PART 2B. SONG POPULARITY

GROUP 9

Importing Libraries

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
import plotly.express as px

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

Loading the dataset

In [ ]:
```
song_path = r'spotifydata.csv'
song_data = pd.read_csv(song_path)
```

In [ ]:
```
print("EDA:")
print('\nSong Data:')
display(song_data.head())
print("Length of song dataset:", len(song_data))
display(song_data.describe())
display(song_data.isna().sum())
display(pd.DataFrame({'Column': song_data.columns, 'DType': [song_data[col].dtype
```

```
EDA:

Song Data:
```

	genre	artist_name	track_name	track_id	popularity	acousticness	danceabi
0	Movie	Henri Salvador	C'est beau de faire un Show	0BRjO6ga9RKCKjfDqeFgWV	0	0.611	0.
1	Movie	Martin & les fées	Perdu d'avance (par Gad Elmaleh)	0BjC1NfoEOOusryehmNudP	1	0.246	0.
2	Movie	Joseph Williams	Don't Let Me Be Lonely Tonight	0CoSDzoNIKCRs124s9uTVy	3	0.952	0.
3	Movie	Henri Salvador	Dis-moi Monsieur Gordon Cooper	0Gc6TVm52BwZD07Ki6tIvf	0	0.703	0.
4	Movie	Fabien Nataf	Ouverture	0IuslXpMROHdEPvSl1fTQK	4	0.950	0.

```
Length of song dataset: 232725
```

	popularity	acousticness	danceability	duration_ms	energy	instrumentaln
count	232725.000000	232725.000000	232725.000000	2.327250e+05	232725.000000	232725.0000
mean	41.127502	0.368560	0.554364	2.351223e+05	0.570958	0.1483
std	18.189948	0.354768	0.185608	1.189359e+05	0.263456	0.3027
min	0.000000	0.000000	0.056900	1.538700e+04	0.000020	0.0000
25%	29.000000	0.037600	0.435000	1.828570e+05	0.385000	0.0000
50%	43.000000	0.232000	0.571000	2.204270e+05	0.605000	0.0000
75%	55.000000	0.722000	0.692000	2.657680e+05	0.787000	0.0358
max	100.000000	0.996000	0.989000	5.552917e+06	0.999000	0.9990

```
genre               0
artist_name         0
track_name          0
track_id            0
popularity          0
acousticness        0
danceability        0
duration_ms         0
energy              0
instrumentalness    0
key                 0
liveness            0
loudness            0
mode                0
speechiness         0
tempo               0
time_signature      0
valence             0
dtype: int64
```

	Column	DType	NUniques
0	genre	object	27
1	artist_name	object	14564
2	track_name	object	148615
3	track_id	object	176774
4	popularity	int64	101
5	acousticness	float64	4734
6	danceability	float64	1295
7	duration_ms	int64	70749
8	energy	float64	2517
9	instrumentalness	float64	5400
10	key	object	12
11	liveness	float64	1732
12	loudness	float64	27923
13	mode	object	2
14	speechiness	float64	1641
15	tempo	float64	78512
16	time_signature	object	5
17	valence	float64	1692

What did we do in the above step? - The code is about Exploratory Data Analysis (EDA) on the dataset. It displays first few data points, its length, statistical summary, count of missing values per column, and a tabulation displaying column names, their data types, and the number of unique values within each column.

In [ ]:

```
#  Retrieve the keys present in the song_data dictionary
song_data.keys()
```

Out[ ]:

```
Index(['genre', 'artist_name', 'track_name', 'track_id', 'popularity',
       'acousticness', 'danceability', 'duration_ms', 'energy',
       'instrumentalness', 'key', 'liveness', 'loudness', 'mode',
       'speechiness', 'tempo', 'time_signature', 'valence'],
      dtype='object')
```

Checking Missing Values

In [ ]:

```
song_data.isna().sum()
```

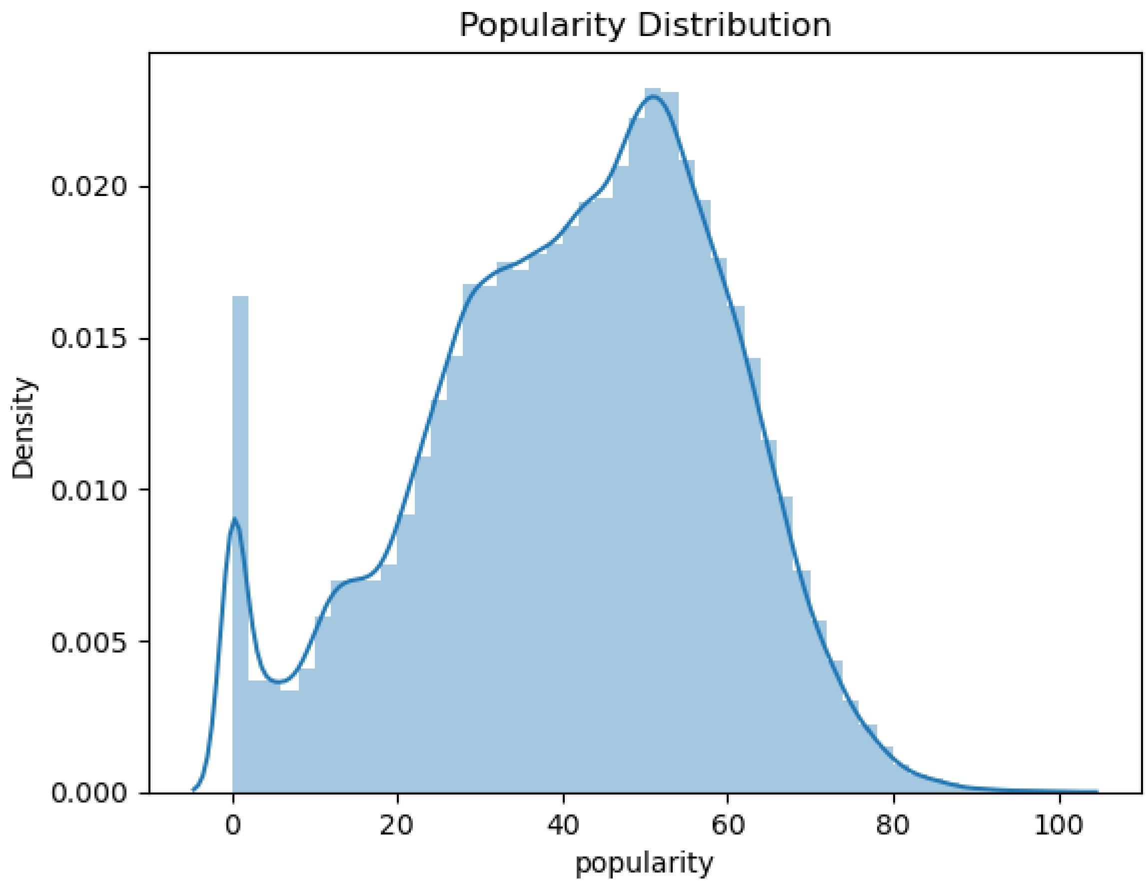
Out[ ]:
```
genre               0
artist_name         0
track_name          0
track_id            0
popularity          0
acousticness        0
danceability        0
duration_ms         0
energy              0
instrumentalness    0
key                 0
liveness            0
loudness            0
mode                0
speechiness         0
tempo               0
time_signature      0
valence             0
dtype: int64
```

Data Visualization

In [ ]:
```
sns.distplot(song_data['popularity']).set_title('Popularity Distribution')
```

```
C:\Users\patel\AppData\Local\Temp\ipykernel_12888\3871686646.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(song_data['popularity']).set_title('Popularity Distribution')
```

Out[ ]:
```
Text(0.5, 1.0, 'Popularity Distribution')
```

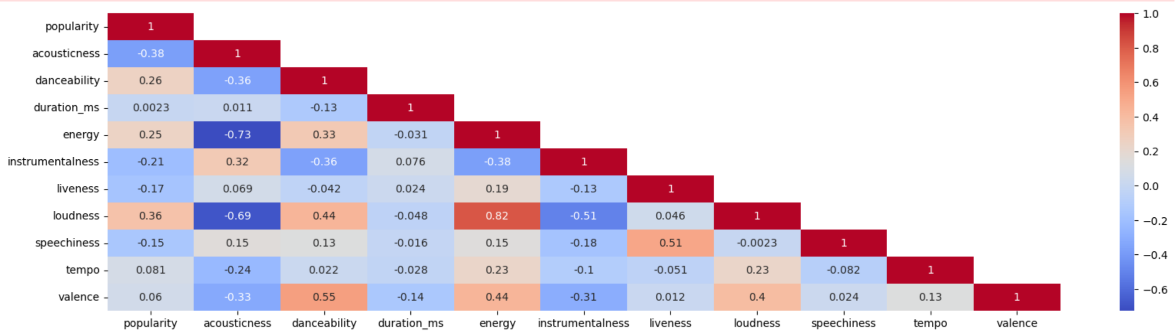


What did we do in the above step? - The code is to plot the distribution plot (distplot) for the 'popularity' column. Using this, we are visualizing the distribution of popularity scores among the songs.

Visualizing Correlation Among Song Data Features Using Heatmap

In [ ]:
```
correlation = song_data.corr()
fig = plt.figure(figsize=(20,5))
mask = np.triu(np.ones_like(correlation, dtype=bool), k=1)
sns.heatmap(correlation, annot=True, cmap="coolwarm", mask=mask)
plt.show()
```

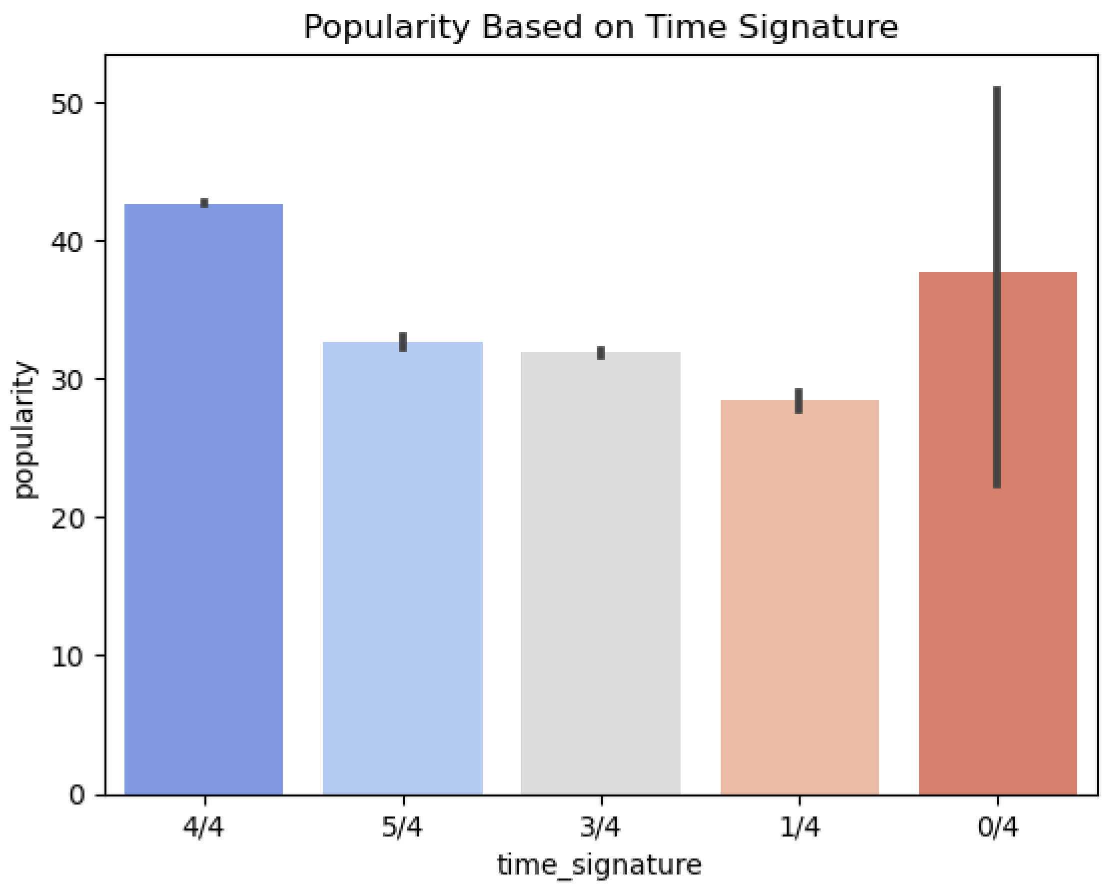
```
C:\Users\patel\AppData\Local\Temp\ipykernel_12888\2112152709.py:1: FutureWarning:
The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
rsion, it will default to False. Select only valid columns or specify the value o
f numeric_only to silence this warning.
  correlation = song_data.corr()
```



Visualization of Popularity Based on Time Signature

In [ ]:
```
sns.barplot(x = 'time_signature', y = 'popularity', data = song_data, palette='co
plt.title('Popularity Based on Time Signature')
```

Out[ ]:
```
Text(0.5, 1.0, 'Popularity Based on Time Signature')
```

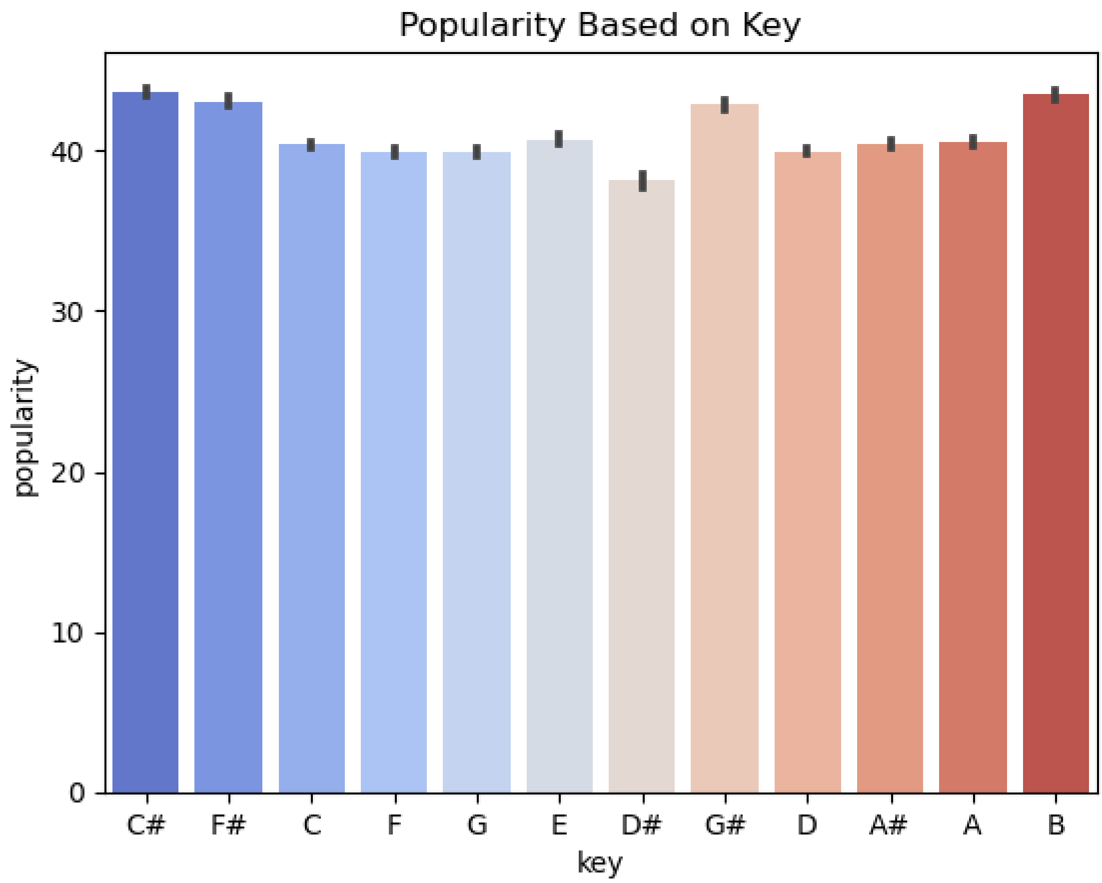


What did we do in the above step? - We created a bar plot to showcase the relationship between the time signature of songs and their respective popularity levels

Popularity Distribution Across Different Musical Keys

In [ ]:
```
sns.barplot(x = 'key', y = 'popularity', data = song_data, palette='coolwarm')
plt.title('Popularity Based on Key')
```

Out[ ]:
```
Text(0.5, 1.0, 'Popularity Based on Key')
```



What did we do in the above step? - We created a bar plot to show how popularity varies across different musical keys, mainly to understand relationships between key and music popularity.

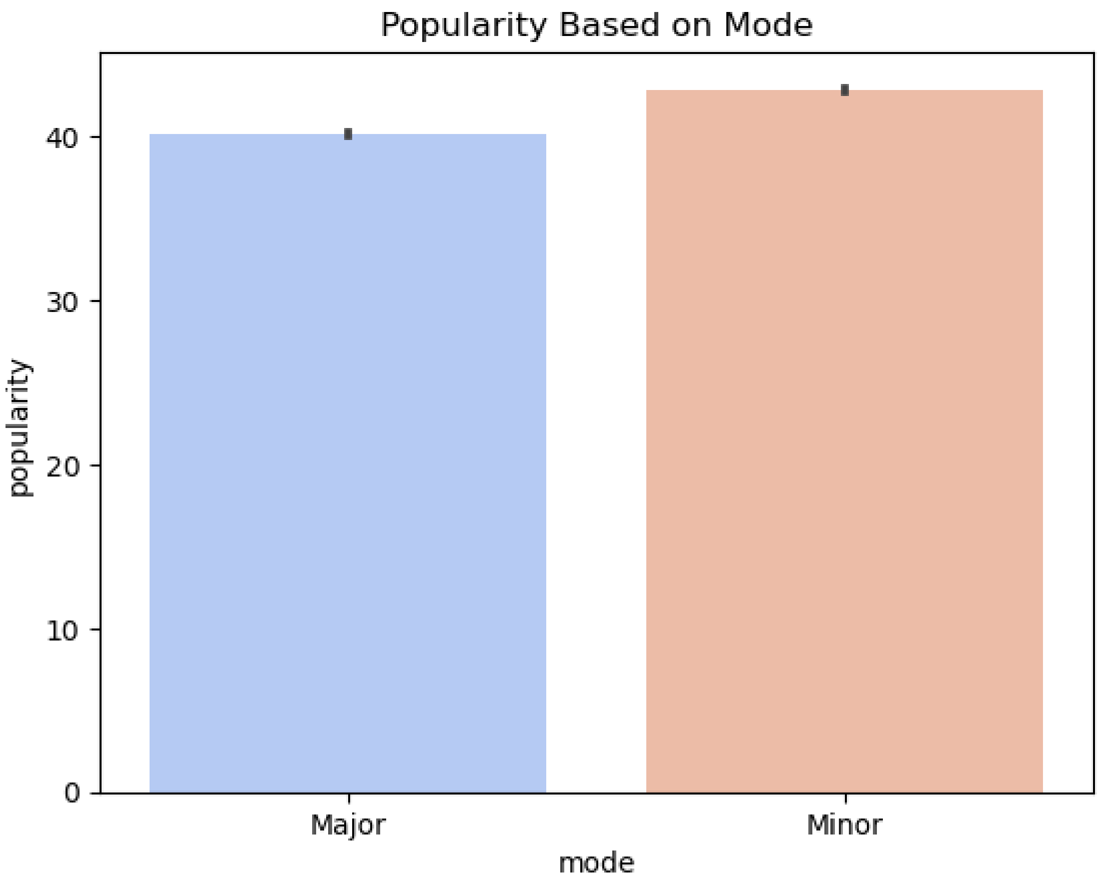
Popularity Based on Musical Mode

In [ ]:

```
sns.barplot(x = 'mode', y = 'popularity', data = song_data, palette='coolwarm')
plt.title('Popularity Based on Mode')
```

Out[ ]:

```
Text(0.5, 1.0, 'Popularity Based on Mode')
```



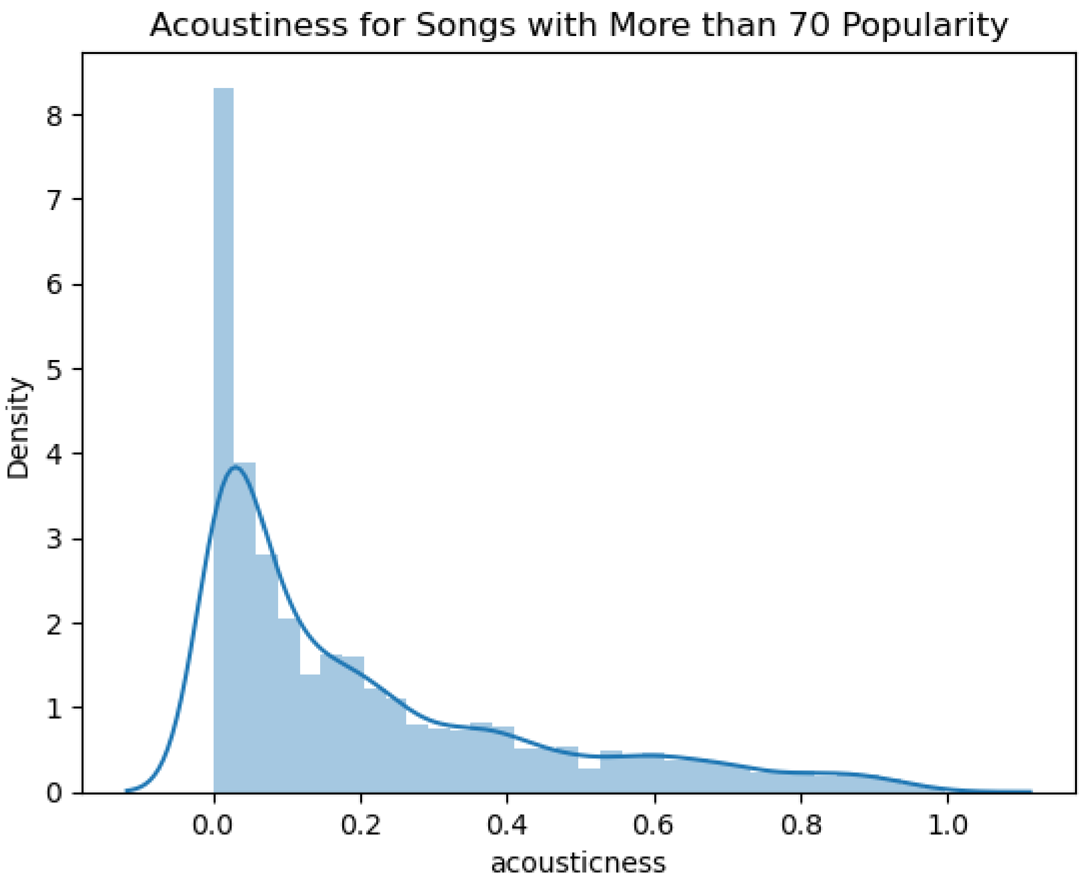
What did we do in the above step? - We created a bar plot to show the relationship between musical mode and song popularity

Distribution of Acousticness in Songs with Popularity Above 70

In [ ]:
```
popular_songs = song_data[song_data.popularity > 70]
sns.distplot(popular_songs['acousticness'])
plt.title('Acoustiness for Songs with More than 70 Popularity')
```

```
C:\Users\patel\AppData\Local\Temp\ipykernel_12888\1018885752.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(popular_songs['acousticness'])
```

Out[ ]:
```
Text(0.5, 1.0, 'Acoustiness for Songs with More than 70 Popularity')
```



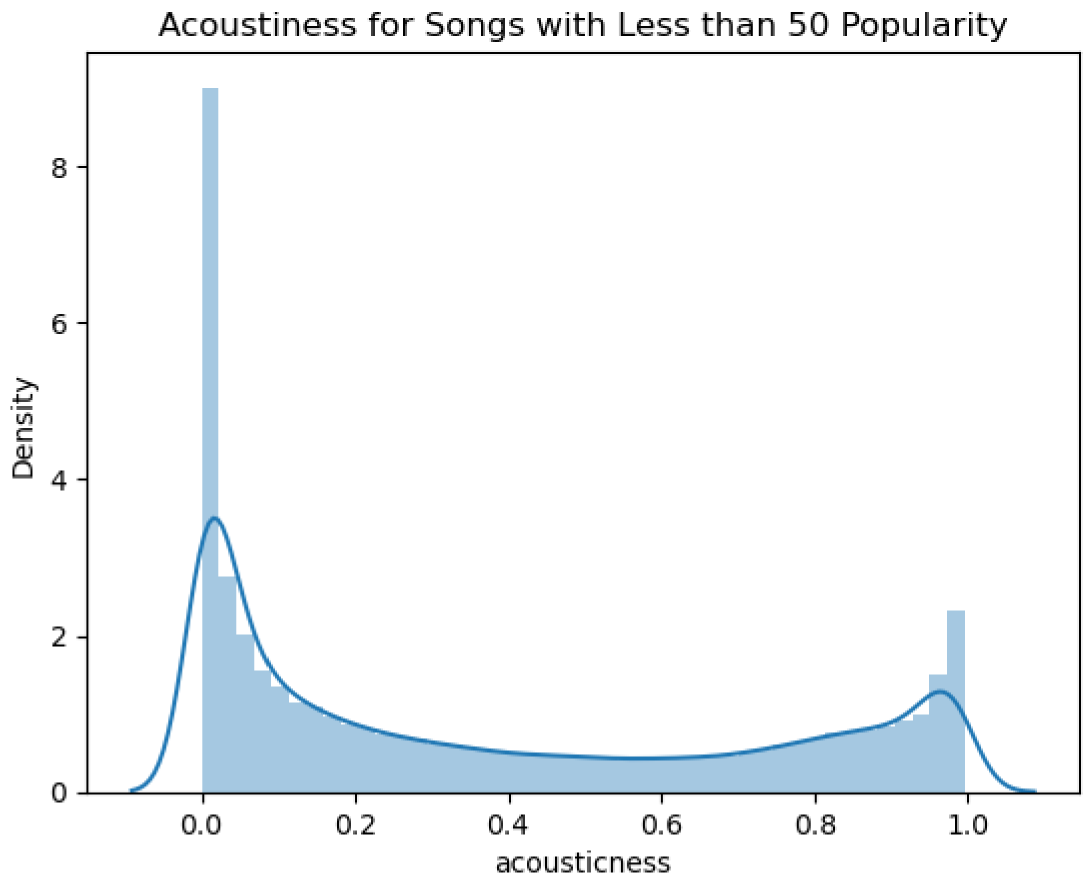
What did we do in the above step? - The code filters songs with a popularity score above 70 from the dataset and visualization is performed specifically for acousticness

Distribution of Acousticness in Songs with Popularity Below 70

In [ ]:
```
unpopular_songs = song_data[song_data.popularity < 70]
sns.distplot(unpopular_songs['acousticness'])
plt.title('Acoustiness for Songs with Less than 50 Popularity')
```

```
C:\Users\patel\AppData\Local\Temp\ipykernel_12888\228728011.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(unpopular_songs['acousticness'])
```

Out[ ]:
```
Text(0.5, 1.0, 'Acoustiness for Songs with Less than 50 Popularity')
```



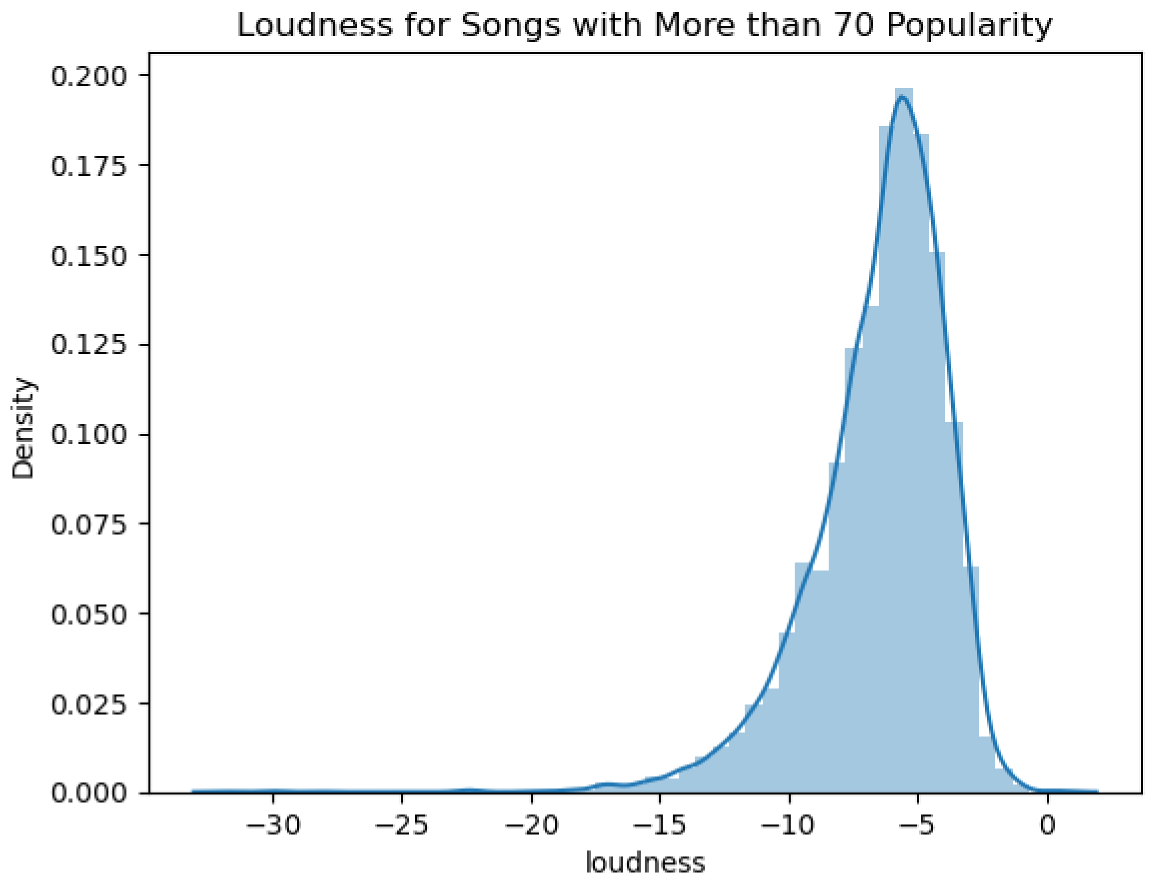
What did we do in the above step? - The code filters songs with a popularity score below 70 from the dataset and visualization is performed specifically for acousticness

Distribution of Loudness for Highly Popular Songs

In [ ]:
```
sns.distplot(popular_songs['loudness'])
plt.title('Loudness for Songs with More than 70 Popularity')
```

```
C:\Users\patel\AppData\Local\Temp\ipykernel_12888\1995242145.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(popular_songs['loudness'])
```

Out[ ]:
```
Text(0.5, 1.0, 'Loudness for Songs with More than 70 Popularity')
```



What did we do in the above step? - Visualizing the distribution of loudness for songs with a popularity above 70, giving information about the loudness patterns within the list of highly popular songs.

Distribution of Loudness for Less Popular Songs

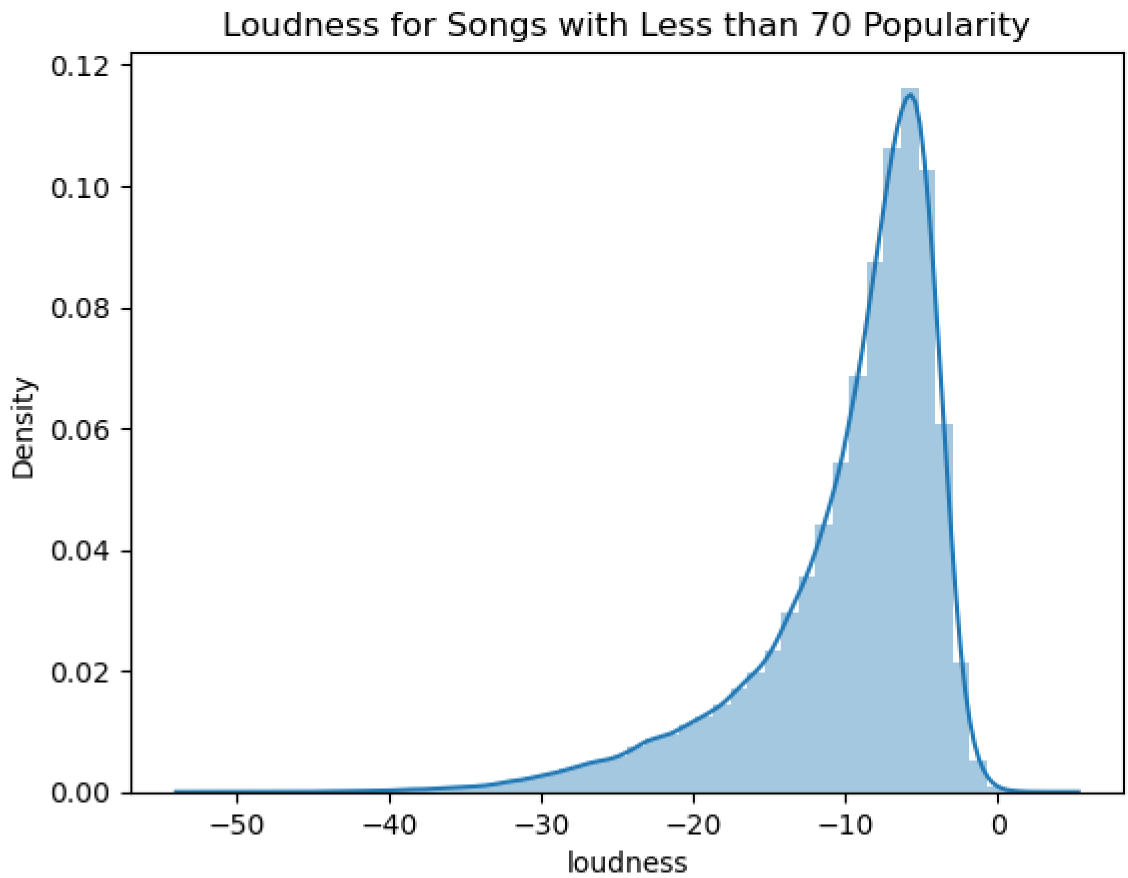
In [ ]:

```
unpopular_songs = song_data[song_data.popularity < 70]
sns.distplot(unpopular_songs['loudness'])
plt.title('Loudness for Songs with Less than 70 Popularity')
```

```
C:\Users\patel\AppData\Local\Temp\ipykernel_12888\1000170378.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(unpopular_songs['loudness'])
```

Out[ ]:

```
Text(0.5, 1.0, 'Loudness for Songs with Less than 70 Popularity')
```



What did we do in the above step? - Visualizing the distribution of loudness for songs with a popularity below 70, giving information about the loudness patterns within the list of less popular songs.

Data Preparation

Encoding Categorical Keys in Song Data

In [ ]:
```
unique_keys = song_data['key'].unique()
for i in range(len(unique_keys)):
    song_data.loc[song_data['key'] == unique_keys[i], 'key'] = i
song_data.sample(5)
```

Out[ ]:

	genre	artist_name	track_name	track_id	popularity	acousticne
48743	Blues	Joe Cocker	Woman To Woman	0K3Dem9aRwRG9DVo0W2T3o	34	0.178
6842	Alternative	Ayelle	Obvious	2ySyV2K8WnOqsQ0CfBNdnx	54	0.284
68302	Hip-Hop	Tyler, The Creator	I Ain't Got Time!	430qNtapCS3Ue1yoSql1oV	65	0.053
109276	Pop	The Foundations	Build Me Up Buttercup	6sPOmDulFtLzfX25zICNrC	74	0.313
210078	World	Rend Collective	Weep With Me - Reprise	4sYJN5wnWsiuFfYPCbuuF4	37	0.782

Mapping Time Signatures to Numerical Categories in Song Data

In [ ]:
```
time_sign = song_data['time_signature'].unique()
for i in range(len(time_sign)):
    song_data.loc[song_data['time_signature'] == time_sign[i], 'time_signature']
song_data.sample(5)
```

Out[ ]:

	genre	artist_name	track_name	track_id	popularity	acousticness
8137	Country	Jerry Garcia	Sugaree	4XoYeolVYTiddO9wZLXLgl	44	0.0914
176845	Jazz	Johnny Mathis	The Last Time I Felt Like This	2hZt9BmpFVRZq5xzOeKSA7	45	0.7730
7876	Country	Roger Creager	Love	7zZKjQDm8JNFkrxRvafHid	36	0.1920
61438	R&B	Sex on Toast	Oh, Loretta!	4HqxTpbXpLO1jgKJppk8Gl	52	0.3470
7105	Country	Alan Jackson	Like Red On a Rose	1ayFArNqsYgGT8gWWSscTD	37	0.6340

Converting Musical Modes to Numerical Representation

In [ ]:
```
song_data.loc[song_data["mode"] == 'Major', "mode"] = 1
song_data.loc[song_data["mode"] == 'Minor', "mode"] = 0
song_data.sample(5)
```

Out[ ]:

	genre	artist_name	track_name	track_id	popularity	acousticness
228826	Soul	Teena Marie	I Need Your Lovin'	0HYCfsLMVE61LZIVI3d1UA	44	0.00889
32360	Anime	SEKAI NO OWARI	Rafflesia	67abPmmiZMrgEW7UFnjJfF	19	0.05080
217548	World	Hildur Guðnadóttir	Elevation	3x4AbXBLj5t3x1OnAAVBiL	37	0.86100
158585	Reggaeton	Brytiago	Dime a Vel (feat. Almighty)	65fV6PGE2bytfHrpPgZPPb	49	0.30300
54919	R&B	The Weeknd	Reminder - Remix	7F1LWA9sIlTorHUo4amGqk	64	0.14900

What did we do in the above step? - Transforming categorical labels 'Major' and 'Minor' to numerical representations '1' and '0' respectively.

Binary Classification of Song Popularity

In [ ]:

```
song_data.loc[song_data['popularity'] < 70, 'popularity'] = 0
song_data.loc[song_data['popularity'] >= 70, 'popularity'] = 1
song_data.loc[song_data['popularity'] == 1]
```

Out[ ]:

	genre	artist_name	track_name	track_id	popularity	acousticness
145	R&B	Mariah Carey	Hero	4FCb4CUbFCMNRkI6lYc1zl	1	0.7350
147	R&B	Jason Derulo	Tip Toe (feat. French Montana)	2z4pcBLQXF2BXKFvd0BuB6	1	0.0233
160	R&B	Jennifer Lopez	Dinero	22mQXNE0nCuWq4yOwcadIn	1	0.4100
161	R&B	Rihanna	Hate That I Love You	7iu0WYLdo4yksKf3seaxzl	1	0.3230
174	R&B	Usher	OMG (feat. will.i.am)	1bM50INir8voAkVoKuvEUI	1	0.1980
...	...	...	...	...	...	...
226102	Rock	Bacilos	Caraluna	4XTMj7kd8DHLl0r7ghmEAr	1	0.1760
226281	Rock	Alejandro Sanz	Corazón partío	0wQCKR9OFjYu5Kzrk7WivJ	1	0.1990
226307	Rock	Elefante	Así Es La Vida	3ge3q3Hz0KWhQX5EAQcwEy	1	0.1310
226413	Rock	Roxette	It Must Have Been Love - From the "Pretty Woma...	6qB7YcFpeBEQa0D6QO482y	1	0.3400
226424	Rock	La Mosca Tse-Tse	Para No Verte Más	19CmuECYssqkPWANF4nLWM	1	0.0168

9001 rows × 18 columns

What did we do in the above step? - Transforming 'popularity' column into a binary classification by setting unpopular songs (below 70) to 0 and popular songs (above 70) to 1. The final line includes only songs marked as highly popular (assigned a value of 1).
- It is our threshold that we consider only songs above 70 as popular songs and those below 70 as unpopular songs

Model Building

Feature Selection

In [ ]:
```
song_features = ["acousticness", "danceability", "duration_ms", "energy", "instru
                 "mode", "speechiness", "tempo", "time_signature", "valence"]
```

What did we do in the above step? - For feature selection, we will select the following features which are only based on music theory and not artist/song information:

acousticness, danceability, duration_ms, energy, instrumentalness, key, liveliness, loudness, mode, speeciness, tempo, time_signature, and valence.

In [ ]:
```
training = song_data.sample(frac = 0.8,random_state = 420)
X_train = training[song_features]
y_train = training['popularity']
X_test = song_data.drop(training.index)[song_features]
```

In [ ]:
```
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size
```

In [ ]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_valid = scaler.transform(X_valid)
```

Model 1: Logistic Regression

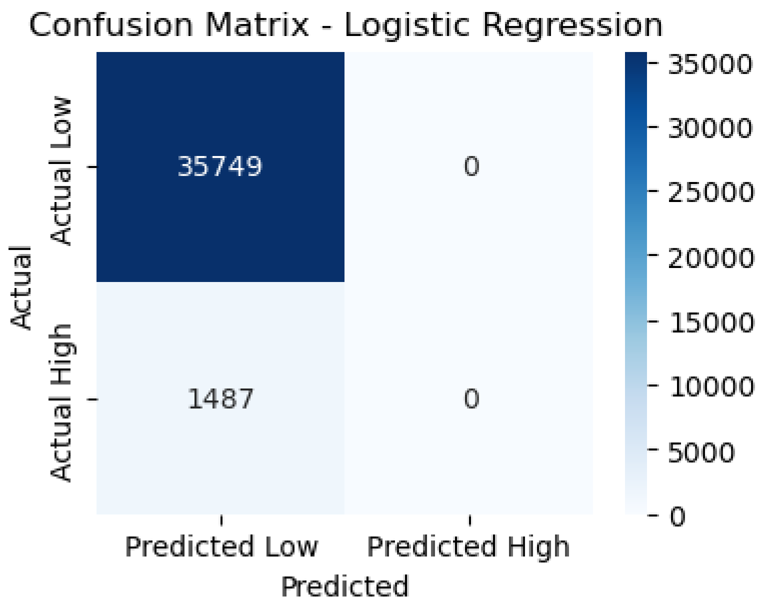
In [ ]:
```
lr_model = LogisticRegression()
lr_model.fit(X_train, y_train)
lr_y_pred = lr_model.predict(X_valid)
lr_accuracy = accuracy_score(y_valid, lr_y_pred)
print("Accuracy: " + str(lr_accuracy))

lr_auc = roc_auc_score(y_valid, lr_y_pred)
print("AUC: " + str(lr_auc))
```

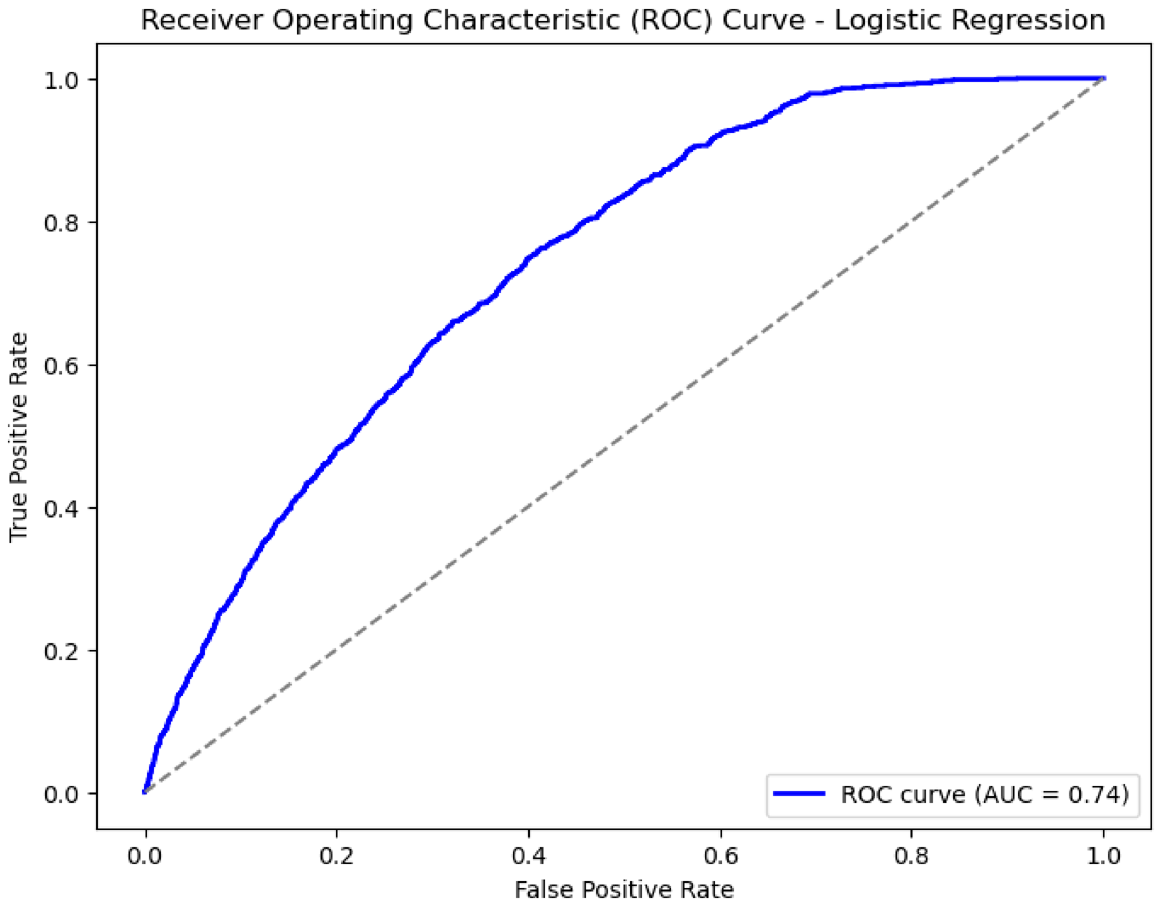
```
Accuracy: 0.9600655279836717
AUC: 0.5
```

In [ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, re

accuracy = accuracy_score(y_valid, lr_y_pred)
conf_matrix = confusion_matrix(y_valid, lr_y_pred)
precision = precision_score(y_valid, lr_y_pred, average='weighted')
recall = recall_score(y_valid, lr_y_pred, average='weighted')
f1 = f1_score(y_valid, lr_y_pred, average='weighted')

tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)

print("Confusion Matrix:")
print(conf_matrix)
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F-measure: {f1:.2f}")
print(f"Specificity: {specificity:.2f}")

plt.figure(figsize=(4, 3))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Low', 'Predicted High'],
            yticklabels=['Actual Low', 'Actual High'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Logistic Regression')
plt.show()

lr_y_pred_proba = lr_model.predict_proba(X_valid)[:, 1]

fpr, tpr, thresholds = roc_curve(y_valid, lr_y_pred_proba)
```

```python
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve - Logistic Regression')
plt.legend(loc='lower right')
plt.show()
```

```
c:\Users\patel\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:146
9: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in label
s with no predicted samples. Use `zero_division` parameter to control this behavi
or.
  _warn_prf(average, modifier, msg_start, len(result))
Confusion Matrix:
[[35749     0]
 [ 1487     0]]
Accuracy: 0.96
Precision: 0.92
Recall: 0.96
F-measure: 0.94
Specificity: 1.00
```





Model 2: Decision Tree Classifier

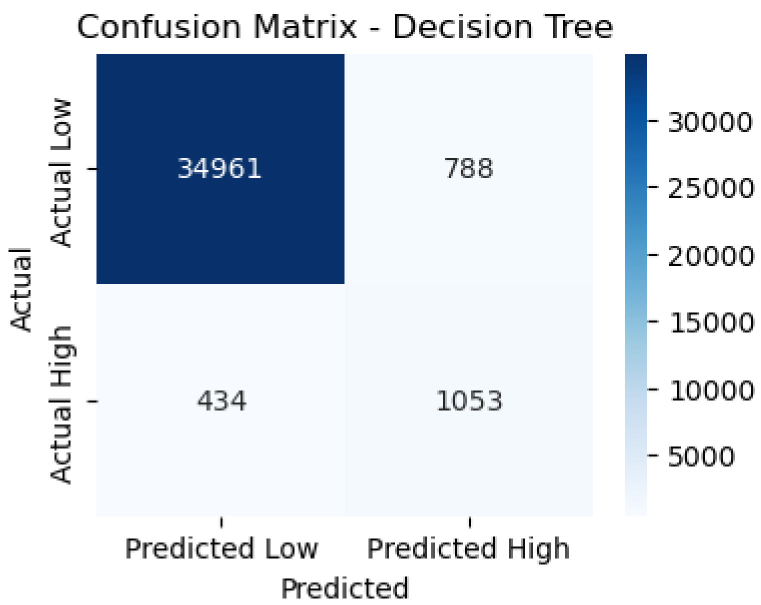
In [ ]:
```
dt_model = DecisionTreeClassifier()
dt_model.fit(X_train, y_train)
dt_y_pred = dt_model.predict(X_valid)
dt_accuracy = accuracy_score(y_valid, dt_y_pred)
print("Accuracy: " + str(dt_accuracy))

dt_auc = roc_auc_score(y_valid, dt_y_pred)
print("AUC: " + str(dt_auc))
```

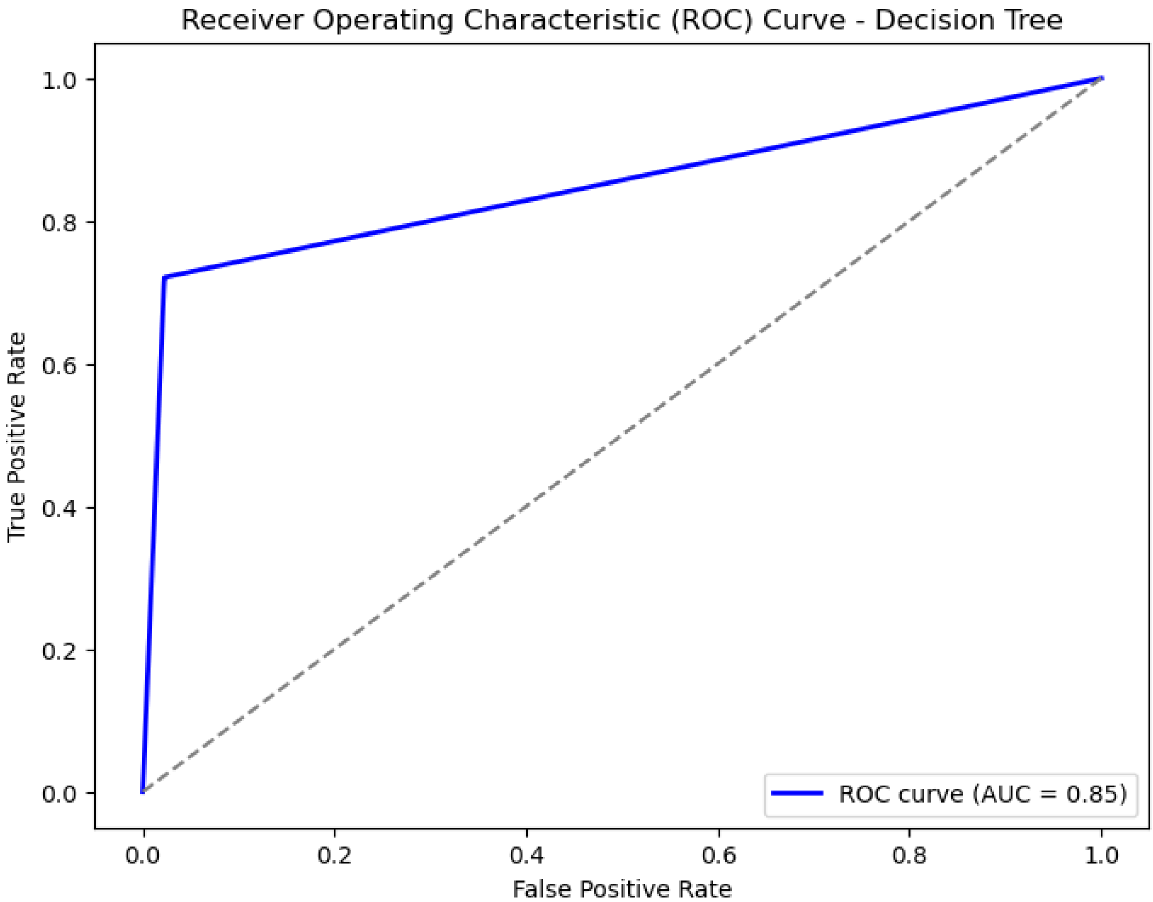
```
Accuracy: 0.9671822967021162
AUC: 0.8430473071768053
```

In [ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, re
import seaborn as sns
import matplotlib.pyplot as plt

accuracy = accuracy_score(y_valid, dt_y_pred)
conf_matrix = confusion_matrix(y_valid, dt_y_pred)
precision = precision_score(y_valid, dt_y_pred, average='weighted')
recall = recall_score(y_valid, dt_y_pred, average='weighted')
f1 = f1_score(y_valid, dt_y_pred, average='weighted')

tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)

print("Confusion Matrix:")
print(conf_matrix)
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
```

```python
print(f"F-measure: {f1:.2f}")
print(f"Specificity: {specificity:.2f}")

plt.figure(figsize=(4, 3))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Low', 'Predicted High'],
            yticklabels=['Actual Low', 'Actual High'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Decision Tree')
plt.show()

dt_y_pred_proba = dt_model.predict_proba(X_valid)[:, 1]

fpr, tpr, thresholds = roc_curve(y_valid, dt_y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve - Decision Tree')
plt.legend(loc='lower right')
plt.show()
```

```
Confusion Matrix:
[[34961   788]
 [  434  1053]]
Accuracy: 0.97
Precision: 0.97
Recall: 0.97
F-measure: 0.97
Specificity: 0.98
```





Model 3: Random Forest Classifier

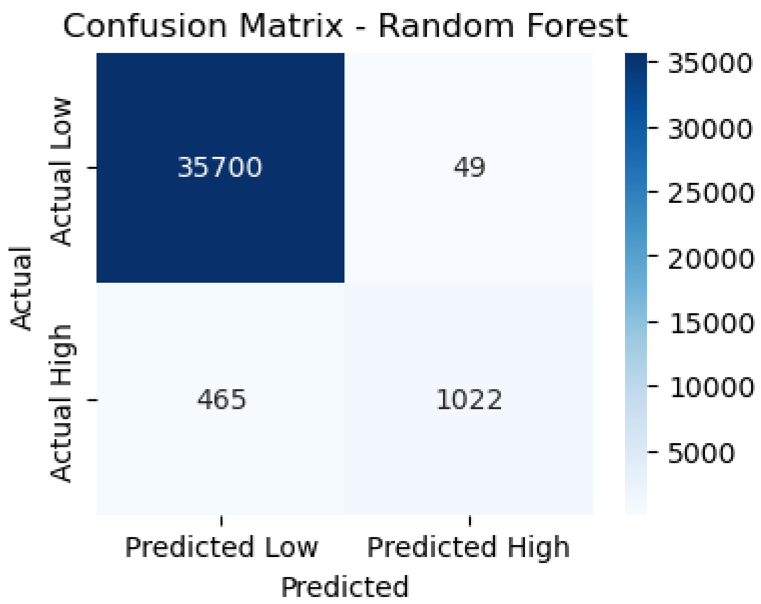
In [ ]:
```
rf_model = RandomForestClassifier()
rf_model.fit(X_train, y_train)
rf_y_pred = rf_model.predict(X_valid)
rf_accuracy = accuracy_score(y_valid, rf_y_pred)
print("Accuracy: " + str(rf_accuracy))

rf_auc = roc_auc_score(y_valid, rf_y_pred)
print("AUC: " + str(rf_auc))
```

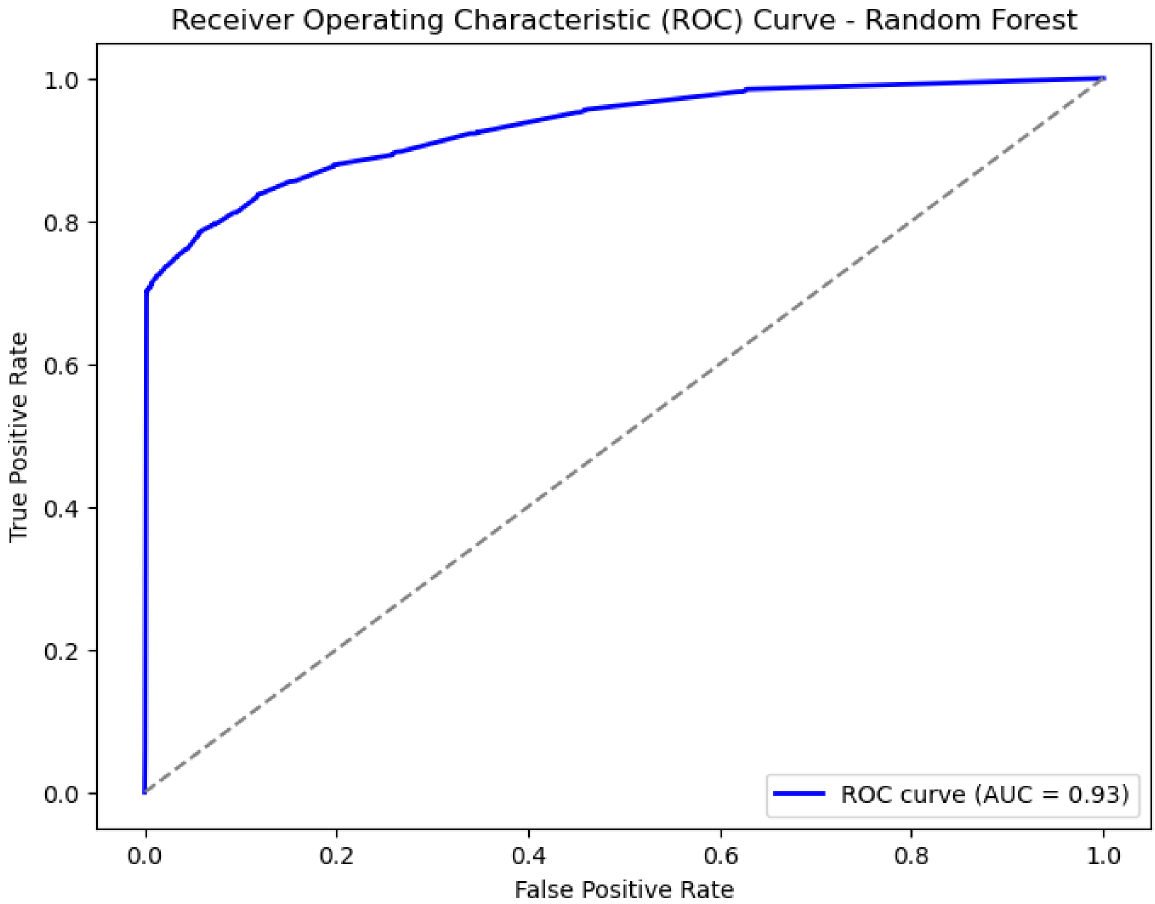
```
Accuracy: 0.986196154259319
AUC: 0.8429595888075875
```

In [ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, re

accuracy = accuracy_score(y_valid, rf_y_pred)
conf_matrix = confusion_matrix(y_valid, rf_y_pred)
precision = precision_score(y_valid, rf_y_pred, average='weighted')
recall = recall_score(y_valid, rf_y_pred, average='weighted')
f1 = f1_score(y_valid, rf_y_pred, average='weighted')

tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)

print("Confusion Matrix:")
print(conf_matrix)
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F-measure: {f1:.2f}")
print(f"Specificity: {specificity:.2f}")
```

```
plt.figure(figsize=(4, 3))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Low', 'Predicted High'],
            yticklabels=['Actual Low', 'Actual High'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Random Forest')
plt.show()

rf_y_pred_proba = rf_model.predict_proba(X_valid)[:, 1]

fpr, tpr, thresholds = roc_curve(y_valid, rf_y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve - Random Forest')
plt.legend(loc='lower right')
plt.show()
```

```
Confusion Matrix:
[[35700    49]
 [  465  1022]]
Accuracy: 0.99
Precision: 0.99
Recall: 0.99
F-measure: 0.99
Specificity: 1.00
```





Model 4: K-Nearest Neighbors Classifier

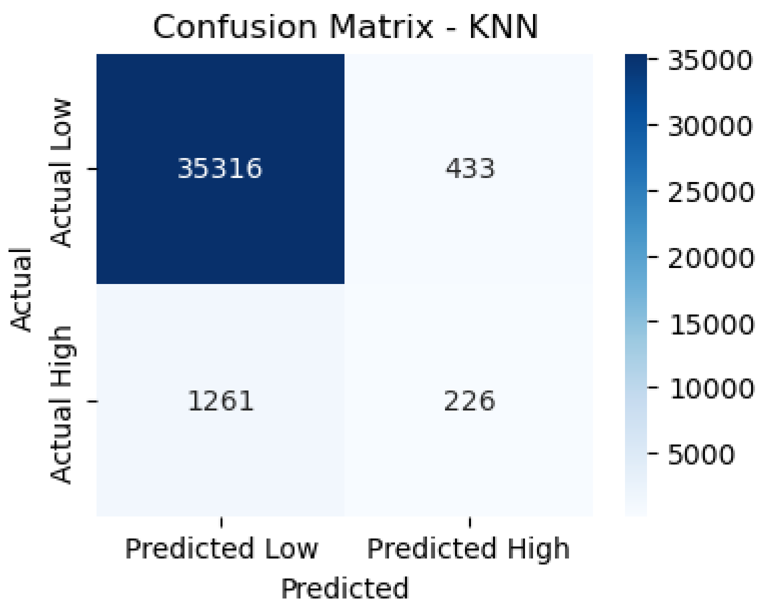
In [ ]:
```
knn_model = KNeighborsClassifier()
knn_model.fit(X_train, y_train)
knn_y_pred = knn_model.predict(X_valid)
knn_accuracy = accuracy_score(y_valid, knn_y_pred)
print("Accuracy: " + str(knn_accuracy))

knn_auc = roc_auc_score(y_valid, knn_y_pred)
print("AUC: " + str(knn_auc))
```

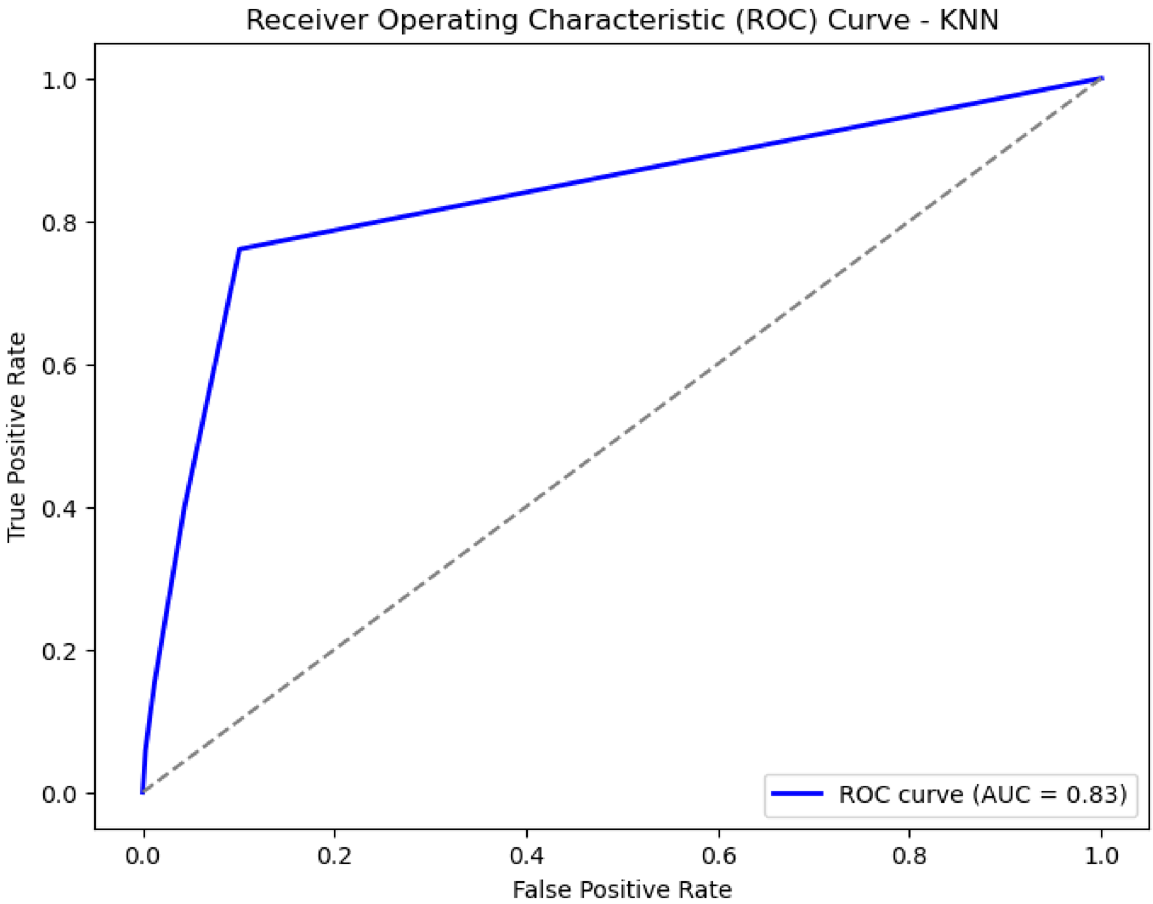
```
Accuracy: 0.9545063916639811
AUC: 0.5699358166028053
```

In [ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, re
import matplotlib.pyplot as plt
import seaborn as sns

accuracy = accuracy_score(y_valid, knn_y_pred)
conf_matrix = confusion_matrix(y_valid, knn_y_pred)
precision = precision_score(y_valid, knn_y_pred, average='weighted')
recall = recall_score(y_valid, knn_y_pred, average='weighted')
f1 = f1_score(y_valid, knn_y_pred, average='weighted')

tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)

print("Confusion Matrix:")
print(conf_matrix)
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
```

```python
print(f"F-measure: {f1:.2f}")
print(f"Specificity: {specificity:.2f}")

plt.figure(figsize=(4, 3))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Low', 'Predicted High'],
            yticklabels=['Actual Low', 'Actual High'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - KNN')
plt.show()

knn_y_pred_proba = knn_model.predict_proba(X_valid)[:, 1]

fpr, tpr, thresholds = roc_curve(y_valid, knn_y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve - KNN')
plt.legend(loc='lower right')
plt.show()
```

```
Confusion Matrix:
[[35316   433]
 [ 1261   226]]
Accuracy: 0.95
Precision: 0.94
Recall: 0.95
F-measure: 0.95
Specificity: 0.99
```





Model 5: SVM with Linear Kernel

Since linear SVM is O(n^3), and the training dataset is large, it would take a lot of operations to train the model. Therefore we will only use 10000 datapoints total.

In [ ]:
```
svm_train = training.sample(10000)
svm_X_train = svm_train[song_features]
svm_y_train = svm_train['popularity']
svm_X_test = song_data.drop(svm_train.index)[song_features]
svm_X_train, X_valid_LSVC, svm_y_train, svm_y_valid = train_test_split(svm_X_trai
```

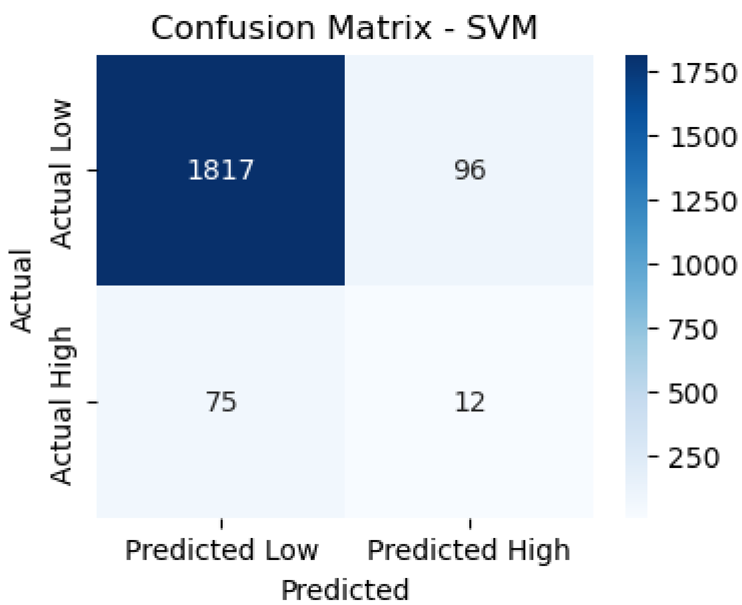
In [ ]:
```
svm_model = DecisionTreeClassifier()
svm_model.fit(svm_X_train, svm_y_train)
svm_y_pred = svm_model.predict(X_valid_LSVC)
svm_accuracy = accuracy_score(svm_y_valid, svm_y_pred)
print("Accuracy: " + str(svm_accuracy))

svm_auc = roc_auc_score(svm_y_valid, svm_y_pred)
print("AUC: " + str(svm_auc))
```

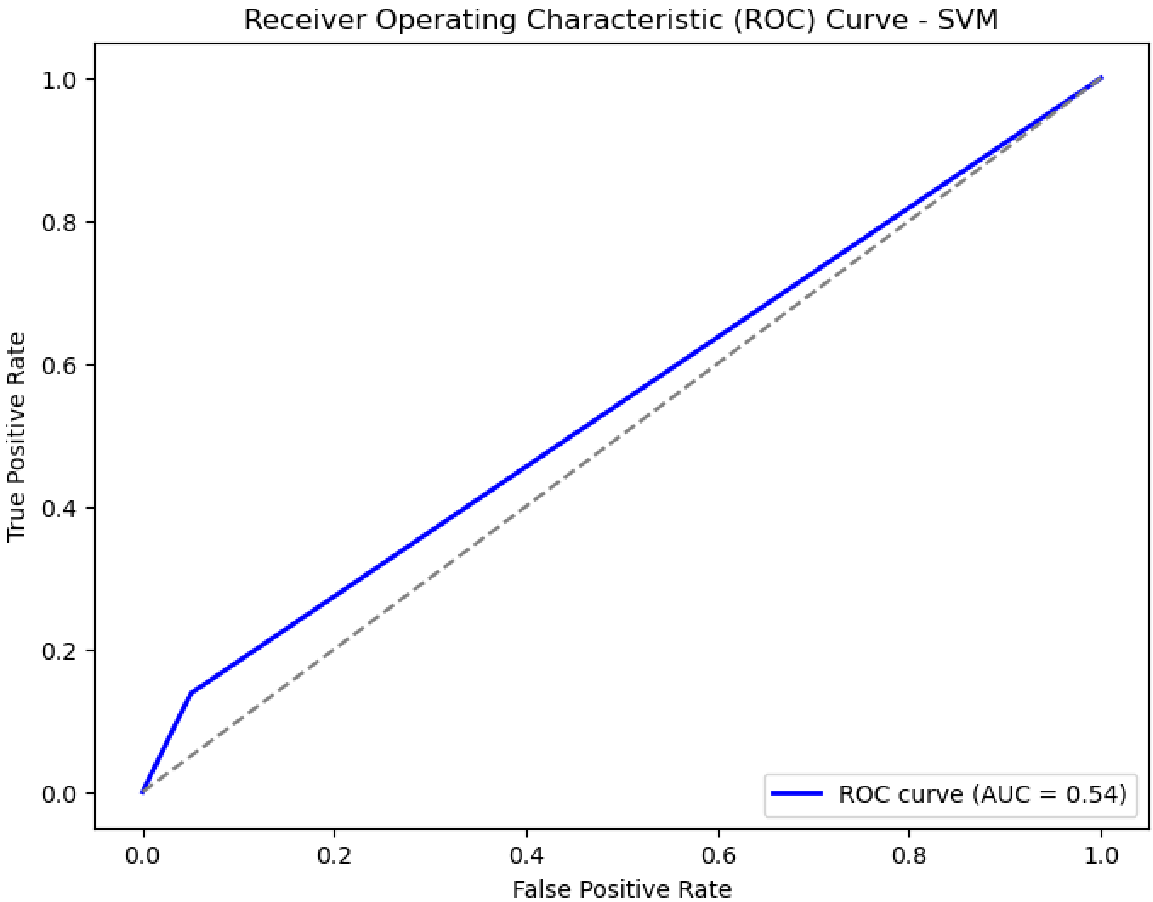
```
Accuracy: 0.9145
AUC: 0.5438740378895759
```

In [ ]:
```
accuracy = accuracy_score(svm_y_valid, svm_y_pred)
conf_matrix = confusion_matrix(svm_y_valid, svm_y_pred)
precision = precision_score(svm_y_valid, svm_y_pred, average='weighted')
recall = recall_score(svm_y_valid, svm_y_pred, average='weighted')
f1 = f1_score(svm_y_valid, svm_y_pred, average='weighted')

tn, fp, fn, tp = conf_matrix.ravel()
specificity = tn / (tn + fp)
```

```python
print("Confusion Matrix:")
print(conf_matrix)
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F-measure: {f1:.2f}")
print(f"Specificity: {specificity:.2f}")

plt.figure(figsize=(4, 3))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Low', 'Predicted High'],
            yticklabels=['Actual Low', 'Actual High'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - SVM')
plt.show()

svm_y_pred_proba = svm_model.predict_proba(X_valid_LSVC)[:, 1]

fpr, tpr, thresholds = roc_curve(svm_y_valid, svm_y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve - SVM')
plt.legend(loc='lower right')
plt.show()
```

```
Confusion Matrix:
[[1817   96]
 [  75   12]]
Accuracy: 0.91
Precision: 0.92
Recall: 0.91
F-measure: 0.92
Specificity: 0.95
```





Model 6: Feedforward Neural Network

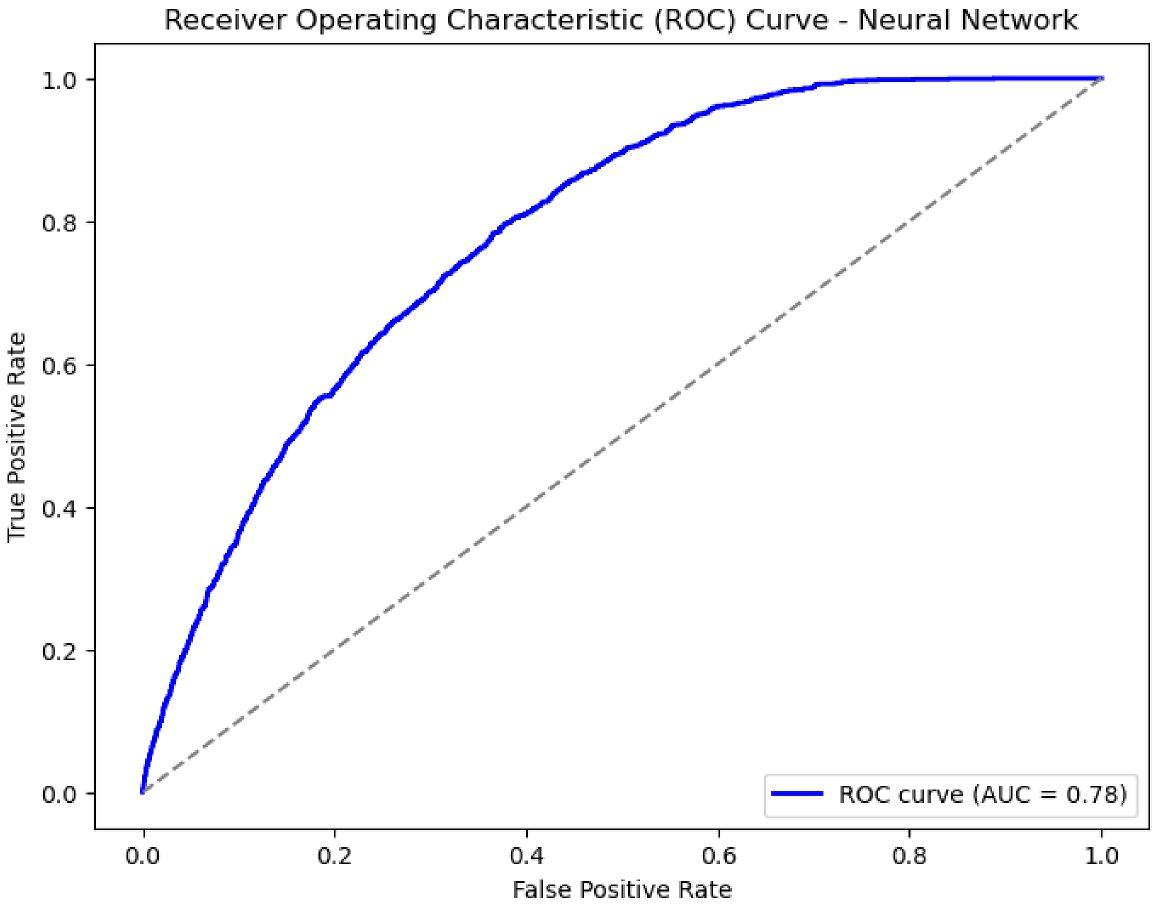
In [ ]:
```
nn_model = Sequential()

nn_model.add(Dense(64, activation='relu', input_shape=(X_train.shape[1],)))
nn_model.add(Dense(32, activation='relu'))
nn_model.add(Dense(1, activation='sigmoid'))

nn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy

nn_model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_valid

eval_metrics = nn_model.evaluate(X_valid, y_valid)
print(f"Accuracy: {eval_metrics[1]}")

nn_y_pred = nn_model.predict(X_valid)

nn_auc = roc_auc_score(y_valid, nn_y_pred)
print(f"AUC: {nn_auc}")
```

```
Epoch 1/10
4655/4655 [==============================] - 12s 2ms/step - loss: 0.1495 - accura
cy: 0.9611 - val_loss: 0.1495 - val_accuracy: 0.9601
Epoch 2/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1453 - accura
cy: 0.9615 - val_loss: 0.1489 - val_accuracy: 0.9601
Epoch 3/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1441 - accura
cy: 0.9615 - val_loss: 0.1488 - val_accuracy: 0.9601
Epoch 4/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1436 - accura
cy: 0.9616 - val_loss: 0.1479 - val_accuracy: 0.9601
Epoch 5/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1428 - accura
cy: 0.9616 - val_loss: 0.1488 - val_accuracy: 0.9601
Epoch 6/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1422 - accura
cy: 0.9616 - val_loss: 0.1485 - val_accuracy: 0.9601
Epoch 7/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1416 - accura
cy: 0.9616 - val_loss: 0.1500 - val_accuracy: 0.9601
Epoch 8/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1409 - accura
cy: 0.9616 - val_loss: 0.1469 - val_accuracy: 0.9600
Epoch 9/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1404 - accura
cy: 0.9616 - val_loss: 0.1466 - val_accuracy: 0.9601
Epoch 10/10
4655/4655 [==============================] - 11s 2ms/step - loss: 0.1398 - accura
cy: 0.9616 - val_loss: 0.1459 - val_accuracy: 0.9600
1164/1164 [==============================] - 2s 2ms/step - loss: 0.1459 - accurac
y: 0.9600
Accuracy: 0.9600118398666382
1164/1164 [==============================] - 2s 2ms/step
AUC: 0.7837994838216982
```

In [ ]:

```python
nn_y_pred_proba = nn_model.predict(X_valid)

fpr, tpr, thresholds = roc_curve(y_valid, nn_y_pred_proba)
nn_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (AUC = %0.2f)' % nn_auc)
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve - Neural Network')
plt.legend(loc='lower right')
plt.show()
```

```
   1/1164 [..............................] - ETA: 44s1164/1164 [=================
=============] - 1s 1ms/step
```



Model Performance

In [ ]:
```
model_performance_accuracy = pd.DataFrame({
    'Model': ['LogisticRegression', 'RandomForestClassifier', 'KNeighborsClassifi
    'Accuracy': [lr_accuracy, rf_accuracy, knn_accuracy, dt_accuracy, svm_accurac
})

model_performance_AUC = pd.DataFrame({
    'Model': ['LogisticRegression', 'RandomForestClassifier', 'KNeighborsClassifi
    'AUC': [lr_auc, rf_auc, knn_auc, dt_auc, svm_auc]
})
```

In [ ]:
```
model_performance_accuracy.sort_values(by = "Accuracy", ascending = False)
```

Out[ ]:

	Model	Accuracy
1	RandomForestClassifier	0.986196
3	DecisionTreeClassifier	0.967182
0	LogisticRegression	0.960066
2	KNeighborsClassifier	0.954506
4	LinearSVC	0.914500

In [ ]:
```
model_performance_AUC.sort_values(by = "AUC", ascending = False)
```

Out[ ]:

	Model	AUC
3	DecisionTreeClassifier	0.843047
1	RandomForestClassifier	0.842960
2	KNeighborsClassifier	0.569936
4	LinearSVC	0.543874
0	LogisticRegression	0.500000

Results - We looked at data from songs on Spotify. We used details like the music's key, mood, and dance style to guess how popular a song might be (if it's rated higher than 70 out of 100) and didn't rely on things like the artist's name, music type, or when the song was released. - The best method we used was the Random Forest Classifier. It guessed accurately about 98 out of 100 times and scored about 84 out of 100 when measuring its performance. The next best method was the Decision Tree Classifier. It got it right about 96 out of 100 times and scored around 84 out of 100 in its performance.

References: 1. Halilovic, I. (2021, July 30). Markdown for Jupyter notebooks cheatsheet - Inge Halilovic - Medium. Medium. https://ingeh.medium.com/markdown-for-jupyter-notebooks-cheatsheet-386c05aeebed 2. Scribbr. (2021, July 30). Free APA citation Generator | with Chrome Extension - Scribbr. https://www.scribbr.com/citation/generator/apa/ 3. Zach. (2023). How to create a distribution plot in Matplotlib. Statology. https://www.statology.org/matplotlib-distribution-plot/ 4. seaborn.displot — seaborn 0.12.2 documentation. (n.d.). https://seaborn.pydata.org/generated/seaborn.displot.html 5. Lau, C. H. (2021, December 7). 5 steps of a Data Science Project Lifecycle - towards Data Science. Medium. https://towardsdatascience.com/5-steps-of-a-data-science-project-lifecycle-26c50372b492 6. Are hit songs becoming less musically diverse? (n.d.). The Pudding. https://pudding.cool/2018/05/similarity/ 7. Nasreldin, M. (2018, July 2). Song Popularity Predictor - towards Data science. Medium. https://towardsdatascience.com/song-popularity-predictor-1ef69735e380 8. Seaborn.Heatmap — seaborn 0.13.0 documentation. (n.d.). Pydata.org. Retrieved October 3, 2023. https://seaborn.pydata.org/generated/seaborn.heatmap.html 9. IBM documentation. (2021, April 8). Ibm.com. https://www.ibm.com/docs/en/watson-studio-local/1.2.3?topic=notebooksmarkdown-jupyter-cheatsheet 10. Spotify Tracks DB. (2019, July 23). Kaggle. https://www.kaggle.com/zaheenhamidani/ultimate-spotify-tracks-db#SpotifyFeatures.csv