.746     0       0.1430        0.0322          0.000001
1  0.1660    1   -17.235     1       0.0763        0.9240          0.000006
2  0.3590    0    -9.734     1       0.0557        0.2100          0.000000
3  0.0596    0   -18.515     1       0.0363        0.9050          0.000071
4  0.4430    2    -9.681     1       0.0526        0.4690          0.000000

   liveness  valence    tempo  time_signature track_genre
0    0.3580    0.715   87.917               4    acoustic
1    0.1010    0.267   77.489               4    acoustic
2    0.1170    0.120   76.332               4    acoustic
3    0.1320    0.143  181.740               3    acoustic
4    0.0829    0.167  119.949               4    acoustic
```

[4]:
```
star_ratings = pd.read_csv('starRatings.csv', header = None)
ratings_data = star_ratings.fillna(0)
ratings_data.head()
```

[4]:
```
   0     1     2     3     4     5     6     7     8     9     …   4990  \
0  0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   …   0.0
1  0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   …   0.0
2  0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   …   0.0
3  0.0   3.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   …   0.0
4  0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   …   4.0

   4991  4992  4993  4994  4995  4996  4997  4998  4999
0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
2   2.0   1.0   0.0   0.0   3.0   0.0   0.0   0.0   0.0
```

```
3   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
4   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0

[5 rows x 5000 columns]
```

[4]:

```

```

0.0.2 1) Is there a relationship between song length and popularity of a song? If so, is it positive or negative?

[5]:

```
df.isna().sum()
```

[5]:

```
songNumber          0
artists             0
album_name          0
track_name          0
popularity          0
duration            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
```

[6]:

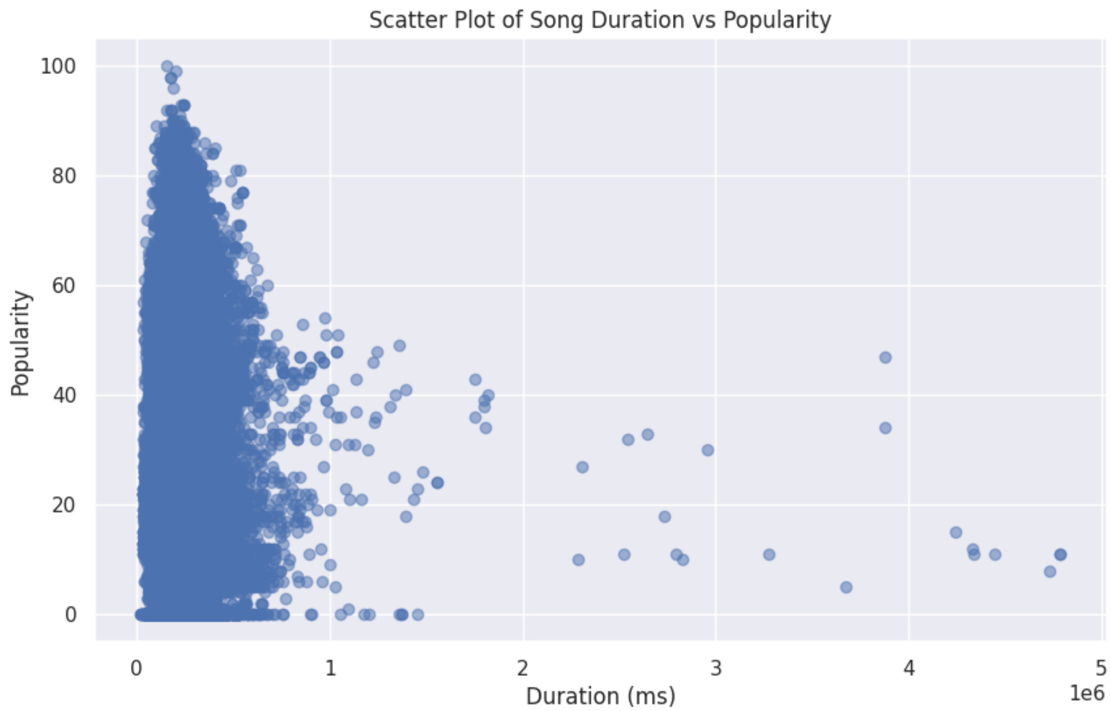
```
# Calculate the Pearson Correlation Coefficient
correlation, p_value = pearsonr(df['duration'], df['popularity'])

# Display the correlation
print("Correlation Coefficient:", correlation)
print("P-value:", p_value)
```

```
Correlation Coefficient: -0.05465119593637635
P-value: 1.069160283049238e-35
```

[7]:

```
plt.figure(figsize=(10, 6))
plt.scatter(df['duration'], df['popularity'], alpha=0.5)
plt.title('Scatter Plot of Song Duration vs Popularity')
```

```
plt.xlabel('Duration (ms)')
plt.ylabel('Popularity')
plt.grid(True)
plt.show()
```



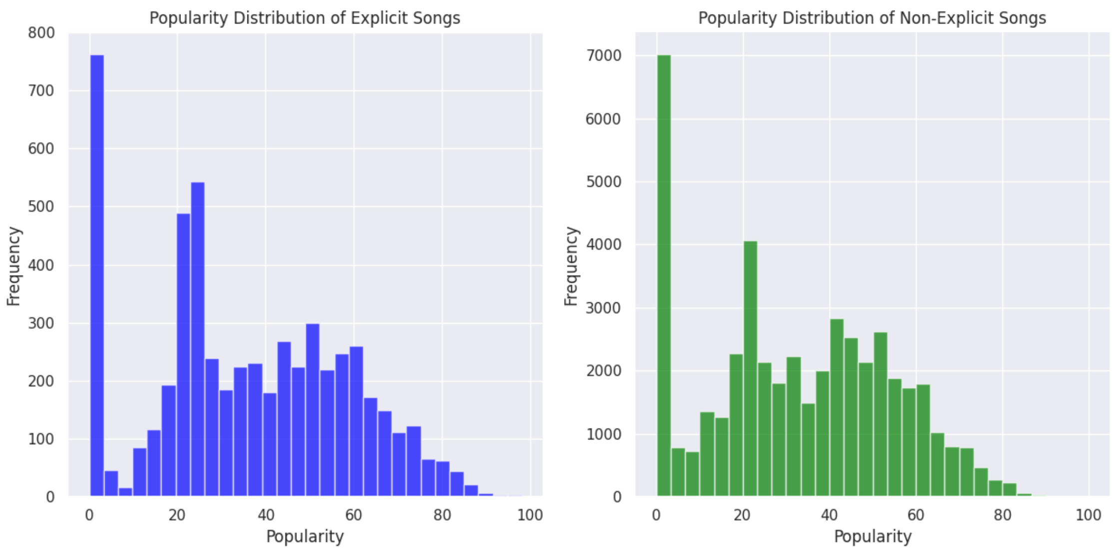
0.0.3 2) Are explicitly rated songs more popular than songs that are not explicit?

[8]:
```
# Segmenting the data into explicit and non-explicit groups
explicit_songs = df[df['explicit'] == True]
non_explicit_songs = df[df['explicit'] == False]

# Calculating average popularity for each group
avg_popularity_explicit = explicit_songs['popularity'].mean()
avg_popularity_non_explicit = non_explicit_songs['popularity'].mean()

avg_popularity_explicit, avg_popularity_non_explicit
```

[8]:
```
(35.81311416830445, 32.790595435639936)
```

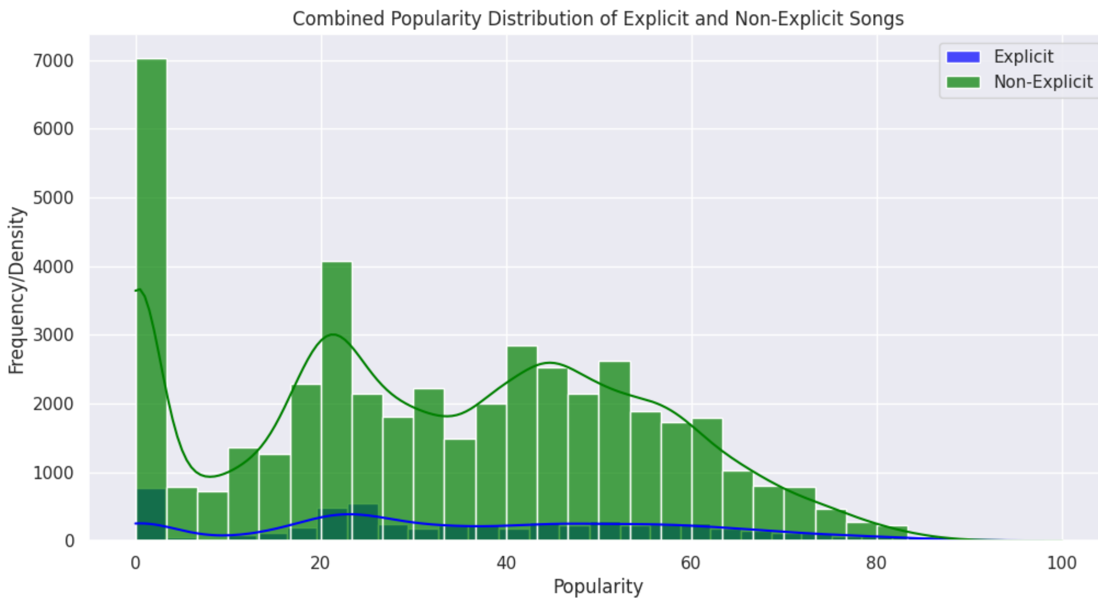
[9]:
```
# Plotting histograms for the popularity of explicit and non-explicit songs
plt.figure(figsize=(12, 6))

# Histogram for explicit songs
```

```
plt.subplot(1, 2, 1)
plt.hist(explicit_songs['popularity'], bins=30, color='blue', alpha=0.7)
plt.title('Popularity Distribution of Explicit Songs')
plt.xlabel('Popularity')
plt.ylabel('Frequency')

# Histogram for non-explicit songs
plt.subplot(1, 2, 2)
plt.hist(non_explicit_songs['popularity'], bins=30, color='green', alpha=0.7)
plt.title('Popularity Distribution of Non-Explicit Songs')
plt.xlabel('Popularity')
plt.ylabel('Frequency')

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



[10]:
```
# Combining the histograms into a single plot and adding a density curve

plt.figure(figsize=(12, 6))

# Histogram and density for explicit songs
sns.histplot(explicit_songs['popularity'], bins=30, color='blue', kde=True,␣
↪label='Explicit', alpha=0.7)

# Histogram and density for non-explicit songs
sns.histplot(non_explicit_songs['popularity'], bins=30, color='green',␣
↪kde=True, label='Non-Explicit', alpha=0.7)
```

```
plt.title('Combined Popularity Distribution of Explicit and Non-Explicit Songs')
plt.xlabel('Popularity')
plt.ylabel('Frequency/Density')
plt.legend()

plt.show()
```



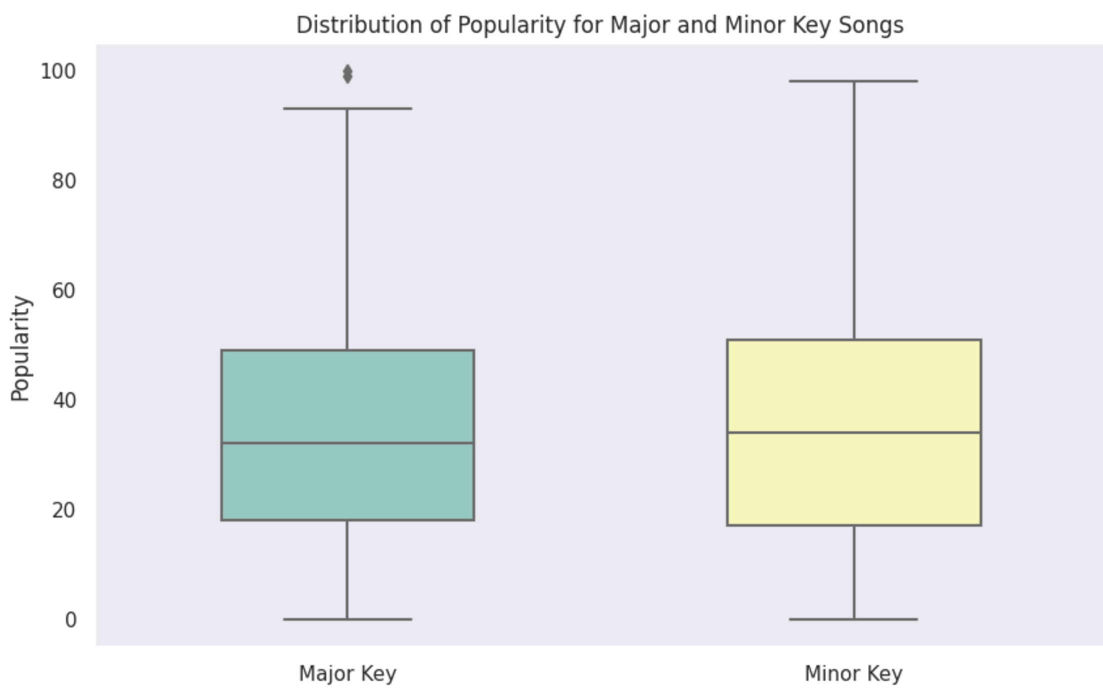
[11]:
```
t_statistic, p_value = stats.ttest_ind(explicit_songs['popularity'],␣
↪non_explicit_songs['popularity'], equal_var=True, alternative='greater')
print(f"t-statistic: {t_statistic}, p-value: {p_value}")
```

```
t-statistic: 9.832950458671839, p-value: 4.250551719953934e-23
```

0.0.4 3) Are songs in major key more popular than songs in minor key?

[12]:
```
# Segmenting the data based on the mode (major or minor key)
major_key_songs = df[df['mode'] == 1]
minor_key_songs = df[df['mode'] == 0]

# Calculating average and median popularity for both groups
avg_popularity_major = major_key_songs['popularity'].mean()
avg_popularity_minor = minor_key_songs['popularity'].mean()
median_popularity_major = major_key_songs['popularity'].median()
median_popularity_minor = minor_key_songs['popularity'].median()

# Preparing data for box plot
```

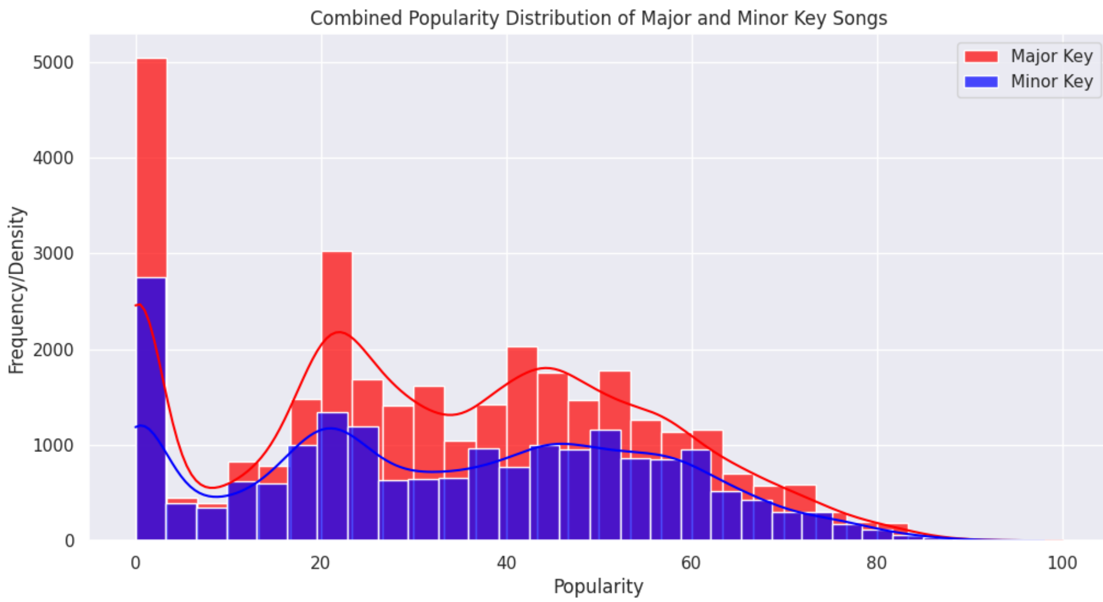
```
popularity_data_by_key = [major_key_songs['popularity'],␣
  ↪minor_key_songs['popularity']]
labels_by_key = ['Major Key', 'Minor Key']

# Creating box plots
plt.figure(figsize=(10, 6))
sns.boxplot(data=popularity_data_by_key, width=0.5, palette="Set3")
plt.xticks([0, 1], labels_by_key)
plt.title('Distribution of Popularity for Major and Minor Key Songs')
plt.ylabel('Popularity')
plt.grid(axis='y')

plt.show()

avg_popularity_major, avg_popularity_minor, median_popularity_major,␣
  ↪median_popularity_minor
```



[12]: (32.75838967614461, 33.70651231577337, 32.0, 34.0)

[13]:
```
plt.figure(figsize=(12, 6))

# Histogram and density for major key songs
sns.histplot(major_key_songs['popularity'], bins=30, color='red', kde=True,␣
  ↪label='Major Key', alpha=0.7)
```

```
# Histogram and density for minor key songs
sns.histplot(minor_key_songs['popularity'], bins=30, color='blue', kde=True,␣
↪label='Minor Key', alpha=0.7)

plt.title('Combined Popularity Distribution of Major and Minor Key Songs')
plt.xlabel('Popularity')
plt.ylabel('Frequency/Density')
plt.legend()

plt.show()
```



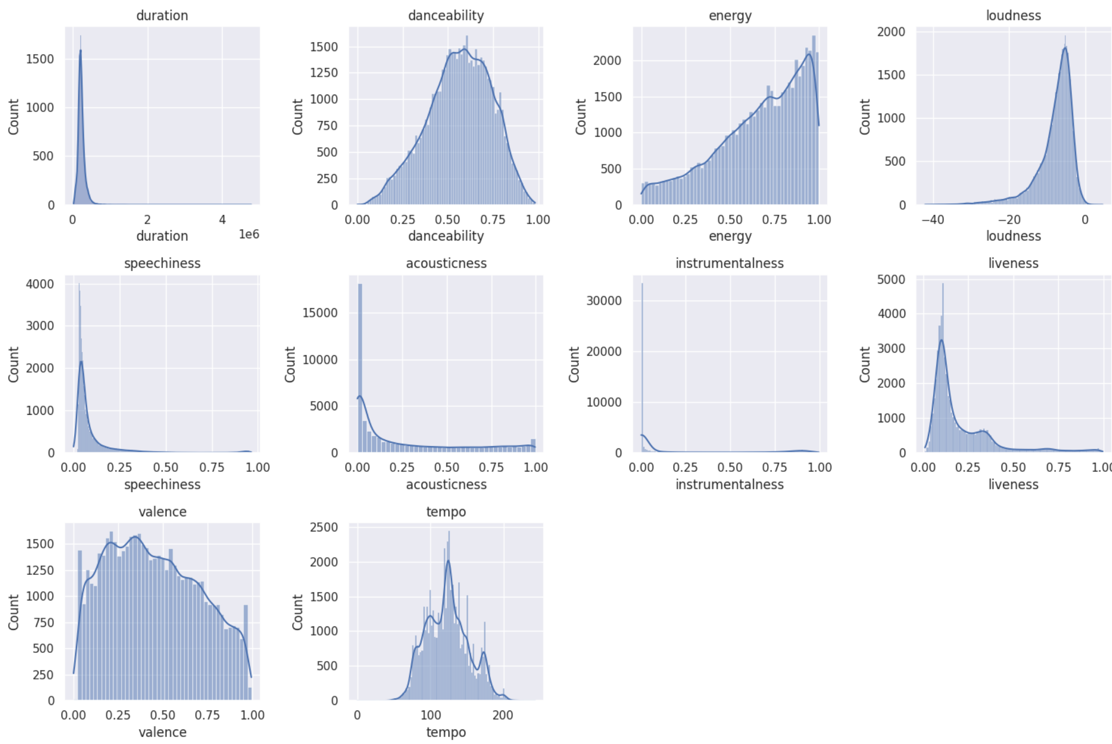
[14]:
```
t_statistic, p_value = stats.ttest_ind(major_key_songs['popularity'],␣
↪minor_key_songs['popularity'], alternative='greater')
print(f"t-statistic: {t_statistic}, p-value: {p_value}")
```

```
t-statistic: -4.82016820942977, p-value: 0.999999280792557
```

0.0.5 4) Which of the following 10 song features: duration, danceability, energy, loudness, speechiness, acousticness, instrumentalness, liveness, valence and tempo predicts popularity best?How good is this model?

[15]:
```
features = ['duration', 'danceability', 'energy', 'loudness', 'speechiness',
            'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo']
plt.figure(figsize=(15, 10))

for i, feature in enumerate(features):
```

```
    plt.subplot(3, 4, i + 1)
    sns.histplot(df[feature], kde=True)
    plt.title(feature)
    plt.tight_layout()

plt.show()
```



[16]:
```
# Features to be tested
features = ['duration', 'danceability', 'energy', 'loudness', 'speechiness',
            'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo']

# Dictionary to store R^2 values for each feature
r2_scores = {}

# Perform linear regression for each feature
for feature in features:
    # Reshaping the data for sklearn
    X = df[[feature]].values.reshape(-1, 1)
    y = df['popularity'].values

    # Fitting the model
    reg = LinearRegression().fit(X, y)
    y_hat = reg.predict(X)
```

```
    # Calculating R^2 score
    r2 = r2_score(y, y_hat)
    r2_scores[feature] = r2

# Converting the results to a DataFrame for easier ranking and visualization
r2_scores_df = pd.DataFrame(list(r2_scores.items()), columns=['Feature', 'R^2␣
↪Score']).sort_values(by='R^2 Score', ascending=False)

r2_scores_df
```

[16]:

	Feature	R^2 Score
6	instrumentalness	0.021017
3	loudness	0.003625
2	energy	0.003128
0	duration	0.002987
4	speechiness	0.002355
7	liveness	0.001922
1	danceability	0.001381
8	valence	0.001279
5	acousticness	0.000688
9	tempo	0.000007

[17]:

```
r2_scores = {}

# Perform random forest regression for each feature
for feature in features:
    # Reshaping the data for sklearn
    X = df[[feature]].values.reshape(-1, 1)
    y = df['popularity'].values

    # Fitting the model
    rf_reg = RandomForestRegressor(n_estimators=100, random_state=19329713)
    rf_reg.fit(X, y)
    y_hat = rf_reg.predict(X)

    # Calculating R^2 score
    r2 = r2_score(y, y_hat)
    r2_scores[feature] = r2

# Converting the results to a DataFrame for easier ranking and visualization
r2_scores_df = pd.DataFrame(list(r2_scores.items()), columns=['Feature', 'R^2␣
↪Score']).sort_values(by='R^2 Score', ascending=False)

r2_scores_df
```

[17]:

	Feature	R^2 Score
0	duration	0.643402
9	tempo	0.606115
3	loudness	0.376893
5	acousticness	0.159760
6	instrumentalness	0.123671
2	energy	0.075572
8	valence	0.066103
7	liveness	0.062653
4	speechiness	0.059608
1	danceability	0.049276

0.0.6 5) Building a model that uses *all* of the song features mentioned in question 4, how well can you predict popularity? How much (if at all) is this model improved compared to the model in question 4). How do you account for this? What happens if you regularize your model?

[18]:
```
from sklearn.linear_model import Ridge

# Multiple linear regression model
X_multivariate = df[features]
y_multivariate = df['popularity']

X_train, X_test, y_train, y_test = train_test_split(X_multivariate,␣
↪y_multivariate, test_size=0.3, random_state=42)

# Building the multivariate linear regression model
multivariate_model = LinearRegression()
multivariate_model.fit(X_train, y_train)

# Predicting and calculating R^2 score for the multivariate model
predictions_multivariate = multivariate_model.predict(X_test)
r2_multivariate = r2_score(y_test, predictions_multivariate)
rmse_multivariate = np.sqrt(mean_squared_error(y_test,␣
↪predictions_multivariate))

# Building and evaluating a regularized model (Ridge Regression)
ridge_model = Ridge(alpha=1.0)
ridge_model.fit(X_train, y_train)
ridge_predictions = ridge_model.predict(X_test)
r2_ridge = r2_score(y_test, ridge_predictions)
rmse_ridge = np.sqrt(mean_squared_error(y_test, ridge_predictions))

# Output R^2 and RMSE
print(f"R^2 (Multivariate): {r2_multivariate}, RMSE (Multivariate):␣
↪{rmse_multivariate}")
print(f"R^2 (Ridge): {r2_ridge}, RMSE (Ridge): {rmse_ridge}")
```

```
R^2 (Multivariate): 0.04634429898242698, RMSE (Multivariate): 21.16323150289822
R^2 (Ridge): 0.04634452088869023, RMSE (Ridge): 21.1632290406606
```

[19]:
```
# Random Forest multivariate model
random_forest_model = RandomForestRegressor(n_estimators=100, random_state=42)
random_forest_model.fit(X_train, y_train)

# Predicting and calculating R^2 score for the Random Forest model
predictions_random_forest = random_forest_model.predict(X_test)
r2_random_forest = r2_score(y_test, predictions_random_forest)
rmse_random_forest = np.sqrt(mean_squared_error(y_test,␣
↪predictions_random_forest))

# Output the R^2 score and RMSE for the Random Forest model
print(f"R^2 (Random Forest): {r2_random_forest}, RMSE (Random Forest):␣
↪{rmse_random_forest}")
```

```
R^2 (Random Forest): 0.40039579330046204, RMSE (Random Forest):
16.781026126511794
```

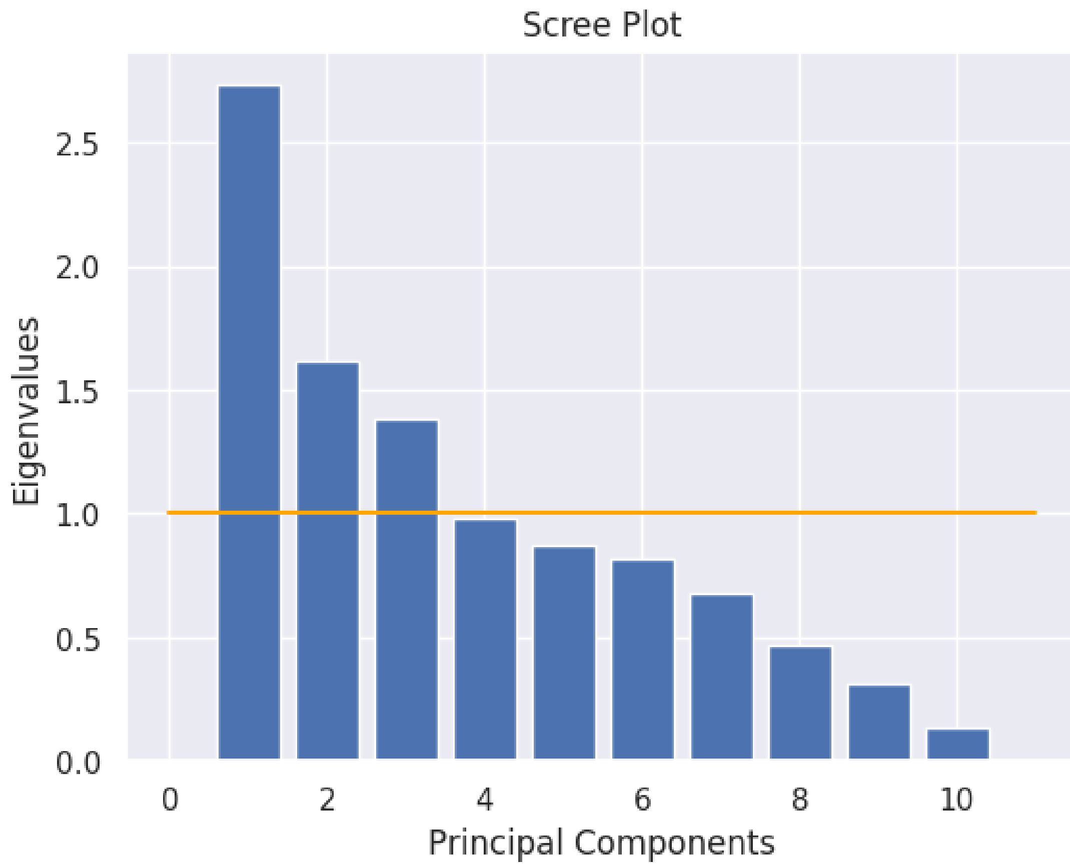
[19]:

```

```

0.0.7 6) When considering the 10 song features in the previous question, how many meaningful principal components can you extract? What proportion of the variance do these principal components account for? Using these principal components, how many clusters can you identify? Do these clusters reasonably correspond to the genre labels in column 20 of the data?

[20]:

```
predictors = df[features]
nComponents = 11
# Z-score the data
zscoredData = stats.zscore(predictors)

# Initialize PCA object and fit to our data
pca = PCA().fit(zscoredData)

# Eigenvalues
eigVals = pca.explained_variance_

# Plot the eigenvalues (scree plot)
numPredictors = len(features)
plt.bar(np.arange(1, numPredictors + 1), eigVals)
plt.plot([0,nComponents],[1,1],color='orange') # Orange Kaiser criterion line␣
↪for the fox
plt.xlabel('Principal Components')
plt.ylabel('Eigenvalues')
plt.title('Scree Plot')
plt.show()
```



[21]:
```
num_components = sum(eigVals > 1)
pca_transformed = PCA(n_components=num_components).fit_transform(zscoredData)
# Get the explained variance ratio of the selected components
explained_variance_ratio = PCA(n_components=num_components).fit(zscoredData).
 ↪explained_variance_ratio_
total_variance_accounted = sum(explained_variance_ratio)

print(f"Total variance accounted for by the first {num_components} components:␣
 ↪{total_variance_accounted * 100:.2f}%")
```

```
Total variance accounted for by the first 3 components: 57.36%
```

[22]:
```
len(df['track_genre'].unique())
```

[22]: 52

[23]:
```
class DBSCAN:
    def region_query (self, p, eps, X):
        '''
```

```
        Generates boolean array of all data points which belong
        in epsilon neighborhood of p
        '''
        _, dim = X.shape
        assert (p.shape == (dim,)) or (p.shape == (1, dim)) or (p.shape == (dim, 1))

        return np.linalg.norm (p - X, axis=1) <= eps

    def index_set (self, y):
        """
        Given a boolean vector, this function returns
        the indices of all True elements in the outputs
        of the region_query function
        """
        assert len (y.shape) == 1

        return set (np.where (y)[0])

    def find_neighbors (self, eps, X):
        """
        Finds epsilon neighbors for all points in the dataset.
        """
        m, d = X.shape
        neighbors = [] # Empty list to start

        for i in range (len (X)):
            n_i = self.index_set (self.region_query (X[i, :], eps, X))
            neighbors.append (n_i)
        assert len (neighbors) == m
        return neighbors

    def find_core_points (self, s, neighbors):
        """
        checks the neigbors list for each point
        and if density is greater than s then the
        point is added as a core point
        """
        assert type (neighbors) is list
        assert all ([type (n) is set for n in neighbors])

        core_set = set ()
        for i, n_i in enumerate (neighbors):
            if len (n_i) >= s:
                core_set.add (i)
        return core_set
```

```
    def expand_cluster (self, p, neighbors, core_set, visited, assignment):
        """
        Given a core point for which cluster label has been assigned, the␣
↪reachable
        points from there is expanded.
        """
        # Assume the caller performs Steps 1 and 2 of the procedure.
        # That means 'p' must be a core point that is part of a cluster.
        assert (p in core_set) and (p in visited) and (p in assignment)

        reachable = set (neighbors[p])  # Step 3
        while reachable:
            q = reachable.pop () # Step 4

            # Put your reordered and correctly indented statements here:
            if q not in visited:
                visited.add (q) # Mark q as visited
                if q in core_set:
                    reachable |= neighbors[q]
            if q not in assignment:
                assignment[q] = assignment[p]

    def __call__(self, eps, s, X):
        """
        Function which puts together all the helper function
        and runs the DBSCAN algorithm.
        """
        clusters = []
        point_to_cluster = {}

        neighbors = self.find_neighbors (eps, X)
        core_set = self.find_core_points (s, neighbors)

        assignment = {}
        next_cluster_id = 0

        visited = set ()
        for i in core_set: # for each core point i
            if i not in visited:
                visited.add (i) # Mark i as visited
                assignment[i] = next_cluster_id
                self.expand_cluster (i, neighbors, core_set,
                                visited, assignment)
                next_cluster_id += 1

        return assignment, core_set
```

[24]:
```
# Initialize DBSCAN instance
dbscan = DBSCAN()

assignment, coreset = dbscan(0.59, 500, pca_transformed)
```

[25]:
```
print ("Number of core points:", len (coreset))
print ("Number of clusters:", max (assignment.values ())+1)
print ("Number of unclassified points:", len (pca_transformed) - len␣
↪(assignment))
```

```
Number of core points: 32555
Number of clusters: 1
Number of unclassified points: 9872
```

[26]:
```
# Assuming `pca_transformed` is your dataset and `assignment` is from DBSCAN
labels = [-1] * len(pca_transformed)
for i, c in assignment.items():
    labels[i] = c

plt.figure(figsize=(12, 8))
plt.scatter(pca_transformed[:, 0], pca_transformed[:, 1], c=labels,␣
↪cmap='Accent')
plt.title("DBSCAN Clustering")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.colorbar(label='Cluster Label')
plt.show()
```

[27]:
```
# Finding the optimal number of clusters using the Elbow Method
inertia = []
silhouette_scores = []
K_range = range(2, 15)  # Range of possible number of clusters

for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(pca_transformed)
    inertia.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(pca_transformed, kmeans.labels_))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
```

```
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
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FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
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/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
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1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```
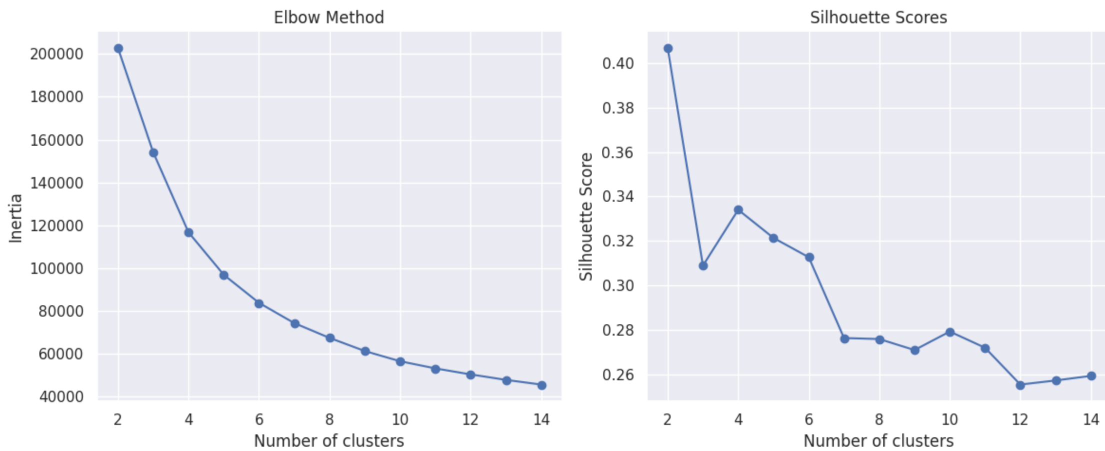

[28]:

```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(K_range, inertia, marker='o')
plt.title('Elbow Method')
```

```
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')

plt.subplot(1, 2, 2)
plt.plot(K_range, silhouette_scores, marker='o')
plt.title('Silhouette Scores')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')

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



With 52 unique genres in the dataset, neither method suggests a close correspondence to this number of clusters. The high number of genres compared to the optimal cluster numbers suggested by the Elbow Method and Silhouette Scores indicates that the genre classification may be too fine-grained or that the features may not capture all the nuances that distinguish 52 separate genres.

0.0.8 7) Can you predict whether a song is in major or minor key from valence using logistic regression or a support vector machine? If so, how good is this prediction? If not, is there a better one?

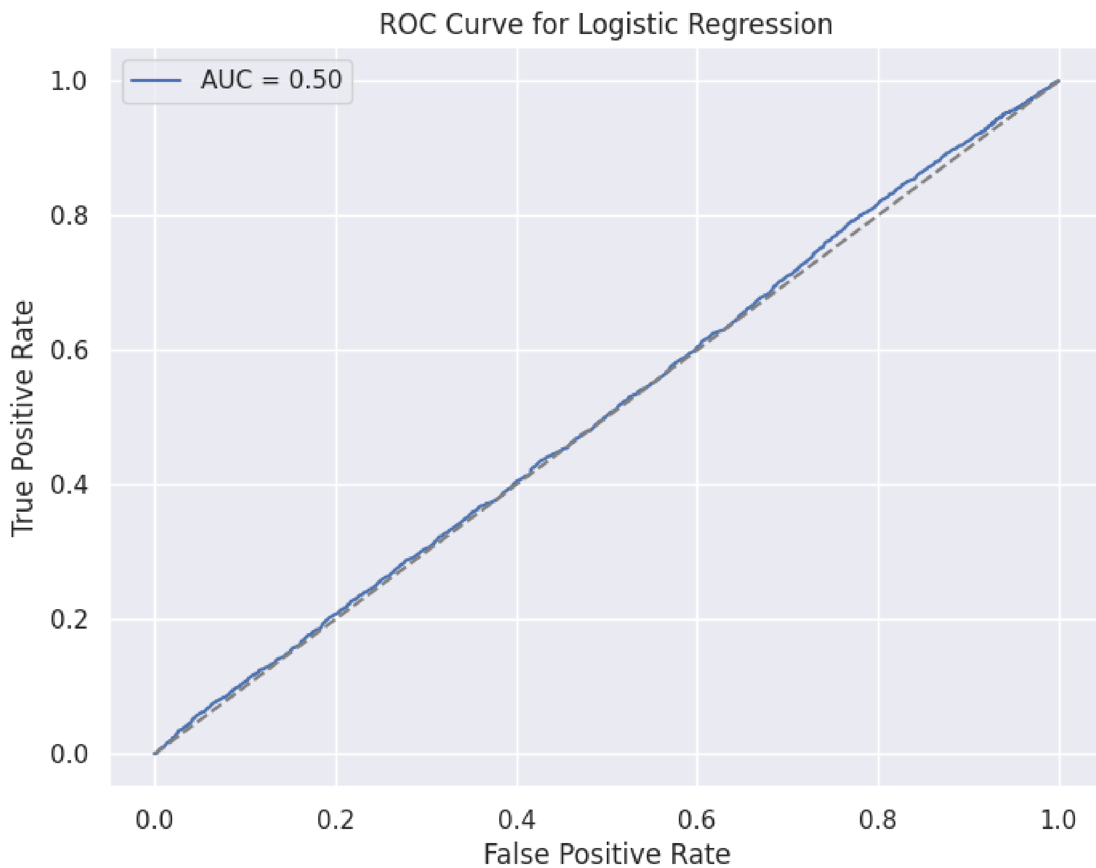
[29]:
```
# Data Preparation
X = df[['valence']].values
y = df['mode'].values

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=19329713)

# Model Training: Logistic Regression
logistic_model = LogisticRegression()
```

```python
logistic_model.fit(X_train, y_train)

# Model Prediction: Logistic Regression
logistic_predictions = logistic_model.predict(X_test)
logistic_probs = logistic_model.predict_proba(X_test)[:, 1]

# Model Evaluation: Logistic Regression
logistic_accuracy = accuracy_score(y_test, logistic_predictions)
logistic_classification_report = classification_report(y_test,␣
↪logistic_predictions)
logistic_roc_auc = roc_auc_score(y_test, logistic_predictions)
print('logistic model accuracy:', logistic_accuracy)
print('logistic classification report:',logistic_classification_report)
print('logistic roc auc:', logistic_roc_auc)


# Calculating the ROC curve
fpr, tpr, thresholds = roc_curve(y_test, logistic_probs)

# Plotting the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'AUC = {logistic_roc_auc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='grey')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Logistic Regression')
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
logistic model accuracy: 0.6230769230769231
logistic classification report:               precision    recall  f1-score
support
```

```
              0       0.00      0.00      0.00      3920
              1       0.62      1.00      0.77      6480

       accuracy                           0.62     10400
      macro avg       0.31      0.50      0.38     10400
   weighted avg       0.39      0.62      0.48     10400

logistic roc auc: 0.5
```

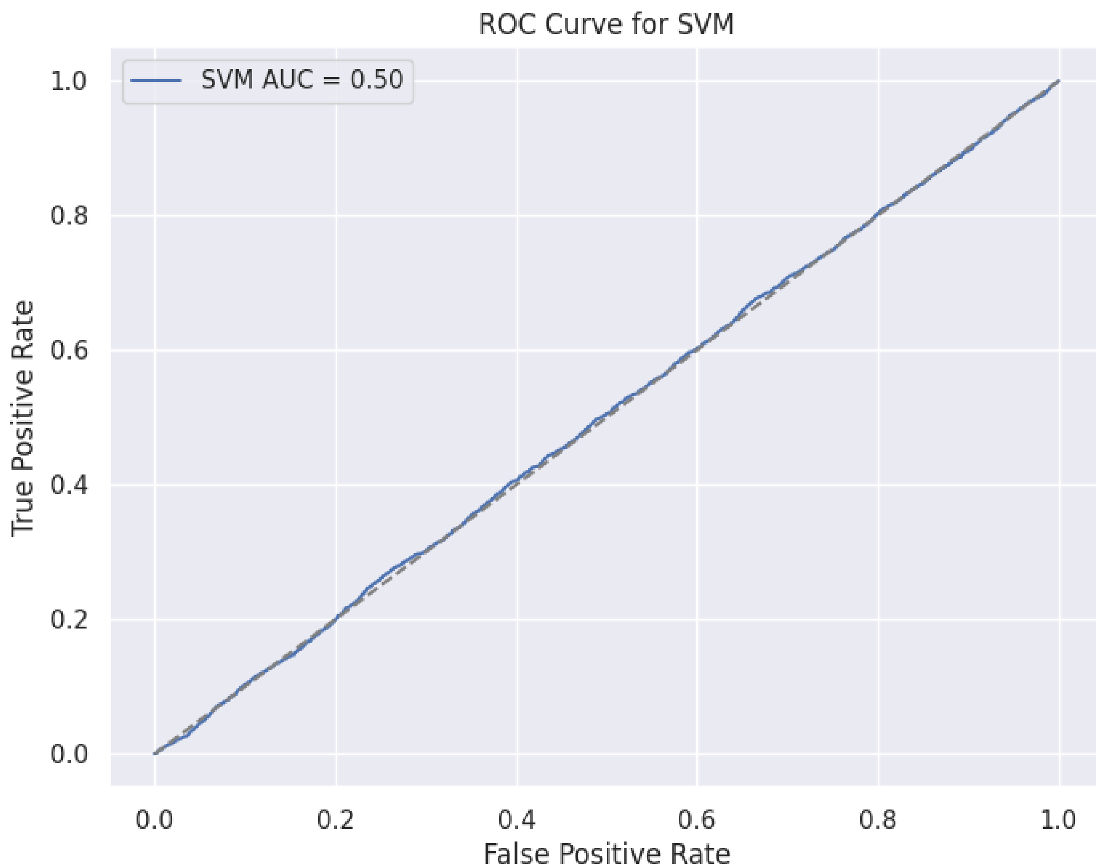


[30]:
```python
# Model Training: Support Vector Machine
svm_model = svm.SVC(probability=True).fit(X_train, y_train)
# Model Prediction: Support Vector Machine
svm_predictions = svm_model.predict(X_test)
svm_probs = svm_model.predict_proba(X_test)[:, 1]

# Model Evaluation: SVM
svm_accuracy = accuracy_score(y_test, svm_predictions)
print('SVM model accuracy:', svm_accuracy)
svm_classification_report = classification_report(y_test, svm_predictions)
```

```python
svm_roc_auc = roc_auc_score(y_test, svm_predictions)
print('svm classification report:',svm_classification_report)
print('svm roc auc:', svm_roc_auc)

# Calculating the ROC curve
fpr_svm, tpr_svm, thresholds_svm = roc_curve(y_test, svm_probs)

# Plotting the ROC curve for SVM
plt.figure(figsize=(8, 6))
plt.plot(fpr_svm, tpr_svm, label=f'SVM AUC = {svm_roc_auc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='grey')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for SVM')
plt.legend()
plt.show()
```

```
SVM model accuracy: 0.6230769230769231
svm classification report:               precision    recall  f1-score   support

           0       0.00      0.00      0.00      3920
           1       0.62      1.00      0.77      6480

    accuracy                           0.62     10400
   macro avg       0.31      0.50      0.38     10400
weighted avg       0.39      0.62      0.48     10400

svm roc auc: 0.5
```

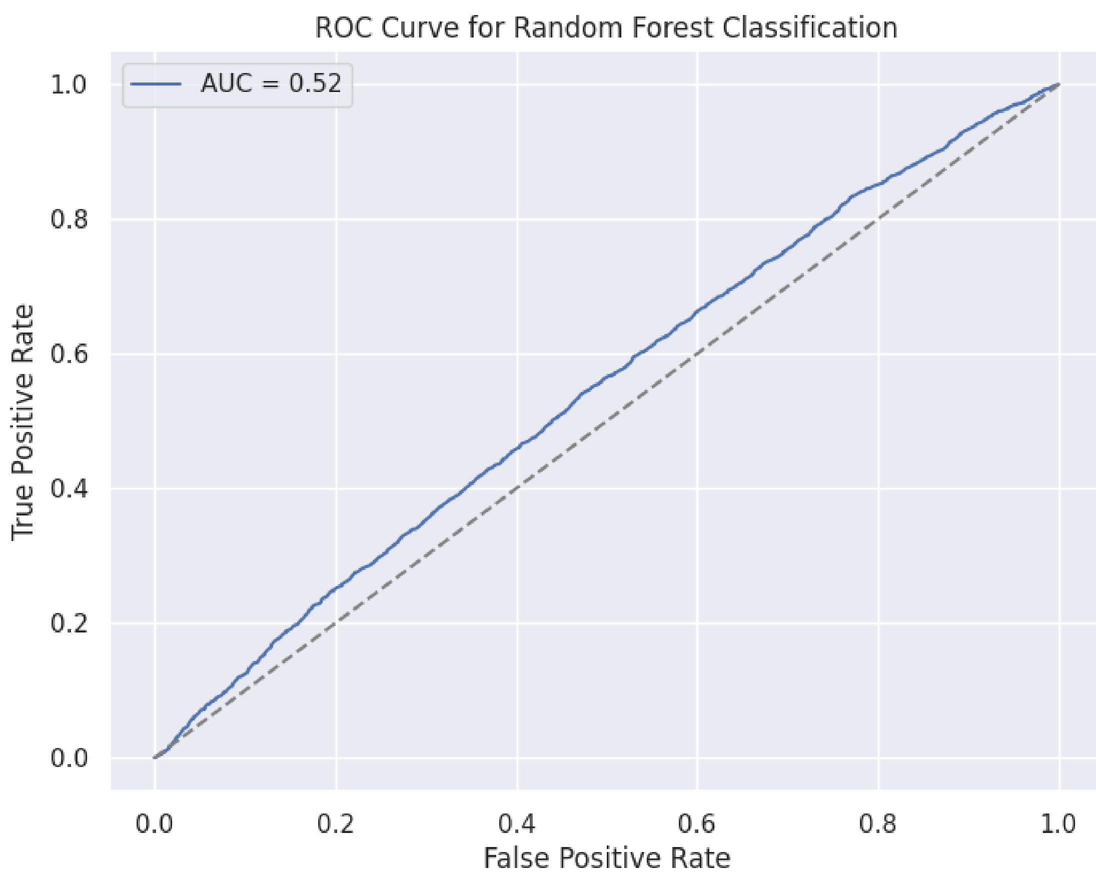
```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



[31]:
```
# Random Forest
forest_model = RandomForestClassifier(random_state=42).fit(X_train, y_train)
forest_pred = forest_model.predict(X_test)
# Output some metrics
forest_auc_roc = roc_auc_score(y_test, forest_pred)
forest_classification_report = classification_report(y_test, forest_pred)
print(forest_classification_report)

forest_probs = forest_model.predict_proba(X_test)[:, 1]
print("Random Forest AUC Score:", forest_auc_roc)

# Calculating the ROC curve
fpr, tpr, thresholds = roc_curve(y_test, forest_probs)

# Plotting the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'AUC = {forest_auc_roc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='grey')
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Random Forest Classification')
plt.legend()
plt.show()
```

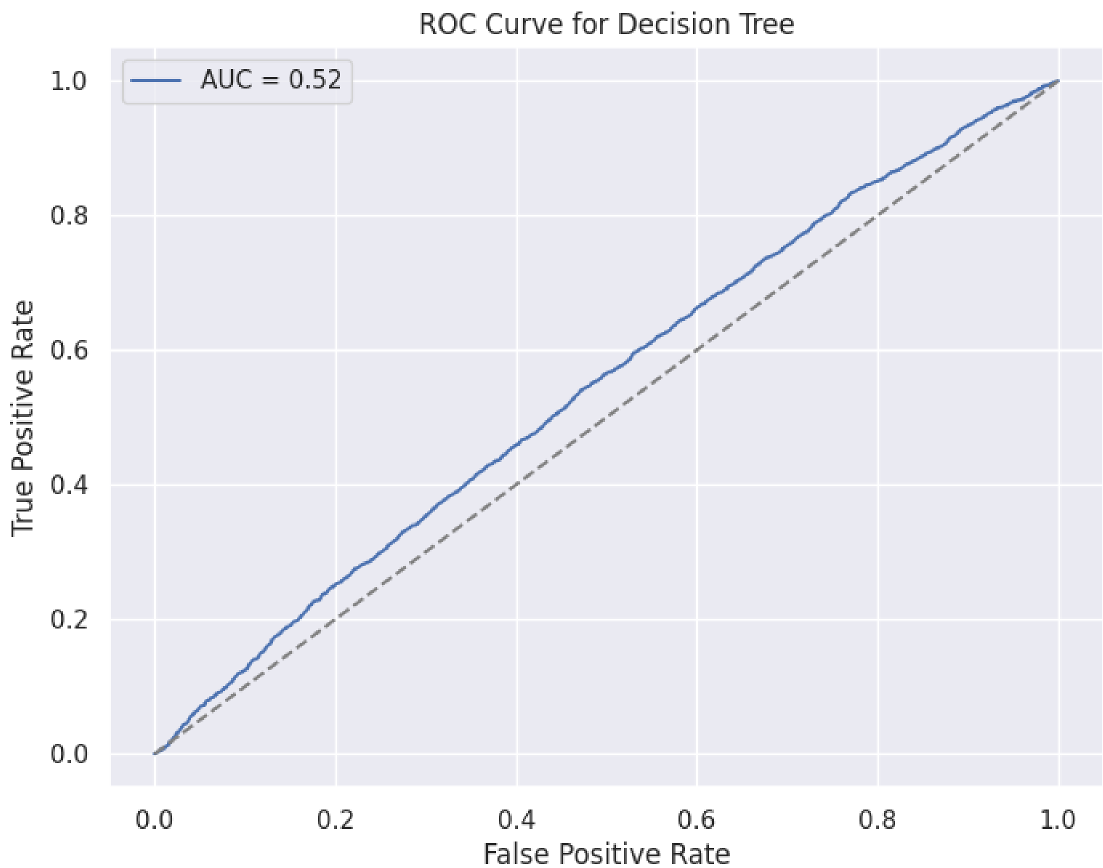
```
              precision    recall  f1-score   support

           0       0.45      0.13      0.20      3920
           1       0.63      0.90      0.74      6480

    accuracy                           0.61     10400
   macro avg       0.54      0.52      0.47     10400
weighted avg       0.56      0.61      0.54     10400

Random Forest AUC Score: 0.5160808767951626
```



[32]:
```
# Decision Tree
tree_model = DecisionTreeClassifier(random_state=42).fit(X_train, y_train)
tree_predictions = tree_model.predict(X_test)
```

```python
# Output some metrics
tree_auc_roc = roc_auc_score(y_test, tree_predictions)
tree_classification_report = classification_report(y_test, tree_predictions)
print(tree_classification_report)

tree_probs = forest_model.predict_proba(X_test)[:, 1]
print("Random Forest AUC Score:", tree_auc_roc)

# Calculating the ROC curve
fpr, tpr, thresholds = roc_curve(y_test, tree_probs)

# Plotting the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'AUC = {tree_auc_roc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='grey')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Decision Tree')
plt.legend()
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.45      0.15      0.23      3920
           1       0.63      0.89      0.74      6480

    accuracy                           0.61     10400
   macro avg       0.54      0.52      0.48     10400
weighted avg       0.56      0.61      0.55     10400

Random Forest AUC Score: 0.5189184933232552
```



0.0.9 8) Can you predict genre by using the 10 song features from question 4 directly or the principal components you extracted in question 6 with a neural network? How well does this work?

[33]:
```
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Base classes for neural network modules
class Module(object):
    def __init__(self):
        self.gradInput = None
        self.output = None

    def forward(self, *input):
        raise NotImplementedError

    def backward(self, *input):
        raise NotImplementedError

class LeastSquareCriterion(Module):
```

```
    # Assuming one-hot encoded target
    def forward(self, x, labels):
        self.output = np.sum((labels - x) ** 2, axis=0)
        return np.sum(self.output)

    def backward(self, x, labels):
        self.gradInput = 2 * (x - labels)
        return self.gradInput

class Linear(Module):
    def __init__(self, in_features, out_features, bias=True):
        self.in_features = in_features
        self.out_features = out_features
        self.weight = np.random.randn(out_features, in_features) * np.sqrt(1. /
 ↪in_features)
        self.bias = np.zeros(out_features) if bias else None
        self.gradWeight = None
        self.gradBias = None

    def forward(self, x):
        self.output = np.dot(x, self.weight.T)
        if self.bias is not None:
            self.output += self.bias.reshape(1, -1)
        return self.output

    def backward(self, x, gradOutput):
        self.gradInput = np.dot(gradOutput, self.weight)
        self.gradWeight = np.dot(gradOutput.T, x)
        self.gradBias = np.sum(gradOutput, axis=0)
        return self.gradInput

    def gradientStep(self, lr):
        self.weight -= lr * self.gradWeight
        if self.bias is not None:
            self.bias -= lr * self.gradBias

class ReLU(Module):
    def forward(self, x):
        self.output = np.maximum(0, x)
        return self.output

    def backward(self, x, gradOutput):
        self.gradInput = gradOutput * (x > 0)
        return self.gradInput

class MLP(Module):
    def __init__(self, in_features, num_classes):
```

```python
        super(MLP, self).__init__()
        self.fc1 = Linear(in_features, 64)
        self.relu1 = ReLU()
        self.fc2 = Linear(64, num_classes)

    def forward(self, x):
        x = self.fc1.forward(x)
        x = self.relu1.forward(x)
        x = self.fc2.forward(x)
        return x

    def backward(self, x, gradient):
        gradient = self.fc2.backward(self.relu1.output, gradient)
        gradient = self.relu1.backward(self.fc1.output, gradient)
        gradient = self.fc1.backward(x, gradient)
        return gradient

    def gradientStep(self, lr):
        self.fc2.gradientStep(lr)
        self.fc1.gradientStep(lr)
```

[34]:

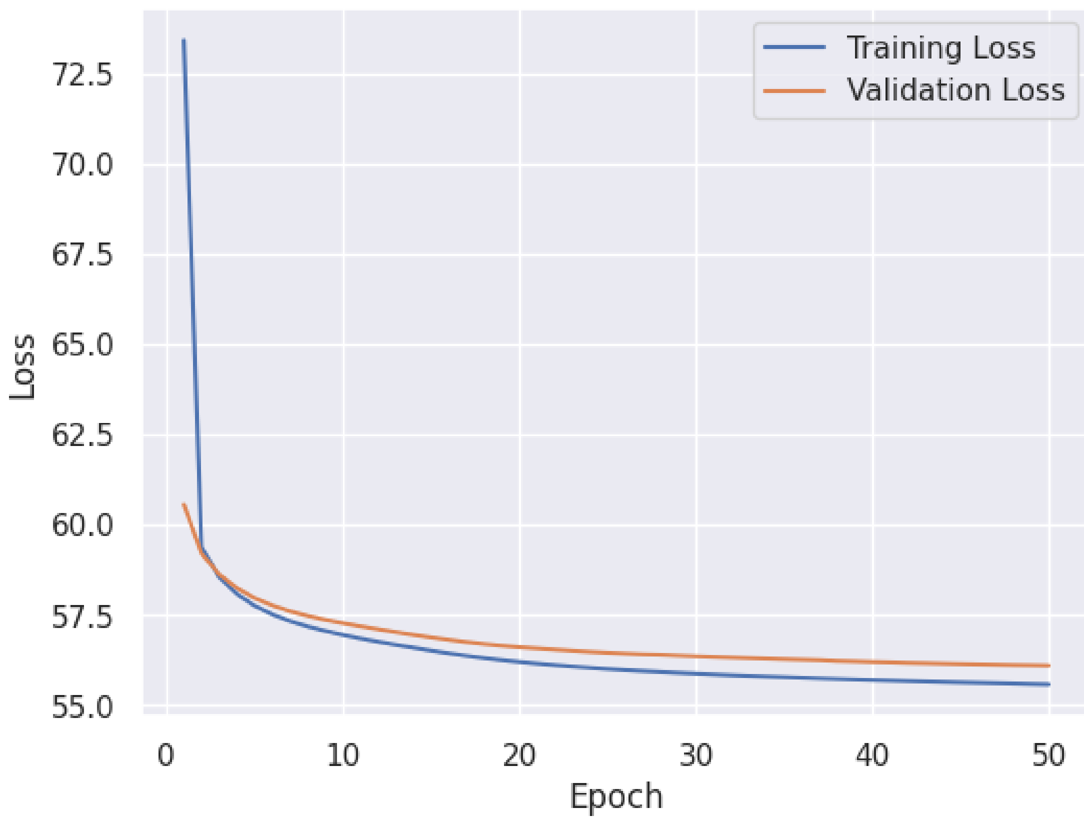
```python
# Function to train the model
def train_model(num_epochs, learn_rate, batch_size, model, criterion,␣
 ↪train_data, train_labels, val_data, val_labels):
    n_train, n_val = len(train_data), len(val_data)
    train_loss = np.empty(num_epochs)
    val_loss = np.empty(num_epochs)

    for epoch in range(num_epochs):
        # Training loop
        for i in range(0, n_train, batch_size):
            x = train_data[i:i+batch_size]
            y = train_labels[i:i+batch_size]
            y_pred = model.forward(x)
            loss = criterion.forward(y_pred, y)
            train_loss[epoch] += loss
            grad0 = criterion.backward(y_pred, y)
            model.backward(x, grad0)
            model.gradientStep(learn_rate)

        train_loss[epoch] /= (n_train // batch_size)

        # Validation loop
        for j in range(0, n_val, batch_size):
            x = val_data[j:j+batch_size]
            y = val_labels[j:j+batch_size]
            y_pred = model.forward(x)
```

```
            val_loss[epoch] += criterion.forward(y_pred, y)

        val_loss[epoch] /= (n_val // batch_size)

        if (epoch + 1) % 10 == 0:
            print(f'Epoch {epoch+1}/{num_epochs} - Train Loss:␣
↪{train_loss[epoch]:.4f}, Val Loss: {val_loss[epoch]:.4f}')

    # Plot training and validation loss
    plt.plot(range(1, num_epochs + 1), train_loss, label='Training Loss')
    plt.plot(range(1, num_epochs + 1), val_loss, label='Validation Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()
```

[35]:
```
# Number of unique genres
num_genres = 52  # Replace with the actual number of unique genres in␣
↪spotify_data

X = StandardScaler().fit_transform(df[features])
y = LabelEncoder().fit_transform(df['track_genre'])
y = np.eye(num_genres)[y]  # Convert labels to one-hot encoding

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Initialize the model and criterion
model = MLP(in_features=len(features), num_classes=num_genres)
criterion = LeastSquareCriterion()

# Train the model
num_epochs = 50
learn_rate = 0.001
batch_size = 64
train_model(num_epochs, learn_rate, batch_size, model, criterion, X_train,␣
↪y_train, X_test, y_test)

# Function to evaluate model accuracy
def evaluate_model(model, data, labels, batch_size):
    correct_predictions = 0
    for i in range(0, len(data), batch_size):
        x = data[i:i+batch_size]
        y = labels[i:i+batch_size]
        y_pred = model.forward(x)
```

```
        correct_predictions += np.sum(np.argmax(y_pred, axis=1) == np.argmax(y,␣
↪axis=1))
    accuracy = correct_predictions / len(data)
    return accuracy

# Evaluate the model
model_accuracy = evaluate_model(model, X_test, y_test, batch_size)
print(f'Model Accuracy: {model_accuracy:.4f}')
```

```
Epoch 10/50 - Train Loss: 56.9466, Val Loss: 57.2732
Epoch 20/50 - Train Loss: 56.1983, Val Loss: 56.6075
Epoch 30/50 - Train Loss: 55.8735, Val Loss: 56.3545
Epoch 40/50 - Train Loss: 55.6964, Val Loss: 56.1972
Epoch 50/50 - Train Loss: 55.5755, Val Loss: 56.0960
```

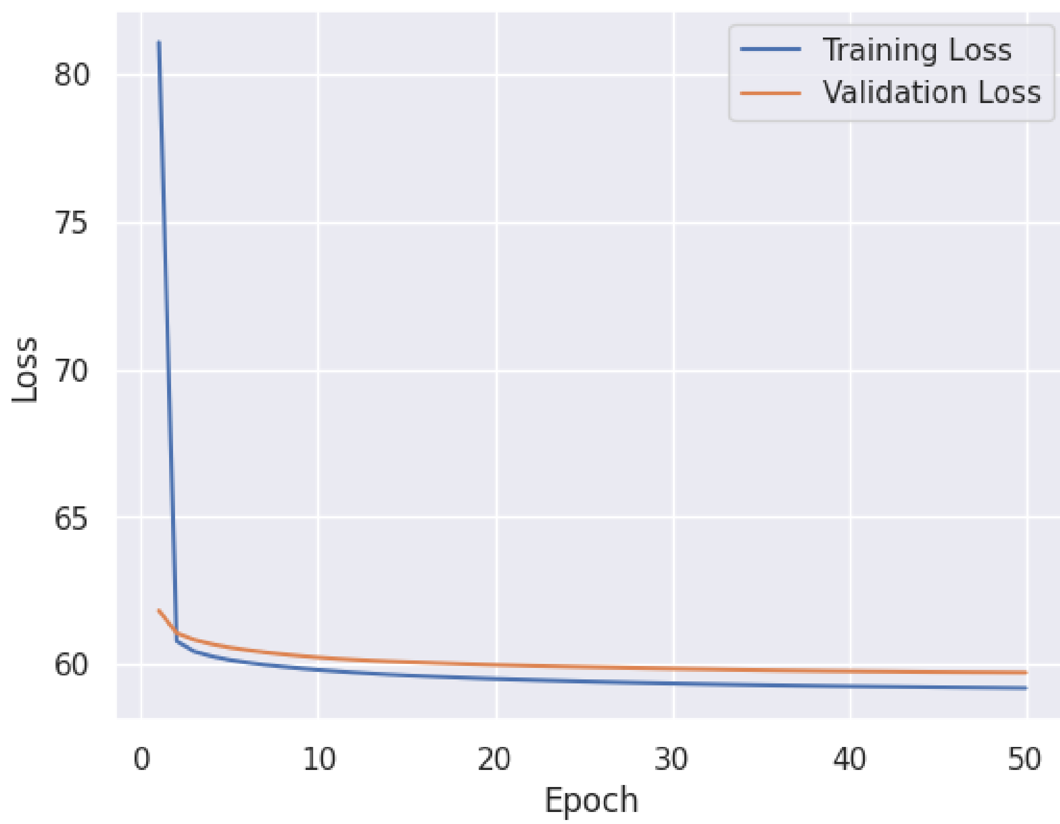



```
Model Accuracy: 0.2462
```

[36]:
```
y = LabelEncoder().fit_transform(df['track_genre'])
y = np.eye(num_genres)[y]  # Convert labels to one-hot encoding

# Split the data
```

```
X_train, X_test, y_train, y_test = train_test_split(pca_transformed, y,␣
↪test_size=0.2, random_state=42)

# Initialize the model with 3 input features (principal components)
model = MLP(in_features=3, num_classes=num_genres)
criterion = LeastSquareCriterion()

# Train the model
num_epochs = 50
learn_rate = 0.001
batch_size = 64
train_model(num_epochs, learn_rate, batch_size, model, criterion, X_train,␣
↪y_train, X_test, y_test)

# Evaluate the model
model_accuracy = evaluate_model(model, X_test, y_test, batch_size)
print(f'Model Accuracy: {model_accuracy:.4f}')
```

```
Epoch 10/50 - Train Loss: 59.8112, Val Loss: 60.2314
Epoch 20/50 - Train Loss: 59.5033, Val Loss: 59.9806
Epoch 30/50 - Train Loss: 59.3517, Val Loss: 59.8517
Epoch 40/50 - Train Loss: 59.2557, Val Loss: 59.7671
Epoch 50/50 - Train Loss: 59.1948, Val Loss: 59.7201
```



```
Model Accuracy: 0.1452
```

0.0.10 9) In recommender systems, the popularity based model is an important baseline. We have a two part question in this regard: a) Is there a relationship between popularity and average star rating for the 5k songs we have explicit feedback for? b) Which 10 songs are in the "greatest hits" (out of the 5k songs), on the basis of the popularity based model?

[37]:
```
average_star_ratings = ratings_data.mean(axis=0)
ratings_data.mean(axis=0).isna().sum()
```

[37]:
```
0
```

[38]:
```
# Calculate the average star rating for each song
average_star_ratings = ratings_data.head(5000).mean(axis=0)

song_ratings_df = df[['album_name','songNumber','track_name',␣
↪'popularity','artists']].head(5000)
song_ratings_df['average_star_rating'] = average_star_ratings.values
song_ratings_df.head()
```

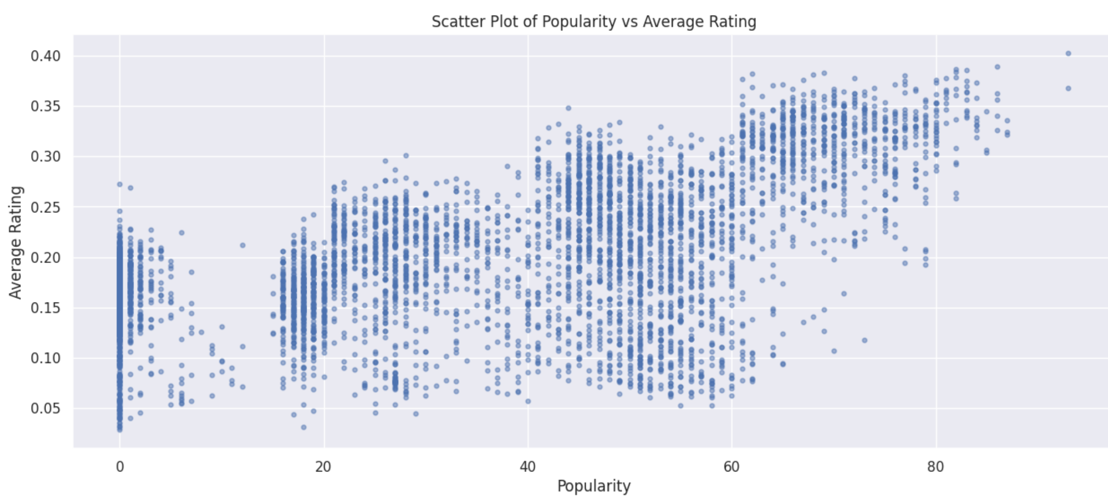
[38]:
```
                                          album_name  songNumber  \
0                                             Comedy           0
1                                   Ghost (Acoustic)           1
2                                     To Begin Again           2
3  Crazy Rich Asians (Original Motion Picture Sou…           3
4                                            Hold On           4

                track_name  popularity                 artists  \
0                   Comedy          73             Gen Hoshino
1         Ghost - Acoustic          55            Ben Woodward
2           To Begin Again          57  Ingrid Michaelson;ZAYN
3  Can't Help Falling In Love          71            Kina Grannis
4                  Hold On          82        Chord Overstreet

   average_star_rating
0               0.3128
1               0.1424
2               0.2442
3               0.1640
4               0.3084
```

[39]:
```
# a) Relationship between popularity and average star rating
# We will use a simple correlation to check the relationship
```

```
correlation_coefficient, p_value =
 ↪pearsonr(song_ratings_df['popularity'],song_ratings_df['average_star_rating'])

correlation_coefficient, p_value
```

[39]: (0.5673412407653671, 0.0)

[40]:
```
plt.figure(figsize=(15, 6))
plt.scatter(song_ratings_df['popularity'],
 ↪song_ratings_df['average_star_rating'], alpha=0.5, s=12)
plt.title('Scatter Plot of Popularity vs Average Rating')
plt.xlabel('Popularity')
plt.ylabel('Average Rating')
plt.grid(True)
plt.show()
```



[41]:
```
# Filter out unique songs
unique_songs = song_ratings_df.drop_duplicates(subset=['track_name','artists'])
unique_songs.head()
```

[41]:
```
                                          album_name  songNumber  \
0                                             Comedy           0
1                                   Ghost (Acoustic)           1
2                                     To Begin Again           2
3  Crazy Rich Asians (Original Motion Picture Sou…          3
4                                            Hold On           4

            track_name  popularity               artists  \
0               Comedy          73           Gen Hoshino
1     Ghost - Acoustic          55          Ben Woodward
```

```
2              To Begin Again          57  Ingrid Michaelson;ZAYN
3  Can't Help Falling In Love          71            Kina Grannis
4                     Hold On          82        Chord Overstreet

   average_star_rating
0               0.3128
1               0.1424
2               0.2442
3               0.1640
4               0.3084
```

[42]:
```
# b) Identifying the top 10 songs based on popularity based model
top_10_greatest_hits = unique_songs.sort_values(by='popularity',␣
 ↪ascending=False).head(10)
top_10_greatest_hits
```

[42]:
```
                                        album_name  songNumber  \
2003                                   I Love You.        2003
2000                                    Wiped Out!        2000
3004                                       abcdefu        3004
2002  Hard To Imagine The Neighbourhood Ever Changing        2002
2053                                   Pablo Honey        2053
3006                    Hybrid Theory (Bonus Edition)        3006
4002                          Cigarettes After Sex        4002
3255                                    Demon Days        3255
2057                                      Elephant        2057
2367                        The Colour And The Shape        2367

             track_name  popularity             artists  average_star_rating
2003     Sweater Weather          93    The Neighbourhood               0.4022
2000        Daddy Issues          87    The Neighbourhood               0.3360
3004             abcdefu          86                GAYLE               0.3890
2002            Softcore          86    The Neighbourhood               0.3264
2053               Creep          85            Radiohead               0.3060
3006          In the End          85          Linkin Park               0.3450
4002          Apocalypse          84  Cigarettes After Sex               0.3386
3255      Feel Good Inc.          84             Gorillaz               0.3312
2057  Seven Nation Army          84     The White Stripes               0.3352
2367            Everlong          84         Foo Fighters               0.3192
```

0.0.11 10) You want to create a "personal mixtape" for all 10k users we have explicit feedback for. This mixtape contains individualized recommendations as to which 10 songs (out of the 5k) a given user will enjoy most. How do these recommendations compare to the "greatest hits" from the previous question and how good is your recommender system in making recommendations?

[43]:
```
from sklearn.metrics.pairwise import cosine_similarity

spotify_data = df.head(5000)

# Remove duplicates in spotify_data while keeping the first occurrence
spotify_data_no_duplicates = spotify_data.drop_duplicates(subset=['track_name',␣
↪'artists'], keep='first')

# Aligning the ratings data with the spotify data
# Map each song in the ratings data to its corresponding row in the spotify data
song_indices = spotify_data_no_duplicates.index
aligned_ratings_data = ratings_data.iloc[:, song_indices]

# Convert the ratings data into a numpy array for similarity computation
ratings_matrix = aligned_ratings_data.to_numpy()

# Calculate the cosine similarity between users
user_similarity_matrix = cosine_similarity(ratings_matrix)

# The similarity matrix is a square matrix with the number of users as its␣
↪dimensions
user_similarity_matrix.shape
```

[43]: (10000, 10000)

[44]:
```
def get_top_n_recommendations(user_id, user_similarity_matrix, ratings_matrix,␣
↪n=10):
    """
    Generate top N song recommendations for a given user based on user-user␣
↪similarity.

    :param user_id: The ID of the user for whom to generate recommendations
    :param user_similarity_matrix: A matrix of user similarities
    :param ratings_matrix: The matrix of user ratings
    :param n: Number of top recommendations to return
    :return: List of song indices representing the top N recommendations
    """
    # Number of top similar users to consider
    num_top_users = 20
```

```python
    # Get the similarity scores for the target user and sort them in descending␣
↪order
    similarity_scores = list(enumerate(user_similarity_matrix[user_id]))
    similarity_scores = sorted(similarity_scores, key=lambda x: x[1],␣
↪reverse=True)

    # Select the top 'num_top_users' users (excluding the target user itself)
    top_users_indices = [user[0] for user in similarity_scores[1:
↪num_top_users+1]]

    # Aggregate the ratings of these users and calculate the mean rating for␣
↪each song
    top_users_ratings = ratings_matrix[top_users_indices, :]
    mean_ratings = np.mean(top_users_ratings, axis=0)

    # Sort the songs based on these mean ratings and get the indices of the top␣
↪'n' songs
    top_songs_indices = np.argsort(mean_ratings)[::-1][:n]

    # Retrieve song details from the Spotify dataset for these top songs
    recommended_songs_details = spotify_data.loc[top_songs_indices,␣
↪['songNumber', 'track_name', 'artists', 'popularity']]
    recommended_songs_details['Average Rating'] =␣
↪mean_ratings[top_songs_indices]

    return recommended_songs_details

# Example: Generate top 10 recommendations for a specific user (e.g., user with␣
↪ID 0)
get_top_n_recommendations(0, user_similarity_matrix, ratings_matrix, n=10)
```

[44]:

```
      songNumber                track_name           artists  popularity  \
1897        1897                Bienvenida     Jorge Drexler          18
2293        2293                   Dragula        Rob Zombie           0
1895        1895                Sincronia  Samuca e a Selva          16
2460        2460  Are You Gonna Be My Girl               Jet          76
2480        2480                Miss World              Hole           0
991          991               Little Life      Frank Turner          25
565          565        Sappy - Early Demo       Kurt Cobain          50
2346        2346           Corazones Rojos   Los Prisioneros           0
37            37   Throwing Good After Bad    Brandi Carlile           0
2613        2613               Cough Syrup   Young the Giant          71

      Average Rating
1897            1.55
2293            1.55
```

```
1895            1.40
2460            1.30
2480            1.20
991             1.15
565             1.05
2346            1.00
37              1.00
2613            1.00
```

[46]:
```python
def get_top_10_user_ratings(ratings_data):
    top_10_ratings = []
    for index, row in ratings_data.iterrows():
        # Sort the songs based on ratings and get the ratings of the top 10␣
 ↪songs
        top_ratings = row.sort_values(ascending=False).head(10).values.tolist()
        top_10_ratings.append(top_ratings)
    return top_10_ratings

# Extract top 10 rated songs (ratings) for each user
actual_data = get_top_10_user_ratings(ratings_data)

'''
predicted_data = []

for user_id in range(len(actual_data)):  # Example for 1000 users
    # Get top 10 recommended song indices
    recommended_songs = get_top_n_recommendations(user_id,␣
 ↪user_similarity_matrix, ratings_matrix, n=10)
    # Retrieve the corresponding ratings for these songs from the user's ratings
    user_ratings = ratings_matrix[user_id, recommended_songs['songNumber']]
    predicted_data.append(user_ratings.tolist())
'''
```

[46]:
```
"\npredicted_data = []\n\nfor user_id in range(len(actual_data)):  # Example for
1000 users\n    # Get top 10 recommended song indices\n    recommended_songs =
get_top_n_recommendations(user_id, user_similarity_matrix, ratings_matrix,
n=10)\n    # Retrieve the corresponding ratings for these songs from the user's
ratings\n    user_ratings = ratings_matrix[user_id,
recommended_songs['songNumber']]\n
predicted_data.append(user_ratings.tolist())\n"
```

[47]:
```python
def convert_to_binary(ratings, threshold=4.0):
    """
    Convert ratings to binary format (liked/not liked) based on a threshold.

    :param ratings: List of ratings
    :param threshold: Threshold above which songs are considered liked
```

```
    :return: Binary list indicating liked (1) or not liked (0)
    """
    return [1 if rating >= threshold else 0 for rating in ratings]

def calculate_precision_recall(predicted_ratings, actual_ratings, threshold=4.
 ↪0):
    """
    Calculate precision and recall for predicted ratings.

    :param predicted_ratings: List of predicted ratings
    :param actual_ratings: List of actual ratings
    :param threshold: Threshold for considering a song as liked
    :return: Tuple containing precision and recall
    """
    predicted_binary = convert_to_binary(predicted_ratings, threshold)
    actual_binary = convert_to_binary(actual_ratings, threshold)

    true_positives = sum(p and a for p, a in zip(predicted_binary,␣
 ↪actual_binary))
    predicted_positives = sum(predicted_binary)
    actual_positives = sum(actual_binary)

    precision = true_positives / predicted_positives if predicted_positives␣
 ↪else 0
    recall = true_positives / actual_positives if actual_positives else 0

    return precision, recall
```

[48]:

```
# Initialize lists to store precision and recall for each user
precisions = []
recalls = []

num_users = 10000
for user_id in range(num_users):
    # Get the actual top-rated songs for the user
    actual_rating = actual_data[user_id]

    # Get top 10 recommended songs for the user
    recommended_songs = get_top_n_recommendations(user_id,␣
 ↪user_similarity_matrix, ratings_matrix, n=10)
    user_ratings = ratings_matrix[user_id, recommended_songs['songNumber']]
    recommended_ratings = user_ratings.tolist()

    # Calculate precision and recall
    precision, recall = calculate_precision_recall(recommended_ratings,␣
 ↪actual_rating)
```

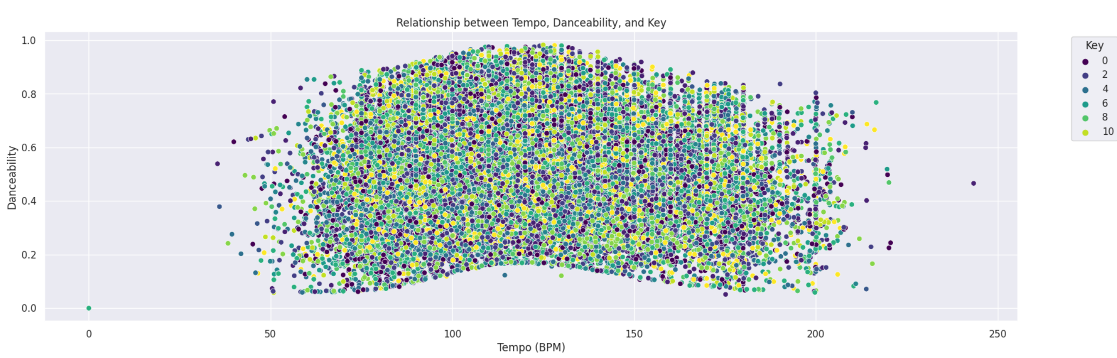
```
    # Append to the lists
    precisions.append(precision)
    recalls.append(recall)

# Calculate average precision and recall across all evaluated users
average_precision = np.mean(precisions)
average_recall = np.mean(recalls)

print(f"Average Precision: {average_precision}")
print(f"Average Recall: {average_recall}")
```

```
Average Precision: 0.9994416666666666
Average Recall: 0.5509674603174604
```

0.0.12 Extra credit: Can we use features tempo and key to predict danceability?

[49]:
```
# Prepare data
X = df[['tempo', 'key']]
y = df['danceability']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state= 19329713)
```

[50]:
```
# Create a scatterplot with tempo, danceability, and key
plt.figure(figsize=(20, 6))
sns.scatterplot(x='tempo', y='danceability', hue='key', data=df,␣
↪palette='viridis')
plt.title('Relationship between Tempo, Danceability, and Key')
plt.xlabel('Tempo (BPM)')
plt.ylabel('Danceability')
plt.legend(title='Key', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



[51]:
```
# Fit random forest
random_forest = RandomForestRegressor(n_estimators=100, random_state=19329713)
random_forest.fit(X_train, y_train)

random_forest_preds = random_forest.predict(X_test)

random_forest_r2 = r2_score(y_test, random_forest_preds)
random_forest_mse = mean_squared_error(y_test, random_forest_preds)
random_forest_rmse = np.sqrt(random_forest_mse)

print(f'Random Forest R-squared: {random_forest_r2}')
print(f'Random Forest RMSE: {random_forest_rmse}')
```

```
Random Forest R-squared: 0.1977481733858264
Random Forest RMSE: 0.15817192131403277
```

[51]:
```

```