Stat 159 Final Project - Predicting Spotify Track Popularity from Audio Features

Collins Tse Jacky Ke Rebecca Bachtra Christy Yau

Thursday 18th December, 2025

Abstract

We study whether a track's quantitative audio features from Spotify (e.g., danceability, energy, loudness, acousticness, valence) can predict Spotify's popularity score (0–100). After cleaning and sampling, our analysis uses 114,000 tracks. Popularity is broadly distributed (mean 33.24, median 35, IQR [17, 50]). Multiple linear regression provides an interpretable baseline, and we compare it against Ridge and LASSO regularization. All three linear models perform similarly, while the best test RMSE is 20.03 popularity points. Correlations between individual audio features and popularity are weak. Multicollinearity is present but modest, largest VIF among predictors is 4.26 for energy. Overall, audio features capture some signal but leave substantial variation unexplained, motivating richer nonlinear models and/or additional contextual covariates.

Group 22

1 1. Introduction

Spotify provides a popularity score intended to summarize a track's overall consumption and engagement on the platform. A natural question is whether we can explain, or even predict this popularity using only the track's audio features derived from Spotify's Web API.

Research question:

Can we predict a song's Spotify popularity score from quantitative audio features such as danceability, energy, loudness, acousticness, and valence?
We focus on an interpretable baseline: multiple linear regression, with Ridge/LASSO as comparisons.

2 2. Data

We use the Spotify Tracks Dataset from Kaggle, curated from the Spotify Web API and spanning tracks from 1921–2020. The dataset includes numerical audio descriptors (e.g., danceability, energy, loudness, tempo, valence) and the target variable `popularity`.

2.1 Data handling and reproducibility

- Raw and cleaned Spofity dataset CSVs are stored under `data/`.
- EDA plots are written to `figures/`.
- Modeling outputs (summary tables, diagnostics, correlation matrix) are written to `results/`.

Because large raw datasets can be inconvenient to version-control directly, our workflow emphasizes reproducible scripts + exported results rather than rerunning heavy computations inside this notebook.

```
from pathlib import Path
import pandas as pd
import numpy as np
from IPython.display import Image, display, Markdown

ROOT = Path(".")
FIG_DIR = ROOT / "figures"
RES_DIR = ROOT / "results"

def show_fig(filename: str, caption: str, width: int = 900):
    path = FIG_DIR / filename
    if not path.exists():
        display(Markdown(f"**Missing figure:** `{path}`"))
        return
    display(Image(filename=str(path), width=width))
    display(Markdown(f"*Figure: {caption}*"))

def load_csv(filename: str) -> pd.DataFrame:
    path = RES_DIR / filename
    if not path.exists():
        raise FileNotFoundError(f"Missing required file: {path}")
    return pd.read_csv(path)
```

3 3. Exploratory Data Analysis

Our group begin by inspecting the distribution of popularity and core audio features. These plots summarizes the cleaned/sampled dataset, and help us anticipate modeling challenges.

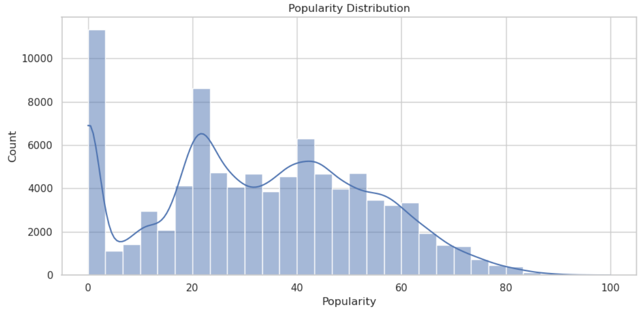
```
popularity_summary = load_csv("popularity_summary.csv")
```

```
if "stat" in popularity_summary.columns:
    popularity_summary = popularity_summary.set_index("stat")
elif "Unnamed: 0" in popularity_summary.columns:
    popularity_summary = popularity_summary.rename(columns={"Unnamed: 0": "stat"}).set_index
else:
    popularity_summary = popularity_summary.set_index(popularity_summary.columns[0])

popularity_summary = popularity_summary.loc[:, ~popularity_summary.columns.str.startswith("U

if "popularity" in popularity_summary.columns:
    popularity_summary = popularity_summary.rename(columns={"popularity": "value"})

display(popularity_summary)
```

	value
stat	
count	114000.000000
mean	33.238535
std	22.305078
min	0.000000
25%	17.000000
50%	35.000000
75%	50.000000
max	100.000000

The popularity score ranges from 0 to 100, with mean 33.24 and median 35. The middle 50% of tracks lie between 17 and 50, indicating substantial spread in popularity.

```
show_fig("popularity_distribution.png", "Distribution of Spotify popularity. The distributio
```

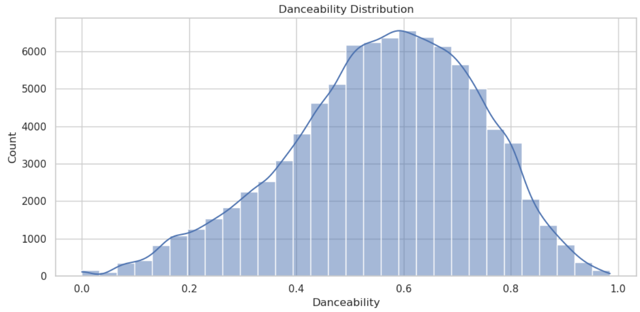



```
<IPython.core.display.Markdown object>
```

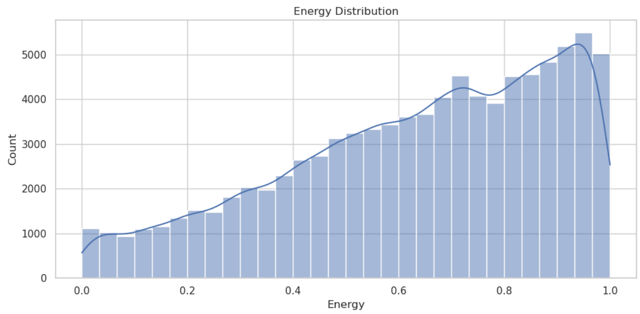
3.1 Audio feature distributions

Below are histograms for several audio features used in our models.

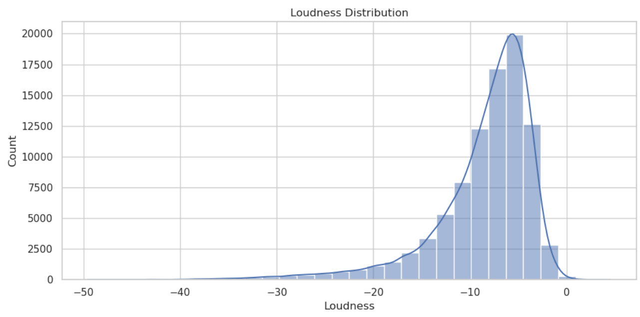
```
show_fig("dance_distribution.png", "Danceability is approximately unimodal, with many tracks
show_fig("energy_distribution.png", "Energy skews high: many tracks in the cleaned sample ha
show_fig("loudness_distribution.png", "Loudness (dB) is concentrated around a typical modern
show_fig("acoustic_distribution.png", "Acousticness shows strong concentration near 0 (non -
show_fig("speech_distribution.png", "Speechiness is strongly right -skewed, with most tracks
show_fig("tempo_distribution.png", "Tempo is multi -modal, with common tempos around typical
show_fig("valence_distribution.png", "Valence (musical positivity) is broadly distributed ac
1 range, with slightly more mass in mid values.")
```



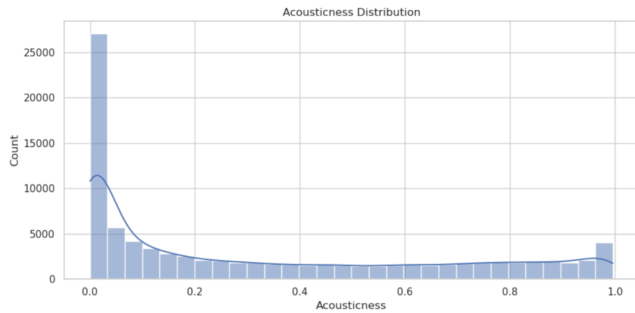
<IPython.core.display.Markdown object>



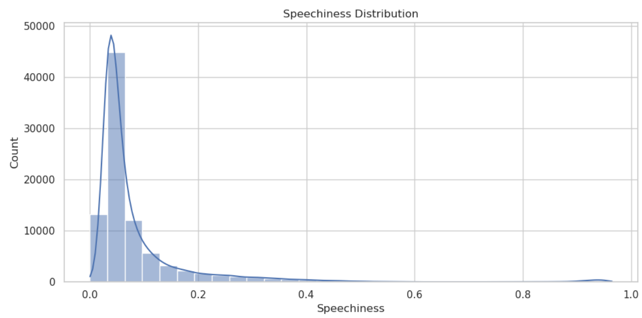
<IPython.core.display.Markdown object>



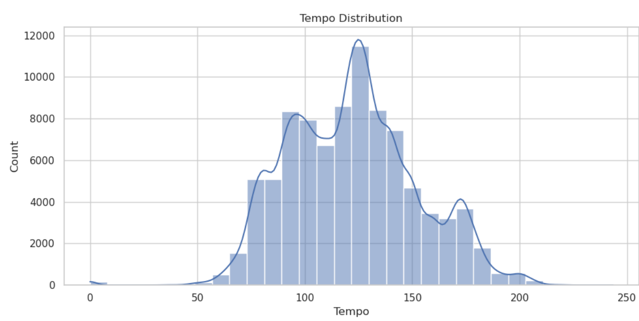
<IPython.core.display.Markdown object>



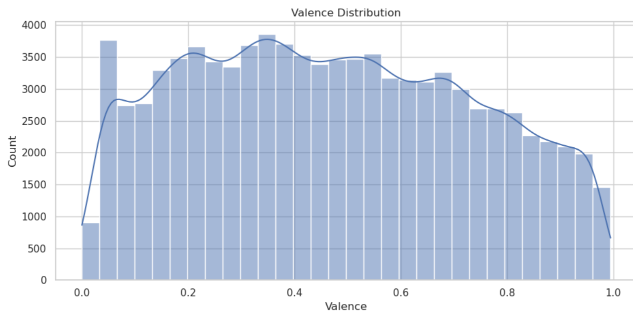
<IPython.core.display.Markdown object>



<IPython.core.display.Markdown object>



<IPython.core.display.Markdown object>




```
<IPython.core.display.Markdown object>
```

4 4. Correlation structure

To understand which variables move together—and to anticipate multicollinearity in regression—we examine the correlation matrix exported from our analysis pipeline.

```
corr = pd.read_csv(RES_DIR / "full_correlation_matrix.csv", index_col=0)
corr = corr.apply(pd.to_numeric, errors="coerce")
display(corr.iloc[:6, :6])
```

	popularity	duration_ms	explicit	danceability	energy	key
popularity	1.000000	-0.023119	NaN	0.064281	0.013728	0.003432
duration_ms	-0.023119	1.000000	NaN	-0.064130	0.063261	0.011286
explicit	NaN	NaN	NaN	NaN	NaN	NaN
danceability	0.064281	-0.064130	NaN	1.000000	0.143914	0.035114
energy	0.013728	0.063261	NaN	0.143914	1.000000	0.046334
key	0.003432	0.011286	NaN	0.035114	0.046334	1.000000

```
pop_corr = corr["popularity"].drop(labels=["popularity"]).dropna().sort_values(key=lambda s
display(pop_corr.head(10).to_frame(name="corr_with_popularity"))

cols = corr.columns.tolist()
pairs = []
for i in range(len(cols)):
    for j in range(i + 1, len(cols)):
        a, b = cols[i], cols[j]
        r = corr.loc[a, b]
```

```
        if pd.isna(r):
            continue
        if a == "popularity" or b == "popularity":
            continue
        if set([a, b]) == set(["duration_ms", "duration_min"]):
            continue
        pairs.append((abs(float(r)), float(r), a, b))

top_pairs = (pd.DataFrame(sorted(pairs, reverse=True)[:10], columns=["abs_r", "r", "feature_
display(top_pairs)
```

	corr_with_popularity
instrumentalness	-0.127465
loudness	0.071676
danceability	0.064281
speechiness	-0.047081
acousticness	-0.038847
time_signature	0.036893
duration_min	-0.023119
duration_ms	-0.023119
mode	-0.016214
liveness	-0.013844

	abs_r	r	feature_1	feature_2
0	0.758774	0.758774	energy	loudness
1	0.732566	-0.732566	energy	acousticness
2	0.582663	-0.582663	loudness	acousticness
3	0.492571	0.492571	danceability	valence
4	0.434717	-0.434717	loudness	instrumentalness
5	0.330759	-0.330759	instrumentalness	valence
6	0.289091	0.289091	loudness	valence
7	0.271839	0.271839	danceability	loudness
8	0.258628	0.258628	energy	tempo
9	0.256313	0.256313	energy	valence

4.1 Strongest feature–feature correlations (by absolute value)

Excluding the engineered duplicate (`duration_ms` vs `duration_min`), the strongest relationships are:

- energy vs loudness: $r = +0.759$

- energy vs acousticness: r = -0.733
- loudness vs acousticness: r = -0.583
- danceability vs valence: r = +0.493
- loudness vs instrumentalness: r = -0.435

These patterns are consistent with musical intuition: tracks with higher energy tend to be louder, and more acoustic tracks tend to have lower energy and loudness.

4.2 Correlations with popularity

Correlations between individual audio features and popularity are generally small in magnitude:

- instrumentalness: r = -0.127
- loudness: r = +0.072
- danceability: r = +0.064
- speechiness: r = -0.047
- acousticness: r = -0.039

The largest (in absolute value) is instrumentalness (negative correlation), suggesting that tracks with more instrumental content tend to be less popular on average in this sample. However, the overall weakness of these correlations signals that linear prediction from audio features alone may be challenging.

5 5. Predictive modeling

We fit a multiple linear regression model to predict popularity from audio features, and compare it to two standard regularized variants:

- Ridge regression (L2 penalty)
- LASSO regression (L1 penalty)

Model fitting, splitting, and cross-validation are performed in separate notebooks; here we only load the exported results. We use RMSE on the same 0–100 popularity scale for evaluation.

```
mlr_models = load_csv("mlr_models_comparison.csv")
mlr_models = mlr_models.drop(columns=[c for c in mlr_models.columns if c.startswith("Unnamed
display(mlr_models)
```

	Model	Train RMSE	Test RMSE	CV Error
0	Multiple Linear Reg	20.278961	20.032047	20.031338
1	+ Ridge	20.278963	20.031911	20.030885
2	+ LASSO	20.278982	20.032112	20.031258

Across these linear approaches, performance is extremely similar. The best is + Ridge, with test RMSE = 20.03, CV error ≈ 20.03.
An RMSE near 20 means on average the model's predictions deviate from true popularity by about 20 points, which is sizable relative to the full 0–100 range.

6 6. Multicollinearity diagnostics (VIF)

Because regression coefficient interpretation can be unstable when predictors are highly collinear, we compute VIF for the regression predictors. A common rule of thumb is that VIF values above ~5 (or 10) indicate concerning multicollinearity.

```
vif = load_csv("regression_vif.csv")
vif = vif.drop(columns=[c for c in vif.columns if c.startswith("Unnamed")], errors="ignore")
display(vif.sort_values("VIF", ascending=False))
```

	feature	VIF
0	const	170.662614
2	energy	4.261457
4	loudness	3.269276
7	acousticness	2.417361
10	valence	1.600743
1	danceability	1.565985
8	instrumentalness	1.470513
9	liveness	1.158525
6	speechiness	1.146349
11	tempo	1.096353
12	time_signature	1.082554
13	duration_min	1.052097
5	mode	1.041646
3	key	1.022827

Excluding the intercept term, the largest VIF values are:

- energy: VIF = 4.26
- loudness: VIF = 3.27

- acousticness: VIF = 2.42

All are below 5, indicating moderate but not severe multicollinearity. The elevated VIFs for energy and loudness align with the strong pairwise correlations observed earlier.

7 7. Discussion

Our results highlight both what audio-feature modeling can and cannot do:

- Audio features alone explain limited variation in Spotify popularity. The weak correlations with popularity and RMSE ≈ 20 suggest that platform-level and social factors likely dominate.
- Collinearity is present but manageable for linear modeling in this feature set (VIF <5), especially if our goal is prediction rather than fine-grained causal interpretation.
- Popularity is a proprietary metric. Spotify's popularity score is not a direct measure of "cultural impact" and may reflect platform-specific dynamics such as playlisting, recency effects, and algorithmic exposure.

7.1 Limitations and future work

- Incorporate nonlinear models (e.g., random forests, gradient boosting/XGBoost) and compare performance and feature importance.
- Add time-aware evaluation (e.g., train on earlier years, test on later years) to study how relationships shift across musical eras.
- Include additional predictors (artist-level popularity, release year, genre) if available and allowed by the project scope.

8 8. Conclusion

- Popularity in this dataset is widely dispersed (mean ≈ 33, median ≈ 35), with many tracks at low popularity.
- Several audio features are strongly related to each other (energy–loudness, energy–acousticness), but individual correlations with popularity are weak.
- Linear models provide a clear baseline but achieve only moderate predictive accuracy (test RMSE ≈ 20), implying that much of popularity is not captured by audio descriptors alone.

9 9. Author Contributions

Collin:

Becca:

Jacky: main.ipynb

Christy: 02_linear_regression.ipynb skeleton Myst website

10 References

We use the Spotify Tracks Dataset from Kaggle for audio features and the Spotify popularity score[]{cite:p spotifytracks_kaggle}.