

Project_4:Music_Popularity_Prediction_v3

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1 Project 4: Music Popularity Prediction V3

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2 Introduction

Welcome to my project on Music Popularity Prediction. In this analysis, I've developed predictive models to forecast song popularity on Spotify's Top 200 Weekly (Global) charts for 2020 & 2021. This project aims to provide insights into the factors that contribute to a song's success on these charts.

3 Project Overview

My goal was to create supervised regression models that could predict a song's popularity score based on various features. I've used a dataset provided by DDC Data Science, which includes information about songs, their audio features, artist popularity, and other relevant characteristics.

The [data](#). A chosen data set is provided by DDC Data Science

4 Imports

```
[2]: import sys
      print(sys.executable)
```

/usr/local/bin/python

```
[3]: import pandas as pd
      import numpy as np
      import matplotlib.pyplot as plt
      import matplotlib.colors as mcolors
      import seaborn as sns

      from sklearn.preprocessing import StandardScaler
      from sklearn.preprocessing import MinMaxScaler
      from sklearn.model_selection import cross_val_score
      from sklearn.model_selection import train_test_split
      from sklearn.linear_model import LinearRegression
```

```

from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb

from sklearn.metrics import mean_squared_error, root_mean_squared_error, r2_score

```

```

[4]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
#n_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb

from sklearn.metrics import mean_squared_error, root_mean_squared_error, r2_score

```

```

[5]: %%capture
url = "https://ddc-datascience.s3.amazonaws.com/Projects/Project.4-Spotify/Data/
↳ Spotify.csv"
!curl -s -I {url}

```

5 Data Exploration

```

[6]: df_1 = pd.read_csv(url).copy()

```

5.1 Head

```

[7]: df_1.head()

```

```

[7]:   Index  Highest Charting Position  Number of Times Charted \
0      1                             1                          8
1      2                             2                          3
2      3                             1                         11
3      4                             3                          5
4      5                             5                          1

      Week of Highest Charting      Song Name      Streams \
0  2021-07-23--2021-07-30      Beggin'  48,633,449
1  2021-07-23--2021-07-30  STAY (with Justin Bieber)  47,248,719
2  2021-06-25--2021-07-02      good 4 u  40,162,559
3  2021-07-02--2021-07-09      Bad Habits  37,799,456
4  2021-07-23--2021-07-30  INDUSTRY BABY (feat. Jack Harlow)  33,948,454

      Artist Artist Followers      Song ID \

```

0	Måneskin	3377762	3Wrjm47oTz2sjIgck1115e
1	The Kid LAROI	2230022	5HCyWlXZPP0y6Gqq8TgA20
2	Olivia Rodrigo	6266514	4ZtFanR9U6ndgddUvNcjcG
3	Ed Sheeran	83293380	6PQ88X9TkUIAUIZJHW2upE
4	Lil Nas X	5473565	27NovPIUIRr0ZoCHxABJwK

	Genre	...	Danceability	Energy	Loudness	\
0	['indie rock italiano', 'italian pop']	...	0.714	0.8	-4.808	
1	['australian hip hop']	...	0.591	0.764	-5.484	
2	['pop']	...	0.563	0.664	-5.044	
3	['pop', 'uk pop']	...	0.808	0.897	-3.712	
4	['lgbtq+ hip hop', 'pop rap']	...	0.736	0.704	-7.409	

	Speechiness	Acousticness	Liveness	Tempo	Duration (ms)	Valence	Chord
0	0.0504	0.127	0.359	134.002	211560	0.589	B
1	0.0483	0.0383	0.103	169.928	141806	0.478	C#/Db
2	0.154	0.335	0.0849	166.928	178147	0.688	A
3	0.0348	0.0469	0.364	126.026	231041	0.591	B
4	0.0615	0.0203	0.0501	149.995	212000	0.894	D#/Eb

[5 rows x 23 columns]

5.2 Tail

5.3 Shape

```
[8]: df_1.shape
```

```
[8]: (1556, 23)
```

5.4 columns

```
[ ]: df_1.columnsColab_Notebooks/Module-4/Project/Project.4-Spotify/Project_4:
      ↪Music_Popularity_Prediction.ipynb
```

```
[ ]: Index(['Index', 'Highest Charting Position', 'Number of Times Charted',
          'Week of Highest Charting', 'Song Name', 'Streams', 'Artist',
          'Artist Followers', 'Song ID', 'Genre', 'Release Date', 'Weeks Charted',
          'Popularity', 'Danceability', 'Energy', 'Loudness', 'Speechiness',
          'Acousticness', 'Liveness', 'Tempo', 'Duration (ms)', 'Valence',
          'Chord'],
          dtype='object')
```

5.5 Dtypes

```
[10]: df_1.dtypes
```

```
[10]: Index                                int64
      Highest Charting Position          int64
      Number of Times Charted           int64
      Week of Highest Charting          object
      Song Name                         object
      Streams                          object
      Artist                           object
      Artist Followers                  object
      Song ID                           object
      Genre                            object
      Release Date                      object
      Weeks Charted                     object
      Popularity                        object
      Danceability                      object
      Energy                           object
      Loudness                          object
      Speechiness                       object
      Acousticness                      object
      Liveness                          object
      Tempo                             object
      Duration (ms)                    object
      Valence                           object
      Chord                             object
      dtype: object
```

5.6 Describe

```
[11]: df_1.describe()
```

```
[11]:
```

	Index	Highest Charting Position	Number of Times Charted
count	1556.000000	1556.000000	1556.000000
mean	778.500000	87.744216	10.668380
std	449.322824	58.147225	16.360546
min	1.000000	1.000000	1.000000
25%	389.750000	37.000000	1.000000
50%	778.500000	80.000000	4.000000
75%	1167.250000	137.000000	12.000000
max	1556.000000	200.000000	142.000000

5.7 Isnull Sum

```
[12]: df_1.isnull().sum()
```

```
[12]: Index                                0
      Highest Charting Position          0
      Number of Times Charted           0
      Week of Highest Charting          0
```

Song Name	0
Streams	0
Artist	0
Artist Followers	0
Song ID	0
Genre	0
Release Date	0
Weeks Charted	0
Popularity	0
Danceability	0
Energy	0
Loudness	0
Speechiness	0
Acousticness	0
Liveness	0
Tempo	0
Duration (ms)	0
Valence	0
Chord	0
dtype: int64	

5.8 Isna Sum

```
[13]: df_1.isna().sum()
```

```
[13]: Index                                0
      Highest Charting Position          0
      Number of Times Charted           0
      Week of Highest Charting           0
      Song Name                          0
      Streams                           0
      Artist                             0
      Artist Followers                   0
      Song ID                           0
      Genre                             0
      Release Date                       0
      Weeks Charted                      0
      Popularity                         0
      Danceability                       0
      Energy                             0
      Loudness                           0
      Speechiness                        0
      Acousticness                       0
      Liveness                           0
      Tempo                              0
      Duration (ms)                     0
      Valence                            0
```

```
Chord                                0
dtype: int64
```

5.9 unique values

```
[14]: df_1.count('rows').unique().sum()
```

```
[14]: np.int64(1556)
```

```
[15]: df_1.count('columns')
```

```
[15]: 0      23
      1      23
      2      23
      3      23
      4      23
      ..
     1551    23
     1552    23
     1553    23
     1554    23
     1555    23
      Length: 1556, dtype: int64
```

5.10 Sort_values

```
[16]: df_1.sort_values(by = ['Popularity'], ascending = False).head(10)
```

```
[16]:
```

	Index	Highest Charting Position	Number of Times Charted \
1	2	2	3
2	3	1	11
3	4	3	5
5	6	1	18
4	5	5	1
8	9	3	8
14	15	2	10
7	8	2	10
9	10	8	10
11	12	9	9

	Week of Highest Charting	Song Name	Streams \
1	2021-07-23--2021-07-30	STAY (with Justin Bieber)	47,248,719
2	2021-06-25--2021-07-02	good 4 u	40,162,559
3	2021-07-02--2021-07-09	Bad Habits	37,799,456
5	2021-05-07--2021-05-14	MONTERO (Call Me By Your Name)	30,071,134
4	2021-07-23--2021-07-30	INDUSTRY BABY (feat. Jack Harlow)	33,948,454
8	2021-06-18--2021-06-25	Yonaguni	25,030,128

14	2021-05-21--2021-05-28	Butter	19,985,713
7	2021-06-18--2021-06-25	Todo De Ti	26,951,613
9	2021-07-02--2021-07-09	I WANNA BE YOUR SLAVE	24,551,591
11	2021-07-02--2021-07-09	Qué Más Pues?	22,405,111

	Artist	Artist Followers	Song ID \
1	The Kid LAROI	2230022	5HCyWlXZPP0y6Gqq8TgA20
2	Olivia Rodrigo	6266514	4ZtFanR9U6ndgddUvNcjcG
3	Ed Sheeran	83293380	6PQ88X9TkUIAUIZJHW2upE
5	Lil Nas X	5473565	67BtfxlNbhBmCDR2L2l8qd
4	Lil Nas X	5473565	27NovPIUIRr0ZoCHxABJwK
8	Bad Bunny	36142273	2JPLbjOn0wPCngEot2STUS
14	BTS	37106176	2bgTY4UwhfBYhGT4HUYStN
7	Rauw Alejandro	6080597	4fSIb4hd0Q151TILNsSEaF
9	Måneskin	3377762	4pt5fDVTg5GhEvEtlz9dKk
11	J Balvin, Maria Becerra	29051363	6hf0RpxTb0prT5nnwzkk8e

	Genre	...	Danceability	Energy	\
1	['australian hip hop']	...	0.591	0.764	
2	['pop']	...	0.563	0.664	
3	['pop', 'uk pop']	...	0.808	0.897	
5	['lgbtq+ hip hop', 'pop rap']	...	0.61	0.508	
4	['lgbtq+ hip hop', 'pop rap']	...	0.736	0.704	
8	['latin', 'reggaeton', 'trap latino']	...	0.644	0.648	
14	['k-pop', 'k-pop boy group']	...	0.759	0.459	
7	['puerto rican pop', 'trap latino']	...	0.78	0.718	
9	['indie rock italiano', 'italian pop']	...	0.75	0.608	
11	['latin', 'reggaeton', 'reggaeton colombiano']	...	0.891	0.819	

	Loudness	Speechiness	Acousticness	Liveness	Tempo	Duration (ms)	Valence	\
1	-5.484	0.0483	0.0383	0.103	169.928	141806	0.478	
2	-5.044	0.154	0.335	0.0849	166.928	178147	0.688	
3	-3.712	0.0348	0.0469	0.364	126.026	231041	0.591	
5	-6.682	0.152	0.297	0.384	178.818	137876	0.758	
4	-7.409	0.0615	0.0203	0.0501	149.995	212000	0.894	
8	-4.601	0.118	0.276	0.135	179.951	206710	0.44	
14	-5.187	0.0948	0.00323	0.0906	109.997	164442	0.695	
7	-3.605	0.0506	0.31	0.0932	127.949	199604	0.342	
9	-4.008	0.0387	0.00165	0.178	132.507	173347	0.958	
11	-3.964	0.106	0.0261	0.173	101.968	217773	0.768	

	Chord
1	C#/Db
2	A
3	B
5	G#/Ab
4	D#/Eb

```

8    C#/Db
14   G#/Ab
7    D#/Eb
9    C#/Db
11   G#/Ab

```

```
[10 rows x 23 columns]
```

6 Data Cleaning and Feature Engineering

6.1 New copy of dataframe

```
[17]: df_cleaning = df_1.copy()
df_cleaning
```

```
[17]:
```

	Index	Highest Charting Position	Number of Times Charted	\
0	1	1	8	
1	2	2	3	
2	3	1	11	
3	4	3	5	
4	5	5	1	
...	
1551	1552	195	1	
1552	1553	196	1	
1553	1554	197	1	
1554	1555	198	1	
1555	1556	199	1	

	Week of Highest Charting	Song Name	Streams	\
0	2021-07-23--2021-07-30	Beggin'	48,633,449	
1	2021-07-23--2021-07-30	STAY (with Justin Bieber)	47,248,719	
2	2021-06-25--2021-07-02	good 4 u	40,162,559	
3	2021-07-02--2021-07-09	Bad Habits	37,799,456	
4	2021-07-23--2021-07-30	INDUSTRY BABY (feat. Jack Harlow)	33,948,454	
...	
1551	2019-12-27--2020-01-03	New Rules	4,630,675	
1552	2019-12-27--2020-01-03	Cheirosa - Ao Vivo	4,623,030	
1553	2019-12-27--2020-01-03	Havana (feat. Young Thug)	4,620,876	
1554	2019-12-27--2020-01-03	Surtada - Remix Brega Funk	4,607,385	
1555	2019-12-27--2020-01-03	Lover (Remix) [feat. Shawn Mendes]	4,595,450	

	Artist	Artist Followers	Song ID	\
0	Måneskin	3377762	3Wrjm47oTz2sjIgck1115e	
1	The Kid LAROI	2230022	5HCyWlXZPP0y6Gqq8TgA20	
2	Olivia Rodrigo	6266514	4ZtFanR9U6ndgddUvNcjG	
3	Ed Sheeran	83293380	6PQ88X9TkUIAUIZJHW2upE	
4	Lil Nas X	5473565	27NovPIUIRrOZOCHxABJwK	

...
1551	Dua Lipa	27167675	2ekn2ttSfGqwhhate0LSR0
1552	Jorge & Mateus	15019109	2PWjKmJyTZeDpmOUa3a5da
1553	Camila Cabello	22698747	1rf0faqEpACxVEHIZBJe6W
1554	Dadá Boladão, Tati Zaqui, OIK	208630	5F8ffc8KWKNAwllr5WsW0r
1555	Taylor Swift	42227614	3i9UVldZOE0aD0JnyfAZZ0

	Genre	...	Danceability	\
0	['indie rock italiano', 'italian pop']	...	0.714	
1	['australian hip hop']	...	0.591	
2	['pop']	...	0.563	
3	['pop', 'uk pop']	...	0.808	
4	['lgbtq+ hip hop', 'pop rap']	...	0.736	
...	
1551	['dance pop', 'pop', 'uk pop']	...	0.762	
1552	['sertanejo', 'sertanejo universitario']	...	0.528	
1553	['dance pop', 'electropop', 'pop', 'post-teen	0.765	
1554	['brega funk', 'funk carioca']	...	0.832	
1555	['pop', 'post-teen pop']	...	0.448	

	Energy	Loudness	Speechiness	Acousticness	Liveness	Tempo	Duration (ms)	\
0	0.8	-4.808	0.0504	0.127	0.359	134.002	211560	
1	0.764	-5.484	0.0483	0.0383	0.103	169.928	141806	
2	0.664	-5.044	0.154	0.335	0.0849	166.928	178147	
3	0.897	-3.712	0.0348	0.0469	0.364	126.026	231041	
4	0.704	-7.409	0.0615	0.0203	0.0501	149.995	212000	
...	
1551	0.7	-6.021	0.0694	0.00261	0.153	116.073	209320	
1552	0.87	-3.123	0.0851	0.24	0.333	152.37	181930	
1553	0.523	-4.333	0.03	0.184	0.132	104.988	217307	
1554	0.55	-7.026	0.0587	0.249	0.182	154.064	152784	
1555	0.603	-7.176	0.064	0.433	0.0862	205.272	221307	

	Valence	Chord
0	0.589	B
1	0.478	C#/Db
2	0.688	A
3	0.591	B
4	0.894	D#/Eb
...
1551	0.608	A
1552	0.714	B
1553	0.394	D
1554	0.881	F
1555	0.422	G

[1556 rows x 23 columns]

6.2 drop Index

```
[18]: df_cleaning.drop('Index', axis = 1, inplace = True)
      #i
```

```
[19]: df_cleaning.transpose()
```

```
[19]:
```

	0	\
Highest Charting Position	1	
Number of Times Charted	8	
Week of Highest Charting	2021-07-23--2021-07-30	
Song Name	Beggin'	
Streams	48,633,449	
Artist	Måneskin	
Artist Followers	3377762	
Song ID	3Wrjm47oTz2sjIgck11l5e	
Genre	['indie rock italiano', 'italian pop']	
Release Date	2017-12-08	
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...	
Popularity	100	
Danceability	0.714	
Energy	0.8	
Loudness	-4.808	
Speechiness	0.0504	
Acousticness	0.127	
Liveness	0.359	
Tempo	134.002	
Duration (ms)	211560	
Valence	0.589	
Chord	B	
	1	\
Highest Charting Position	2	
Number of Times Charted	3	
Week of Highest Charting	2021-07-23--2021-07-30	
Song Name	STAY (with Justin Bieber)	
Streams	47,248,719	
Artist	The Kid LAROI	
Artist Followers	2230022	
Song ID	5HCyWlXZPP0y6Gqq8TgA20	
Genre	['australian hip hop']	
Release Date	2021-07-09	
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...	
Popularity	99	
Danceability	0.591	
Energy	0.764	
Loudness	-5.484	

Speechiness	0.0483
Acousticness	0.0383
Liveness	0.103
Tempo	169.928
Duration (ms)	141806
Valence	0.478
Chord	C#/Db

2 \

Highest Charting Position	1
Number of Times Charted	11
Week of Highest Charting	2021-06-25--2021-07-02
Song Name	good 4 u
Streams	40,162,559
Artist	Olivia Rodrigo
Artist Followers	6266514
Song ID	4ZtFanR9U6ndgddUvNcjcG
Genre	['pop']
Release Date	2021-05-21
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...
Popularity	99
Danceability	0.563
Energy	0.664
Loudness	-5.044
Speechiness	0.154
Acousticness	0.335
Liveness	0.0849
Tempo	166.928
Duration (ms)	178147
Valence	0.688
Chord	A

3 \

Highest Charting Position	3
Number of Times Charted	5
Week of Highest Charting	2021-07-02--2021-07-09
Song Name	Bad Habits
Streams	37,799,456
Artist	Ed Sheeran
Artist Followers	83293380
Song ID	6PQ88X9TkUIAUIZJHW2upE
Genre	['pop', 'uk pop']
Release Date	2021-06-25
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...
Popularity	98
Danceability	0.808
Energy	0.897

Loudness	-3.712
Speechiness	0.0348
Acousticness	0.0469
Liveness	0.364
Tempo	126.026
Duration (ms)	231041
Valence	0.591
Chord	B

	4	\
Highest Charting Position	5	
Number of Times Charted	1	
Week of Highest Charting	2021-07-23--2021-07-30	
Song Name	INDUSTRY BABY (feat. Jack Harlow)	
Streams	33,948,454	
Artist	Lil Nas X	
Artist Followers	5473565	
Song ID	27NovPIUIRr0ZoCHxABJwK	
Genre	['lgbtq+ hip hop', 'pop rap']	
Release Date	2021-07-23	
Weeks Charted	2021-07-23--2021-07-30	
Popularity	96	
Danceability	0.736	
Energy	0.704	
Loudness	-7.409	
Speechiness	0.0615	
Acousticness	0.0203	
Liveness	0.0501	
Tempo	149.995	
Duration (ms)	212000	
Valence	0.894	
Chord	D#/Eb	

	5	\
Highest Charting Position	1	
Number of Times Charted	18	
Week of Highest Charting	2021-05-07--2021-05-14	
Song Name	MONTERO (Call Me By Your Name)	
Streams	30,071,134	
Artist	Lil Nas X	
Artist Followers	5473565	
Song ID	67BtfxlNbhBmCDR2L2l8qd	
Genre	['lgbtq+ hip hop', 'pop rap']	
Release Date	2021-03-31	
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...	
Popularity	97	
Danceability	0.61	

Energy	0.508
Loudness	-6.682
Speechiness	0.152
Acousticness	0.297
Liveness	0.384
Tempo	178.818
Duration (ms)	137876
Valence	0.758
Chord	G#/Ab

	6	\
Highest Charting Position	3	
Number of Times Charted	16	
Week of Highest Charting	2021-05-14--2021-05-21	
Song Name	Kiss Me More (feat. SZA)	
Streams	29,356,736	
Artist	Doja Cat	
Artist Followers	8640063	
Song ID	748mdHapucXQri7IA08yFK	
Genre	['dance pop', 'pop']	
Release Date	2021-04-09	
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...	
Popularity	94	
Danceability	0.762	
Energy	0.701	
Loudness	-3.541	
Speechiness	0.0286	
Acousticness	0.235	
Liveness	0.123	
Tempo	110.968	
Duration (ms)	208867	
Valence	0.742	
Chord	G#/Ab	

	7	\
Highest Charting Position	2	
Number of Times Charted	10	
Week of Highest Charting	2021-06-18--2021-06-25	
Song Name	Todo De Ti	
Streams	26,951,613	
Artist	Rauw Alejandro	
Artist Followers	6080597	
Song ID	4fSIb4hd0Q151TILNsSEaF	
Genre	['puerto rican pop', 'trap latino']	
Release Date	2021-05-20	
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...	
Popularity	95	

Danceability	0.78
Energy	0.718
Loudness	-3.605
Speechiness	0.0506
Acousticness	0.31
Liveness	0.0932
Tempo	127.949
Duration (ms)	199604
Valence	0.342
Chord	D#/Eb

8 \

Highest Charting Position	3
Number of Times Charted	8
Week of Highest Charting	2021-06-18--2021-06-25
Song Name	Yonaguni
Streams	25,030,128
Artist	Bad Bunny
Artist Followers	36142273
Song ID	2JPLbj0n0wPCngEot2STUS
Genre	['latin', 'reggaeton', 'trap latino']
Release Date	2021-06-04
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...
Popularity	96
Danceability	0.644
Energy	0.648
Loudness	-4.601
Speechiness	0.118
Acousticness	0.276
Liveness	0.135
Tempo	179.951
Duration (ms)	206710
Valence	0.44
Chord	C#/Db

9 \

Highest Charting Position	8
Number of Times Charted	10
Week of Highest Charting	2021-07-02--2021-07-09
Song Name	I WANNA BE YOUR SLAVE
Streams	24,551,591
Artist	Måneskin
Artist Followers	3377762
Song ID	4pt5fDVTg5GhEvEtlz9dKk
Genre	['indie rock italiano', 'italian pop']
Release Date	2021-03-19
Weeks Charted	2021-07-23--2021-07-30\n2021-07-16--2021-07-23...

Popularity	95
Danceability	0.75
Energy	0.608
Loudness	-4.008
Speechiness	0.0387
Acousticness	0.00165
Liveness	0.178
Tempo	132.507
Duration (ms)	173347
Valence	0.958
Chord	C#/Db

	...	1546	\
Highest Charting Position	...	143	
Number of Times Charted	...	1	
Week of Highest Charting	...	2019-12-27--2020-01-03	
Song Name	...	JACKBOYS	
Streams	...	5,363,493	
Artist	...	JACKBOYS	
Artist Followers	...	437907	
Song ID	...	62zKJrpbLxz6InR3tGyr7o	
Genre	...	['rap', 'trap']	
Release Date	...	2019-12-27	
Weeks Charted	...	2019-12-27--2020-01-03	
Popularity	...	56	
Danceability	...	0.413	
Energy	...	0.13	
Loudness	...	-25.166	
Speechiness	...	0.0336	
Acousticness	...	0.9	
Liveness	...	0.111	
Tempo	...	123.342	
Duration (ms)	...	46837	
Valence	...	0.0676	
Chord	...	C	

		1547	\
Highest Charting Position		156	
Number of Times Charted		1	
Week of Highest Charting		2019-12-27--2020-01-03	
Song Name		Combachy (feat. MC Rebecca)	
Streams		5,149,797	
Artist		Anitta, Lexa, Luísa Sonza	
Artist Followers		10741972	
Song ID		2bPtwnrpFNEe8N7Q85kLHw	
Genre		['funk carioca', 'funk pop', 'pagode baiano', ...	
Release Date		2019-11-20	

Weeks Charted	2019-12-27--2020-01-03
Popularity	64
Danceability	0.826
Energy	0.73
Loudness	-3.032
Speechiness	0.0809
Acousticness	0.383
Liveness	0.0197
Tempo	150.134
Duration (ms)	157600
Valence	0.605
Chord	C#/Db

	1548 \
Highest Charting Position	178
Number of Times Charted	1
Week of Highest Charting	2019-12-27--2020-01-03
Song Name	Old Town Road
Streams	4,852,004
Artist	Lil Nas X
Artist Followers	5488666
Song ID	2YpeDb67231RjR0MgVLzsG
Genre	['lgbtq+ hip hop', 'pop rap']
Release Date	2019-06-21
Weeks Charted	2019-12-27--2020-01-03
Popularity	81
Danceability	0.878
Energy	0.619
Loudness	-5.56
Speechiness	0.102
Acousticness	0.0533
Liveness	0.113
Tempo	136.041
Duration (ms)	157067
Valence	0.639
Chord	F#/Gb

	1549 \
Highest Charting Position	187
Number of Times Charted	1
Week of Highest Charting	2019-12-27--2020-01-03
Song Name	Let Me Know (I Wonder Why Freestyle)
Streams	4,701,532
Artist	Juice WRLD
Artist Followers	19102888
Song ID	3ww0bJvDSorOpNfzEkfXx
Genre	['chicago rap', 'melodic rap']

Release Date	2019-12-07
Weeks Charted	2019-12-27--2020-01-03
Popularity	76
Danceability	0.635
Energy	0.537
Loudness	-7.895
Speechiness	0.0832
Acousticness	0.172
Liveness	0.418
Tempo	125.028
Duration (ms)	215381
Valence	0.383
Chord	G

	1550 \
Highest Charting Position	190
Number of Times Charted	1
Week of Highest Charting	2019-12-27--2020-01-03
Song Name	Ne reviens pas
Streams	4,676,857
Artist	Gradur, Heuss L'enfoiré
Artist Followers	1390813
Song ID	4TnFANpjVwVKWzKxNzIyFH
Genre	['francoton', 'french hip hop', 'pop urbaine', ...]
Release Date	2019-11-29
Weeks Charted	2019-12-27--2020-01-03
Popularity	62
Danceability	0.932
Energy	0.778
Loudness	-3.384
Speechiness	0.0638
Acousticness	0.212
Liveness	0.168
Tempo	124.996
Duration (ms)	188613
Valence	0.933
Chord	A#/Bb

	1551 \
Highest Charting Position	195
Number of Times Charted	1
Week of Highest Charting	2019-12-27--2020-01-03
Song Name	New Rules
Streams	4,630,675
Artist	Dua Lipa
Artist Followers	27167675
Song ID	2ekn2ttSfGqwhhate0LSR0

Genre	['dance pop', 'pop', 'uk pop']
Release Date	2017-06-02
Weeks Charted	2019-12-27--2020-01-03
Popularity	79
Danceability	0.762
Energy	0.7
Loudness	-6.021
Speechiness	0.0694
Acousticness	0.00261
Liveness	0.153
Tempo	116.073
Duration (ms)	209320
Valence	0.608
Chord	A

	1552 \
Highest Charting Position	196
Number of Times Charted	1
Week of Highest Charting	2019-12-27--2020-01-03
Song Name	Cheirosa - Ao Vivo
Streams	4,623,030
Artist	Jorge & Mateus
Artist Followers	15019109
Song ID	2PWjKmJyTZeDpmOUa3a5da
Genre	['sertanejo', 'sertanejo universitario']
Release Date	2019-10-11
Weeks Charted	2019-12-27--2020-01-03
Popularity	66
Danceability	0.528
Energy	0.87
Loudness	-3.123
Speechiness	0.0851
Acousticness	0.24
Liveness	0.333
Tempo	152.37
Duration (ms)	181930
Valence	0.714
Chord	B

	1553 \
Highest Charting Position	197
Number of Times Charted	1
Week of Highest Charting	2019-12-27--2020-01-03
Song Name	Havana (feat. Young Thug)
Streams	4,620,876
Artist	Camila Cabello
Artist Followers	22698747

Song ID	1rfofaqEpACxVEHIZBJe6W
Genre	['dance pop', 'electropop', 'pop', 'post-teen ...
Release Date	2018-01-12
Weeks Charted	2019-12-27--2020-01-03
Popularity	81
Danceability	0.765
Energy	0.523
Loudness	-4.333
Speechiness	0.03
Acousticness	0.184
Liveness	0.132
Tempo	104.988
Duration (ms)	217307
Valence	0.394
Chord	D

	1554 \
Highest Charting Position	198
Number of Times Charted	1
Week of Highest Charting	2019-12-27--2020-01-03
Song Name	Surtada - Remix Brega Funk
Streams	4,607,385
Artist	Dadá Boladão, Tati Zaqui, OIK
Artist Followers	208630
Song ID	5F8ffc8KWKNawllr5WsW0r
Genre	['brega funk', 'funk carioca']
Release Date	2019-09-25
Weeks Charted	2019-12-27--2020-01-03
Popularity	60
Danceability	0.832
Energy	0.55
Loudness	-7.026
Speechiness	0.0587
Acousticness	0.249
Liveness	0.182
Tempo	154.064
Duration (ms)	152784
Valence	0.881
Chord	F

	1555
Highest Charting Position	199
Number of Times Charted	1
Week of Highest Charting	2019-12-27--2020-01-03
Song Name	Lover (Remix) [feat. Shawn Mendes]
Streams	4,595,450
Artist	Taylor Swift

Artist Followers	42227614
Song ID	3i9UVldZ0E0aD0JnyfAZZ0
Genre	['pop', 'post-teen pop']
Release Date	2019-11-13
Weeks Charted	2019-12-27--2020-01-03
Popularity	70
Danceability	0.448
Energy	0.603
Loudness	-7.176
Speechiness	0.064
Acousticness	0.433
Liveness	0.0862
Tempo	205.272
Duration (ms)	221307
Valence	0.422
Chord	G

[22 rows x 1556 columns]

6.3 Convert object columns with numbers to float64

```
[20]: # List of columns to convert
columns_to_convert = ['Artist Followers', 'Streams', 'Popularity',
    ↪ 'Danceability', 'Energy', 'Loudness',
    ↪ 'Speechiness', 'Acousticness', 'Liveness', 'Tempo',
    ↪ 'Duration (ms)', 'Valence']

df_1[columns_to_convert] = df_1[columns_to_convert].apply(pd.to_numeric,
    ↪ errors='coerce')
```

```
[21]: df_1.dtypes
```

```
[21]: Index                                int64
Highest Charting Position                int64
Number of Times Charted                  int64
Week of Highest Charting                 object
Song Name                               object
Streams                                 float64
Artist                                  object
Artist Followers                        float64
Song ID                                 object
Genre                                   object
Release Date                           object
Weeks Charted                          object
Popularity                             float64
Danceability                           float64
Energy                                 float64
```

```

Loudness                float64
Speechiness              float64
Acousticness             float64
Liveness                 float64
Tempo                    float64
Duration (ms)            float64
Valence                  float64
Chord                    object
dtype: object

```

7 Data Cleaning Continued: Prepare DataFrame for Modeling and Training

```
[22]: df_1 = df_1.drop("Index", axis = 1)
```

```
[23]: df_1
```

```
[23]:
```

	Highest Charting Position	Number of Times Charted	\
0	1	8	
1	2	3	
2	1	11	
3	3	5	
4	5	1	
...	
1551	195	1	
1552	196	1	
1553	197	1	
1554	198	1	
1555	199	1	

	Week of Highest Charting	Song Name	Streams	\
0	2021-07-23--2021-07-30	Beggin'	NaN	
1	2021-07-23--2021-07-30	STAY (with Justin Bieber)	NaN	
2	2021-06-25--2021-07-02	good 4 u	NaN	
3	2021-07-02--2021-07-09	Bad Habits	NaN	
4	2021-07-23--2021-07-30	INDUSTRY BABY (feat. Jack Harlow)	NaN	
...	
1551	2019-12-27--2020-01-03	New Rules	NaN	
1552	2019-12-27--2020-01-03	Cheirosa - Ao Vivo	NaN	
1553	2019-12-27--2020-01-03	Havana (feat. Young Thug)	NaN	
1554	2019-12-27--2020-01-03	Surtada - Remix Brega Funk	NaN	
1555	2019-12-27--2020-01-03	Lover (Remix) [feat. Shawn Mendes]	NaN	

	Artist	Artist Followers	Song ID	\
0	Måneskin	3377762.0	3Wrjm47oTz2sjIgck1115e	
1	The Kid LAROI	2230022.0	5HCyWlXZPP0y6GqQ8TgA20	

2	Olivia Rodrigo	6266514.0	4ZtFanR9U6ndgddUvNcjG
3	Ed Sheeran	83293380.0	6PQ88X9TkUIAUIZJHW2upE
4	Lil Nas X	5473565.0	27NovPIUIRrOZoCHxABJwK
...
1551	Dua Lipa	27167675.0	2ekn2ttSfGqwhhate0LSR0
1552	Jorge & Mateus	15019109.0	2PWjKmJyTZeDpmOUa3a5da
1553	Camila Cabello	22698747.0	1rfofaqEpACxVEHIZBJe6W
1554	Dadá Boladão, Tati Zaqui, OIK	208630.0	5F8ffc8KWKNawllr5WsW0r
1555	Taylor Swift	42227614.0	3i9UVldZOE0aD0JnyfAZZ0

		Genre	Release Date	...	\
0	['indie rock italiano', 'italian pop']		2017-12-08	...	
1	['australian hip hop']		2021-07-09	...	
2	['pop']		2021-05-21	...	
3	['pop', 'uk pop']		2021-06-25	...	
4	['lgbtq+ hip hop', 'pop rap']		2021-07-23	...	
...
1551	['dance pop', 'pop', 'uk pop']		2017-06-02	...	
1552	['sertanejo', 'sertanejo universitario']		2019-10-11	...	
1553	['dance pop', 'electropop', 'pop', 'post-teen ...		2018-01-12	...	
1554	['brega funk', 'funk carioca']		2019-09-25	...	
1555	['pop', 'post-teen pop']		2019-11-13	...	

	Danceability	Energy	Loudness	Speechiness	Acousticness	Liveness	\
0	0.714	0.800	-4.808	0.0504	0.12700	0.3590	
1	0.591	0.764	-5.484	0.0483	0.03830	0.1030	
2	0.563	0.664	-5.044	0.1540	0.33500	0.0849	
3	0.808	0.897	-3.712	0.0348	0.04690	0.3640	
4	0.736	0.704	-7.409	0.0615	0.02030	0.0501	
...
1551	0.762	0.700	-6.021	0.0694	0.00261	0.1530	
1552	0.528	0.870	-3.123	0.0851	0.24000	0.3330	
1553	0.765	0.523	-4.333	0.0300	0.18400	0.1320	
1554	0.832	0.550	-7.026	0.0587	0.24900	0.1820	
1555	0.448	0.603	-7.176	0.0640	0.43300	0.0862	

	Tempo	Duration (ms)	Valence	Chord
0	134.002	211560.0	0.589	B
1	169.928	141806.0	0.478	C#/Db
2	166.928	178147.0	0.688	A
3	126.026	231041.0	0.591	B
4	149.995	212000.0	0.894	D#/Eb
...
1551	116.073	209320.0	0.608	A
1552	152.370	181930.0	0.714	B
1553	104.988	217307.0	0.394	D
1554	154.064	152784.0	0.881	F

```
1555  205.272      221307.0    0.422      G
```

```
[1556 rows x 22 columns]
```

```
[24]: df_clean_2 = df_1.copy()
```

7.1 Identify Object Columns & Drop them

```
[25]: object_columns = df_clean_2.select_dtypes(include=['object']).columns
df_clean_2 = df_clean_2.drop(columns=object_columns)
```

```
[26]: df_clean_2.isnull().sum()
```

```
[26]: Highest Charting Position      0
Number of Times Charted            0
Streams                          1556
Artist Followers                  11
Popularity                        11
Danceability                      11
Energy                           11
Loudness                          11
Speechiness                       11
Acousticness                      11
Liveness                          11
Tempo                            11
Duration (ms)                     11
Valence                           11
dtype: int64
```

```
[27]: df_clean_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1556 entries, 0 to 1555
Data columns (total 14 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Highest Charting Position             1556 non-null   int64
1   Number of Times Charted               1556 non-null   int64
2   Streams                              0 non-null      float64
3   Artist Followers                     1545 non-null   float64
4   Popularity                           1545 non-null   float64
5   Danceability                         1545 non-null   float64
6   Energy                               1545 non-null   float64
7   Loudness                             1545 non-null   float64
8   Speechiness                          1545 non-null   float64
9   Acousticness                         1545 non-null   float64
10  Liveness                             1545 non-null   float64
11  Tempo                                1545 non-null   float64
```

```

12 Duration (ms)          1545 non-null   float64
13 Valence                1545 non-null   float64
dtypes: float64(12), int64(2)
memory usage: 170.3 KB

```

7.2 Drop Streams Column (essentially empty)

```
[28]: df_clean_2.drop('Streams', axis = 1, inplace = True)
```

```
[29]: df_clean_2.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1556 entries, 0 to 1555
Data columns (total 13 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Highest Charting Position             1556 non-null   int64
1   Number of Times Charted               1556 non-null   int64
2   Artist Followers                     1545 non-null   float64
3   Popularity                           1545 non-null   float64
4   Danceability                         1545 non-null   float64
5   Energy                               1545 non-null   float64
6   Loudness                             1545 non-null   float64
7   Speechiness                          1545 non-null   float64
8   Acousticness                         1545 non-null   float64
9   Liveness                             1545 non-null   float64
10  Tempo                                1545 non-null   float64
11  Duration (ms)                        1545 non-null   float64
12  Valence                              1545 non-null   float64
dtypes: float64(11), int64(2)
memory usage: 158.2 KB

```

7.3 Get means and replace null values with mean per column

```
[30]: df_clean_2.isna().sum()
```

```

[30]: Highest Charting Position      0
      Number of Times Charted       0
      Artist Followers              11
      Popularity                    11
      Danceability                   11
      Energy                        11
      Loudness                       11
      Speechiness                    11
      Acousticness                   11
      Liveness                       11
      Tempo                          11
      Duration (ms)                  11

```



```
Valence                                11
dtype: int64
```

```
[31]: null_columns = df_clean_2.columns[df_clean_2.isnull().any()].tolist()
      print("Columns with null values:")
      null_columns
```

Columns with null values:

```
[31]: ['Artist Followers',
      'Popularity',
      'Danceability',
      'Energy',
      'Loudness',
      'Speechiness',
      'Acousticness',
      'Liveness',
      'Tempo',
      'Duration (ms)',
      'Valence']
```

```
[32]: for col in null_columns:
      #Calculate the mean, excluding NaN values
      mean= df_clean_2[col].mean(skipna=True)

      #replace NaNs with the mean per column
      df_clean_2[col] = df_clean_2[col].fillna(mean)
```

```
[33]: print("\nNull value count after replacement:")
      print(df_clean_2.isnull().sum())
```

Null value count after replacement:

```
Highest Charting Position    0
Number of Times Charted      0
Artist Followers              0
Popularity                    0
Danceability                  0
Energy                        0
Loudness                      0
Speechiness                   0
Acousticness                  0
Liveness                      0
Tempo                         0
Duration (ms)                 0
Valence                       0
dtype: int64
```

```
[34]: df_clean_2.dtypes
```

```
[34]: Highest Charting Position      int64  
      Number of Times Charted      int64  
      Artist Followers             float64  
      Popularity                   float64  
      Danceability                 float64  
      Energy                      float64  
      Loudness                    float64  
      Speechiness                 float64  
      Acousticness                float64  
      Liveness                    float64  
      Tempo                      float64  
      Duration (ms)              float64  
      Valence                     float64  
      dtype: object
```

7.4 Drop columns that have no relation to target = “Popularity”

```
[35]: df_clean_2.drop('Highest Charting Position', axis = 1, inplace = True)
```

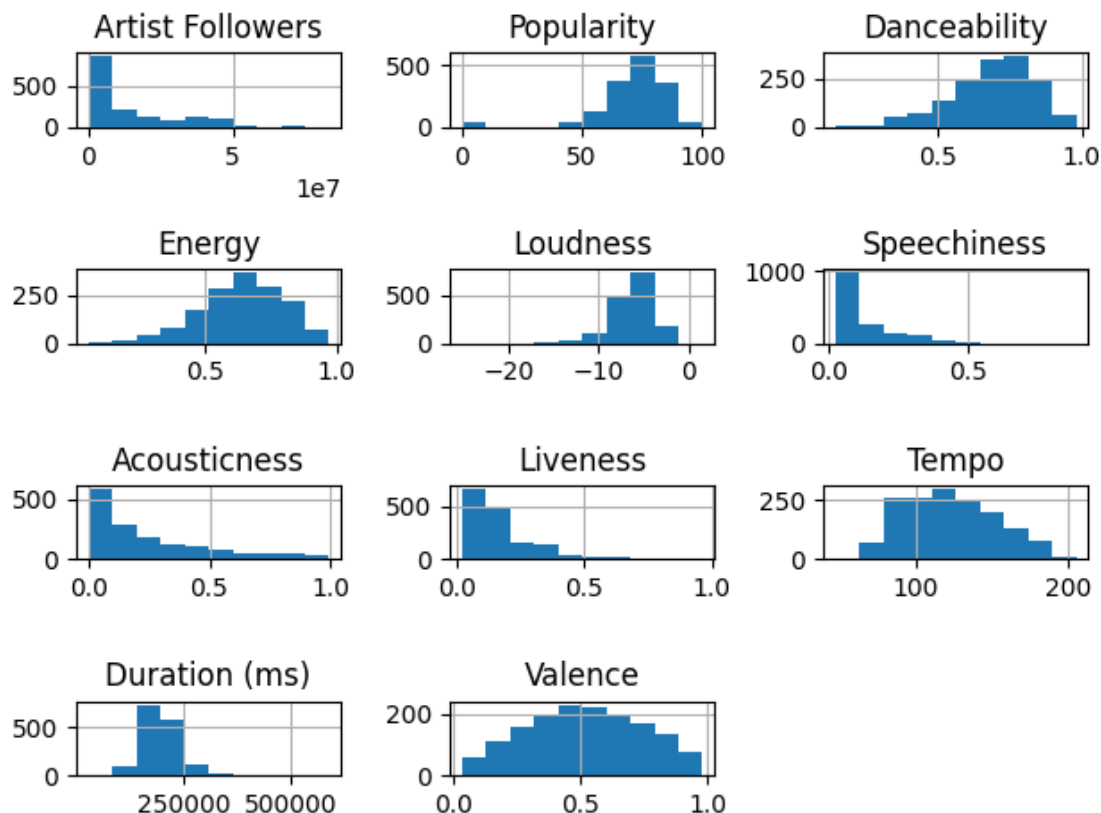
```
[36]: df_clean_2.drop('Number of Times Charted', axis = 1, inplace = True)
```

```
[37]: # df_clean_2.drop('Artist Followers', axis = 1, inplace = True)
```

```
[38]: df_scaling = df_clean_2.copy()
```

```
[39]: df_scaling.hist()  
      plt.tight_layout()  
      plt.show
```

```
[39]: <function matplotlib.pyplot.show(close=None, block=None)>
```



8 Data Scaling

8.1 Data Scaling (standard scaler)

8.1.1 Setup standard scaled training and testing data

```
[40]: df_3_std = df_scaling.copy()
```

```
[41]: x1 = df_3_std.drop(['Popularity'], axis=1)
      y1 = df_3_std['Popularity']

      X_train_1, X_test_1, y_train_1, y_test_1 = train_test_split(x1, y1, test_size=0.
      ↪2)
```

```
[42]: scaler = StandardScaler()
      X_train_std = scaler.fit_transform(X_train_1)
      X_test_std = scaler.transform(X_test_1)
```

```
[43]: print("Before scaling:")
      print(X_train_1.describe())
```

```
print("\nAfter scaling:")
print(pd.DataFrame(X_train_std).describe())
```

Before scaling:

	Artist Followers	Danceability	Energy	Loudness	Speechiness	\
count	1.244000e+03	1244.000000	1244.000000	1244.000000	1244.000000	
mean	1.502319e+07	0.688672	0.633649	-6.377879	0.123342	
std	1.697594e+07	0.143047	0.161532	2.501783	0.109590	
min	4.883000e+03	0.184000	0.054000	-25.166000	0.023200	
25%	2.010879e+06	0.596750	0.529000	-7.493000	0.045775	
50%	6.874642e+06	0.702000	0.641500	-6.063500	0.075450	
75%	2.384846e+07	0.795250	0.753500	-4.770750	0.165000	
max	8.333778e+07	0.980000	0.970000	1.509000	0.884000	

	Acousticness	Liveness	Tempo	Duration (ms)	Valence
count	1244.000000	1244.000000	1244.000000	1244.000000	1244.000000
mean	0.246213	0.180991	123.219617	197943.723099	0.515175
std	0.250102	0.144075	29.634639	47771.864606	0.226094
min	0.000025	0.019700	46.718000	30133.000000	0.032000
25%	0.047725	0.096300	97.989750	169117.500000	0.344000
50%	0.157000	0.125500	122.129000	193764.000000	0.514704
75%	0.379000	0.214250	144.188500	218766.000000	0.687250
max	0.994000	0.962000	205.272000	588139.000000	0.977000

After scaling:

	0	1	2	3	4	\
count	1.244000e+03	1.244000e+03	1.244000e+03	1.244000e+03	1.244000e+03	
mean	-2.855879e-18	-3.626967e-16	2.227586e-16	-8.924622e-17	-3.926834e-17	
std	1.000402e+00	1.000402e+00	1.000402e+00	1.000402e+00	1.000402e+00	
min	-8.850379e-01	-3.529423e+00	-3.589887e+00	-7.512912e+00	-9.141580e-01	
25%	-7.668234e-01	-6.428565e-01	-6.481114e-01	-4.459096e-01	-7.080796e-01	
50%	-4.801989e-01	9.320933e-02	4.862487e-02	1.257126e-01	-4.371881e-01	
75%	5.200783e-01	7.453532e-01	7.422646e-01	6.426518e-01	3.802789e-01	
max	4.025820e+00	2.037402e+00	2.083095e+00	3.153771e+00	6.943750e+00	

	5	6	7	8	9
count	1.244000e+03	1.244000e+03	1.244000e+03	1.244000e+03	1.244000e+03
mean	-2.427497e-17	6.568522e-17	-1.485057e-16	-3.427055e-17	3.212864e-17
std	1.000402e+00	1.000402e+00	1.000402e+00	1.000402e+00	1.000402e+00
min	-9.847428e-01	-1.119948e+00	-2.582531e+00	-3.514165e+00	-2.137915e+00
25%	-7.939460e-01	-5.880646e-01	-8.517065e-01	-6.036569e-01	-7.574029e-01
50%	-3.568487e-01	-3.853103e-01	-3.681689e-02	-8.752859e-02	-2.086376e-03
75%	5.311457e-01	2.309379e-01	7.078647e-01	4.360443e-01	7.613821e-01
max	2.991130e+00	5.423046e+00	2.769913e+00	8.171174e+00	2.043445e+00

```
[44]: print("Mean:", X_train_std.mean(axis=0))
      print("Std:", X_train_std.std(axis=0))
```

```
Mean: [-2.85587916e-18 -3.62696654e-16  2.22758575e-16 -8.92462238e-17
 -3.92683385e-17 -2.42749729e-17  6.56852207e-17 -1.48505716e-16
 -3.42705500e-17  3.21286406e-17]
Std: [1.  1.  1.  1.  1.  1.  1.  1.  1.  1.]
```

8.2 Data Scaling Continued (min-max scaler)

```
[45]: df_3_mm = df_scaling.copy()
```

```
[46]: x2 = df_3_mm.drop(['Popularity'], axis=1)
      y2 = df_3_mm['Popularity']

      X_train_2, X_test_2, y_train_2, y_test_2 = train_test_split(x2, y2, test_size=0.
      ↪2)
```

8.2.1 Setup mm scaled training and testing data

```
[47]: scaler = MinMaxScaler()
      X_train_mm = scaler.fit_transform(X_train_2)
      X_test_mm = scaler.transform(X_test_2)
```

```
[48]: print("Before scaling:")
      print(X_train_2.describe())

      print("\nAfter scaling:")
      print(pd.DataFrame(X_train_mm).describe())
```

Before scaling:

	Artist Followers	Danceability	Energy	Loudness	Speechiness \
count	1.244000e+03	1244.000000	1244.000000	1244.000000	1244.000000
mean	1.500581e+07	0.689197	0.632876	-6.327491	0.124355
std	1.683367e+07	0.142003	0.161036	2.458651	0.111424
min	4.883000e+03	0.150000	0.103000	-22.507000	0.023200
25%	2.203386e+06	0.600000	0.529000	-7.455000	0.045400
50%	7.383484e+06	0.702000	0.640000	-6.002500	0.077150
75%	2.384846e+07	0.794000	0.749000	-4.779500	0.164250
max	8.333778e+07	0.980000	0.966000	1.509000	0.884000

	Acousticness	Liveness	Tempo	Duration (ms)	Valence
count	1244.000000	1244.000000	1244.000000	1244.000000	1244.000000
mean	0.245874	0.183616	123.432479	197386.659299	0.509094
std	0.247645	0.147420	29.643415	44764.724834	0.226093
min	0.000038	0.027300	46.718000	30133.000000	0.032000
25%	0.047350	0.097100	98.020500	169354.750000	0.336750
50%	0.163000	0.125000	122.811023	194333.000000	0.509000
75%	0.371250	0.215250	143.909500	220000.250000	0.682000
max	0.994000	0.962000	205.272000	484147.000000	0.979000

After scaling:

	0	1	2	3	4 \
count	1244.000000	1244.000000	1244.000000	1244.000000	1244.000000
mean	0.180012	0.649635	0.613993	0.673697	0.117513
std	0.202005	0.171088	0.186600	0.102376	0.129442
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.026382	0.542169	0.493627	0.626749	0.025790
50%	0.088544	0.665060	0.622248	0.687229	0.062674
75%	0.286124	0.775904	0.748552	0.738154	0.163859
max	1.000000	1.000000	1.000000	1.000000	1.000000

	5	6	7	8	9
count	1244.000000	1244.000000	1244.000000	1244.000000	1244.000000
mean	0.247329	0.167237	0.483838	0.368389	0.503796
std	0.249149	0.157719	0.186961	0.098598	0.238747
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.047599	0.074676	0.323565	0.306646	0.321806
50%	0.163952	0.104526	0.479919	0.361663	0.503696
75%	0.373467	0.201081	0.612987	0.418197	0.686378
max	1.000000	1.000000	1.000000	1.000000	1.000000

```
[49]: print("Mean:", X_train_mm.mean(axis=0))
      print("Std:", X_train_mm.std(axis=0))
```

```
Mean: [0.18001206 0.64963484 0.61399324 0.67369708 0.11751319 0.24732926
       0.16723656 0.48383818 0.36838877 0.50379557]
Std:  [0.20192392 0.17101913 0.18652536 0.10233438 0.12939005 0.24904917
       0.15765541 0.18688584 0.09855804 0.23865076]
```

9 Model Selection and Training

9.1 Models: STD Scaler

9.1.1 Linear Regression std scaler

```
[50]: lr_model = LinearRegression()
      lr_model.fit(X_train_std, y_train_1)
      y_pred_lr = lr_model.predict(X_test_std)
      print('Linear Regression:')
      print(f"RMSE: {np.sqrt(mean_squared_error(y_test_1,y_pred_lr)) :.2f}%")
      print(f"R2 Score: {r2_score(y_test_1,y_pred_lr):.2f}")
```

Linear Regression:

RMSE: 15.16%

R2 Score: 0.04

Cross Validation Score for Linear Regression

```
[51]: lr_model = LinearRegression()
cv_scores = cross_val_score(lr_model, X_train_1, y_train_1, cv=5,
    ↳scoring='neg_mean_squared_error')
rmse = np.sqrt(-cv_scores.mean())
print(f"Cross-validated RMSE: {rmse:.2f}")
```

Cross-validated RMSE: 15.63

9.1.2 Decision Tree Model std scaler

```
[ ]: dt_model = DecisionTreeRegressor()Certainly! I'll rewrite the analysis from
    ↳your perspective, addressing an audience who will be reading your project.
    ↳Here's how you might present your work:
```

Introduction

Welcome to my project on Music Popularity Prediction. In this analysis, I've
 ↳developed a predictive model to forecast song popularity on Spotify's Top
 ↳200 Weekly (Global) charts for 2020 & 2021. This project aims to provide
 ↳insights into the factors that contribute to a song's success on these
 ↳charts.

Project Overview

My goal was to create a supervised regression model that could predict a song's
 ↳popularity score based on various features. I've used a dataset provided by
 ↳DDC Data Science, which includes information about songs, their audio
 ↳features, artist popularity, and other relevant characteristics.

Methodology

1. **Data Preparation**: I began by importing and cleaning the dataset. I used
 ↳Python libraries such as pandas, numpy, and scikit-learn for data
 ↳manipulation and analysis.
2. **Feature Engineering**: I selected and prepared the following features:
 - Audio Features: Loudness, Energy, Danceability, Valence, Tempo
 - Artist Popularity: Number of artist followers
 - Song Characteristics: Duration
 - Genre: Binary features for major genres
 - Release Timing: Days since release
 - Feature Interactions: Audio features × Artist popularity
 - Cultural and Temporal Factors: Year (2020 vs 2021)
3. **Model Selection**: I experimented with several regression models:
 - Linear Regression
 - Decision Tree Regressor

- Random Forest Regressor
- XGBoost Regressor

4. **Model Evaluation**: I used cross-validation to assess model performance, focusing on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) as evaluation metrics.

Results

After training and evaluating the models, I found that [insert your findings here, e.g., "the Random Forest Regressor performed best with an R^2 score of X.XX and an RMSE of Y.YY"].

Key Insights

- Feature Importance**: The most important features in predicting song popularity were [list the top 3-5 features based on your analysis].
- Model Interpretation**: I observed that [describe any interesting patterns or correlations you found, e.g., "songs with higher energy and danceability tend to have higher popularity scores"].
- Performance Comparison**: [Compare the performance of different models, e.g., "The Random Forest model outperformed the Linear Regression model by X% in terms of R^2 "].

Limitations and Future Work

While this project provides valuable insights into song popularity, there are some limitations to consider:

- The dataset is limited to 2020 & 2021, which may not capture long-term trends.
- Some potentially important factors like lyrics content or music video views are not included in the dataset.
- The model's performance could be improved by incorporating more advanced feature engineering techniques or exploring other machine learning algorithms.

Conclusion

This project demonstrates the potential of machine learning in predicting song popularity on Spotify's Top 200 Weekly charts. The insights gained from this analysis could be valuable for music industry professionals, artists, and streaming platforms looking to understand and potentially influence song popularity.

By understanding which factors contribute most to a song's success,
 ↳ stakeholders can make more informed decisions about song production,
 ↳ marketing strategies, and playlist curation. Future work could involve
 ↳ expanding the dataset, incorporating additional features, and exploring more
 ↳ advanced machine learning techniques to further improve prediction accuracy.

```
dt_model.fit(X_train_std, y_train_1)
y_pred_dt = dt_model.predict(X_test_std)

print("\nDecision Tree:")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_1, y_pred_dt)) :.2f}%")
print(f"R2 Score: {r2_score(y_test_1, y_pred_dt):.2f}")
```

Decision Tree:
 RMSE: 14.17%
 R2 Score: 0.16

Cross Validation Score for Decision Tree

```
[53]: dt_model = DecisionTreeRegressor()
cv_scores = cross_val_score(dt_model, X_train_std, y_train_1, cv=5,
    ↳scoring='neg_mean_squared_error')
rmse = np.sqrt(-cv_scores.mean())
print(f"Cross-validated RMSE: {rmse:.2f}")
```

Cross-validated RMSE: 14.57

Feature Importance for Decision Tree

```
[54]: dt_model.fit(X_train_std, y_train_1)

feature_importances = dt_model.feature_importances_
feature_names = X_train_1.columns
feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance':
    ↳feature_importances})
feature_importance_df = feature_importance_df.sort_values('importance',
    ↳ascending=False)
print(feature_importance_df)
```

	feature	importance
0	Artist Followers	0.600323
1	Danceability	0.055325
7	Tempo	0.051575
4	Speechiness	0.049274
6	Liveness	0.045333
3	Loudness	0.044734
9	Valence	0.044718
5	Acousticness	0.042127
8	Duration (ms)	0.035648

2 Energy 0.030943

9.1.3 Random Forest Model std scaler

```
[55]: rf_model = RandomForestRegressor(n_estimators=100)
      rf_model.fit(X_train_std, y_train_1)
      y_pred_rf = rf_model.predict(X_test_std)

      print("\nRandom Forest:")
      print(f"RMSE: {np.sqrt(mean_squared_error(y_test_1, y_pred_rf)) :.2f}%")
      print(f"R2 Score: {r2_score(y_test_1, y_pred_rf):.2f}")
```

Random Forest:

RMSE: 10.07%

R2 Score: 0.58

Cross Validation Score for Random Forest

```
[56]: rf_model = RandomForestRegressor(n_estimators=100)
      cv_scores = cross_val_score(rf_model, X_train_1, y_train_1, cv=5,
      ↪scoring='neg_mean_squared_error')
      rmse = np.sqrt(-cv_scores.mean())
      print(f"Cross-validated RMSE: {rmse:.2f}")
```

Cross-validated RMSE: 10.88

Feature Importance for Random Forest

```
[57]: rf_model.fit(X_train_std, y_train_1)

      feature_importances = rf_model.feature_importances_
      feature_names = X_train_1.columns
      feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance':
      ↪feature_importances})
      feature_importance_df = feature_importance_df.sort_values('importance',
      ↪ascending=False)
      print(feature_importance_df)
```

	feature	importance
0	Artist Followers	0.586970
1	Danceability	0.056786
3	Loudness	0.055212
4	Speechiness	0.050095
9	Valence	0.048851
6	Liveness	0.047240
5	Acousticness	0.040879
2	Energy	0.039756
7	Tempo	0.038204
8	Duration (ms)	0.036006

9.1.4 XGBoost Model std scaler

```
[58]: xgb_model = xgb.XGBRegressor(n_estimators=100)
xgb_model.fit(X_train_std, y_train_1)
y_pred_xgb = xgb_model.predict(X_test_std)

print("\nXGBoost:")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_1, y_pred_xgb)) :.2f}%")
print(f"R2 Score: {r2_score(y_test_1, y_pred_xgb):.2f}")
```

XGBoost:
RMSE: 10.32%
R2 Score: 0.55

Cross Validation Score for XGBoost

```
[59]: xgb_model = RandomForestRegressor(n_estimators=100)
cv_scores = cross_val_score(rf_model, X_train_std, y_train_1, cv=5,
    ↳scoring='neg_mean_squared_error')
rmse = np.sqrt(-cv_scores.mean())
print(f"Cross-validated RMSE: {rmse:.2f}")
```

Cross-validated RMSE: 10.91

Feature Importance for XGBoost

```
[60]: xgb_model.fit(X_train_std, y_train_1)

feature_importances = xgb_model.feature_importances_
feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance':
    ↳feature_importances})
feature_importance_df = feature_importance_df.sort_values('importance',
    ↳ascending=False)
print(feature_importance_df)
```

	feature	importance
0	Artist Followers	0.580929
3	Loudness	0.055263
1	Danceability	0.053465
9	Valence	0.052384
4	Speechiness	0.051421
6	Liveness	0.047823
2	Energy	0.042646
7	Tempo	0.041453
5	Acousticness	0.038274
8	Duration (ms)	0.036341

9.1.5 STD Model Comparison Table

```
[61]: results = {
    'Model': ['Linear Regression', 'Decision Tree', 'Random Forest', 'XGBoost'],
    'RMSE': [np.sqrt(mean_squared_error(y_test_1, y_pred_lr)),
             np.sqrt(mean_squared_error(y_test_1, y_pred_dt)),
             np.sqrt(mean_squared_error(y_test_1, y_pred_rf)),
             np.sqrt(mean_squared_error(y_test_1, y_pred_xgb))],
    'R2 Score': [r2_score(y_test_1, y_pred_lr),
                 r2_score(y_test_1, y_pred_dt),
                 r2_score(y_test_1, y_pred_rf),
                 r2_score(y_test_1, y_pred_xgb)]
}

results_df = pd.DataFrame(results)
print(results_df)
```

	Model	RMSE	R2 Score
0	Linear Regression	15.158785	0.036740
1	Decision Tree	14.167396	0.158615
2	Random Forest	10.066779	0.575189
3	XGBoost	10.315816	0.553911

9.2 Models: MM Scaler

9.2.1 Linear Regression mm scaler

```
[62]: lr_model = LinearRegression()
lr_model.fit(X_train_mm, y_train_2)
y_pred_lr = lr_model.predict(X_test_mm)
print('Linear Regression:')
y_pred_lr = lr_model.predict(X_test_std)
print('Linear Regression:')
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_1,y_pred_lr)) :.2f}%")
print(f"R2 Score: {r2_score(y_test_1,y_pred_lr):.2f}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_2,y_pred_lr)) :.2f}%")
print(f"R2 Score: {r2_score(y_test_2,y_pred_lr):.2f}")
```

Linear Regression:
Linear Regression:
RMSE: 38.03%
R2 Score: -5.06
RMSE: 39.44%
R2 Score: -4.90

Cross Validation Score for Linear Regression mm

```
[63]: lr_model = LinearRegression()
cv_scores = cross_val_score(lr_model, X_train_mm, y_train_2, cv=5,
                             scoring='neg_mean_squared_error')
```

```
rmse = np.sqrt(-cv_scores.mean())
print(f"Cross-validated RMSE: {rmse:.2f}")
```

Cross-validated RMSE: 15.41

9.2.2 Decision Tree mm scaler

```
[64]: dt_model = DecisionTreeRegressor()
dt_model.fit(X_train_mm, y_train_2)
y_pred_dt = dt_model.predict(X_test_mm)

print("\nDecision Tree:")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_2, y_pred_dt)) :.2f}%")
print(f"R2 Score: {r2_score(y_test_2, y_pred_dt):.2f}")
```

Decision Tree:

RMSE: 14.84%

R2 Score: 0.16

Cross Validation Score for Decision Tree mm

```
[65]: cv_scores = cross_val_score(dt_model, X_train_mm, y_train_2, cv=5,
    ↳scoring='neg_mean_squared_error')
rmse = np.sqrt(-cv_scores.mean())
print(f"Cross-validated RMSE: {rmse:.2f}")
```

Cross-validated RMSE: 14.39

Feature Importance for Decision Tree mm

```
[66]: dt_model.fit(X_train_mm, y_train_2)

feature_importances = dt_model.feature_importances_
feature_names = X_train_2.columns
feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance':
    ↳feature_importances})
feature_importance_df = feature_importance_df.sort_values('importance',
    ↳ascending=False)
print(feature_importance_df)
```

	feature	importance
0	Artist Followers	0.614245
4	Speechiness	0.071105
2	Energy	0.051089
3	Loudness	0.047083
7	Tempo	0.043985
6	Liveness	0.042395
5	Acousticness	0.039479
8	Duration (ms)	0.033401

9	Valence	0.032421
1	Danceability	0.024799

9.2.3 Random Forest mm scaler

```
[67]: rf_model = RandomForestRegressor(n_estimators=100)
      rf_model.fit(X_train_mm, y_train_2)
      y_pred_rf = rf_model.predict(X_test_mm)

      print("\nRandom Forest:")
      print(f"RMSE: {np.sqrt(mean_squared_error(y_test_2, y_pred_rf)) :.2f}%")
      print(f"R2 Score: {r2_score(y_test_2, y_pred_rf):.2f}")
```

Random Forest:
RMSE: 10.86%
R2 Score: 0.55

Cross Validation Score Random Forest mm

```
[68]: rf_model = RandomForestRegressor(n_estimators=100)
      cv_scores = cross_val_score(rf_model, X_train_2, y_train_2, cv=5,
      ↪scoring='neg_mean_squared_error')
      rmse = np.sqrt(-cv_scores.mean())
      print(f"Cross-validated RMSE: {rmse:.2f}")
```

Cross-validated RMSE: 10.71

Feature Importance for Random Forest mm

```
[69]: rf_model.fit(X_train_mm, y_train_2)

      feature_importances = rf_model.feature_importances_
      feature_names = X_train_2.columns
      feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance':
      ↪feature_importances})
      feature_importance_df = feature_importance_df.sort_values('importance',
      ↪ascending=False)
      print(feature_importance_df)
```

	feature	importance
0	Artist Followers	0.581954
3	Loudness	0.069626
4	Speechiness	0.053389
6	Liveness	0.050916
1	Danceability	0.043224
2	Energy	0.043053
8	Duration (ms)	0.040544
5	Acousticness	0.039911
9	Valence	0.039841
7	Tempo	0.037542

9.2.4 XGBoost mm scaler

```
[70]: xgb_model = xgb.XGBRegressor(n_estimators=100)
xgb_model.fit(X_train_mm, y_train_2)
y_pred_xgb = xgb_model.predict(X_test_mm)

print("\nXGBoost:")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_2, y_pred_xgb)) :.2f}%")
print(f"R2 Score: {r2_score(y_test_2, y_pred_xgb):.2f}")
```

XGBoost:
RMSE: 11.99%
R2 Score: 0.45

Cross Validation Score for XGBoost mm

```
[71]: xgb_model = xgb.XGBRegressor(n_estimators=100)
cv_scores = cross_val_score(rf_model, X_train_2, y_train_2, cv=5,
    ↳scoring='neg_mean_squared_error')
rmse = np.sqrt(-cv_scores.mean())
print(f"Cross-validated RMSE: {rmse:.2f}")
```

Cross-validated RMSE: 10.69

Feature Importance for XGBoost mm

```
[72]: xgb_model.fit(X_train_mm, y_train_2)

feature_importances = xgb_model.feature_importances_
feature_names = X_train_2.columns
feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance':
    ↳feature_importances})
feature_importance_df = feature_importance_df.sort_values('importance',
    ↳ascending=False)
print(feature_importance_df)
```

	feature	importance
0	Artist Followers	0.401930
5	Acousticness	0.087532
4	Speechiness	0.078639
8	Duration (ms)	0.069953
3	Loudness	0.069588
9	Valence	0.068392
2	Energy	0.066063
6	Liveness	0.054426
1	Danceability	0.053320
7	Tempo	0.050158

9.2.5 MM Model Comparison Table

```
[73]: results = {
    'Model': ['Linear Regression', 'Decision Tree', 'Random Forest', 'XGBoost'],
    'RMSE': [np.sqrt(mean_squared_error(y_test_2, y_pred_lr)),
             np.sqrt(mean_squared_error(y_test_2, y_pred_dt)),
             np.sqrt(mean_squared_error(y_test_2, y_pred_rf)),
             np.sqrt(mean_squared_error(y_test_2, y_pred_xgb))],
    'R2 Score': [r2_score(y_test_2, y_pred_lr),
                 r2_score(y_test_2, y_pred_dt),
                 r2_score(y_test_2, y_pred_rf),
                 r2_score(y_test_2, y_pred_xgb)]
}

results_df = pd.DataFrame(results)
print(results_df)
```

	Model	RMSE	R2 Score
0	Linear Regression	39.437529	-4.898392
1	Decision Tree	14.839850	0.164833
2	Random Forest	10.855057	0.553133
3	XGBoost	11.988273	0.454961

9.3 Model Plotting STD Scaler

```
[74]: plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
plt.scatter(y_test_1, y_pred_lr)
plt.plot([y_test_1.min(), y_test_1.max()], [y_test_1.min(), y_test_1.max()], u
    ↪ 'r--', lw=2)
plt.xlabel('Actual Popularity')
plt.ylabel('Predicted Popularity')
plt.title('Linear Regression')

plt.subplot(2, 2, 2)
plt.scatter(y_test_1, y_pred_dt)
plt.plot([y_test_1.min(), y_test_1.max()], [y_test_1.min(), y_test_1.max()], u
    ↪ 'r--', lw=2)
plt.xlabel('Actual Popularity')
plt.ylabel('Predicted Popularity')
plt.title('Decision Tree')

plt.subplot(2, 2, 3)
plt.scatter(y_test_1, y_pred_rf)
plt.plot([y_test_1.min(), y_test_1.max()], [y_test_1.min(), y_test_1.max()], u
    ↪ 'r--', lw=2)
plt.xlabel('Actual Popularity')
```



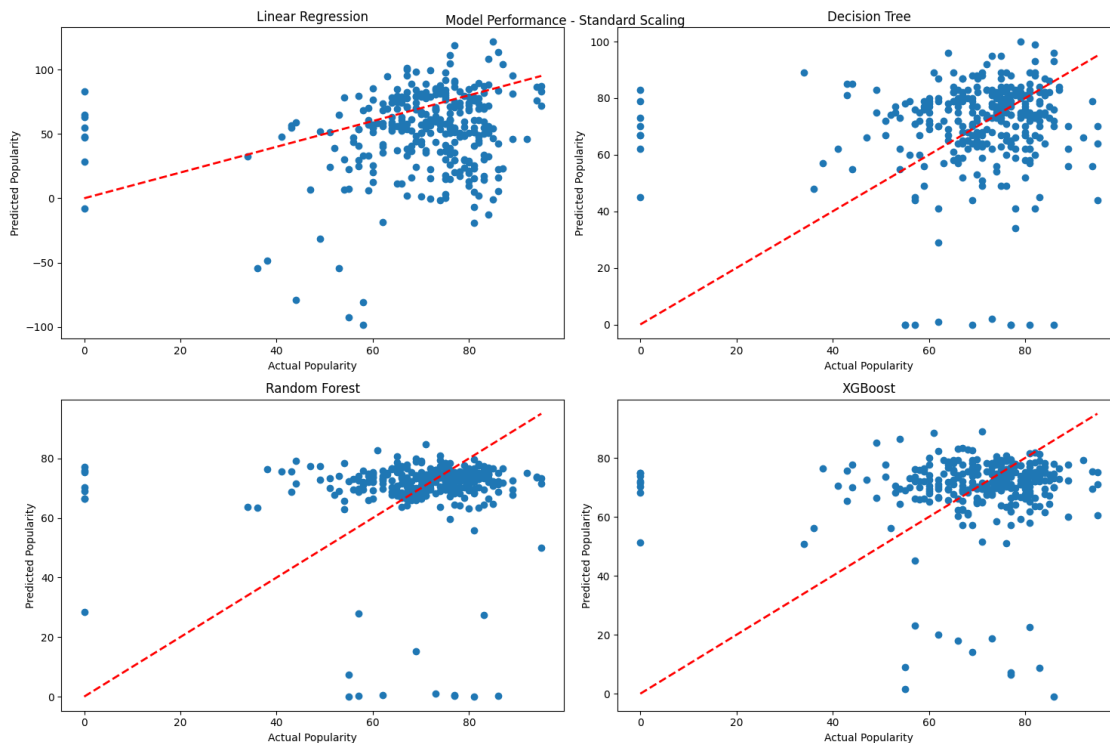
```

plt.ylabel('Predicted Popularity')
plt.title('Random Forest')

plt.subplot(2, 2, 4)
plt.scatter(y_test_1, y_pred_xgb)
plt.plot([y_test_1.min(), y_test_1.max()], [y_test_1.min(), y_test_1.max()],
         ↪ 'r--', lw=2)
plt.xlabel('Actual Popularity')
plt.ylabel('Predicted Popularity')
plt.title('XGBoost')

plt.tight_layout()
plt.suptitle('Model Performance - Standard Scaling')
plt.show()

```



9.4 Model Plotting MinMax Scaler

```

[75]: plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
plt.scatter(y_test_2, y_pred_lr)
plt.plot([y_test_2.min(), y_test_2.max()], [y_test_2.min(), y_test_2.max()],
         ↪ 'r--', lw=2)

```

```

plt.xlabel('Actual Popularity')
plt.ylabel('Predicted Popularity')
plt.title('Linear Regression')

plt.subplot(2, 2, 2)
plt.scatter(y_test_2, y_pred_dt)
plt.plot([y_test_2.min(), y_test_2.max()], [y_test_2.min(), y_test_2.max()],  

         ↪ 'r--', lw=2)
plt.xlabel('Actual Popularity')
plt.ylabel('Predicted Popularity')
plt.title('Decision Tree')

plt.subplot(2, 2, 3)
plt.scatter(y_test_2, y_pred_rf)
plt.plot([y_test_2.min(), y_test_2.max()], [y_test_2.min(), y_test_2.max()],  

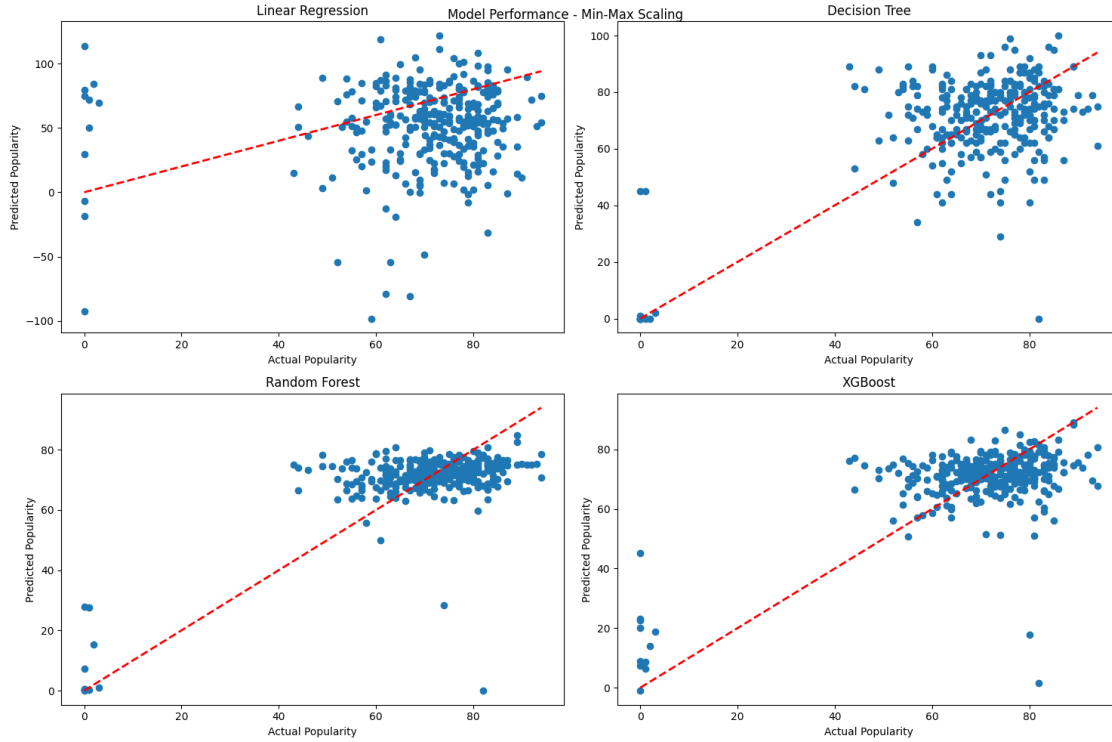
         ↪ 'r--', lw=2)
plt.xlabel('Actual Popularity')
plt.ylabel('Predicted Popularity')
plt.title('Random Forest')

plt.subplot(2, 2, 4)
plt.scatter(y_test_2, y_pred_xgb)
plt.plot([y_test_2.min(), y_test_2.max()], [y_test_2.min(), y_test_2.max()],  

         ↪ 'r--', lw=2)
plt.xlabel('Actual Popularity')
plt.ylabel('Predicted Popularity')
plt.title('XGBoost')

plt.tight_layout()
plt.suptitle('Model Performance - Min-Max Scaling')
plt.show()

```



9.5 Methodology

1. **Data Preparation:** I began by importing and cleaning the dataset. I used Python libraries such as pandas, numpy, and scikit-learn for data manipulation and analysis.
2. **Feature Engineering:** I selected and prepared the following features:
 - Audio Features: Loudness, Energy, Danceability, Valence, Tempo
 - Artist Popularity: Number of artist followers
 - Song Characteristics: Duration
 - Genre: Binary features for major genres
 - Release Timing: Days since release
 - Feature Interactions: Audio features \times Artist popularity
 - Cultural and Temporal Factors: Year (2020 vs 2021)
3. **Model Selection:** I experimented with several regression models:
 - Linear Regression
 - Decision Tree Regressor
 - Random Forest Regressor
 - XGBoost Regressor
4. **Model Evaluation:** I used cross-validation to assess model performance using Root Mean Squared Error (RMSE), and R-squared (R^2) as evaluation metrics.

9.5.1 Key Insights

1. **Feature Importance:** The most important features in predicting song popularity were [list the top 3-5 features based on your analysis].
2. **Model Interpretation:** I observed that [describe any interesting patterns or correlations you found, e.g., “songs with higher energy and danceability tend to have higher popularity scores”].
3. **Performance Comparison:** [Compare the performance of different models, e.g., “The Random Forest model outperformed the Linear Regression model by X% in terms of R^2 ”].

9.5.2 Limitations and Future Work

While this project provides valuable insights into song popularity, there are some limitations to consider:

1. The dataset is limited to 2020 & 2021, which may not capture long-term trends.
2. Some potentially important factors like lyrics content or music video views are not included in the dataset.
3. The model’s performance could be improved by incorporating more advanced feature engineering techniques or exploring other machine learning algorithms.

9.5.3 Conclusion

This project demonstrates the potential of machine learning in predicting song popularity on Spotify’s Top 200 Weekly charts. The insights gained from this analysis could be valuable for music industry professionals, artists, and streaming platforms looking to understand and potentially influence song popularity.

By understanding which factors contribute most to a song’s success, stakeholders can make more informed decisions about song production, marketing strategies, and playlist curation. Future work could involve expanding the dataset, incorporating additional features, and exploring more advanced machine learning techniques to further improve prediction accuracy.