

The background of the image is a light gray, semi-transparent sheet of musical notation. It features multiple staves with various musical symbols, including treble and bass clefs, notes, rests, and dynamic markings such as 'ff' (fortissimo) and 'mf' (mezzo-forte). The notation is slightly blurred and angled, creating a textured, artistic backdrop for the text.

# Hit or miss?

Oskar Diyali and Logan Smith

# Motivation and Reasoning

## **Motivation:**

Can song features and lyrics of a song predict hits?

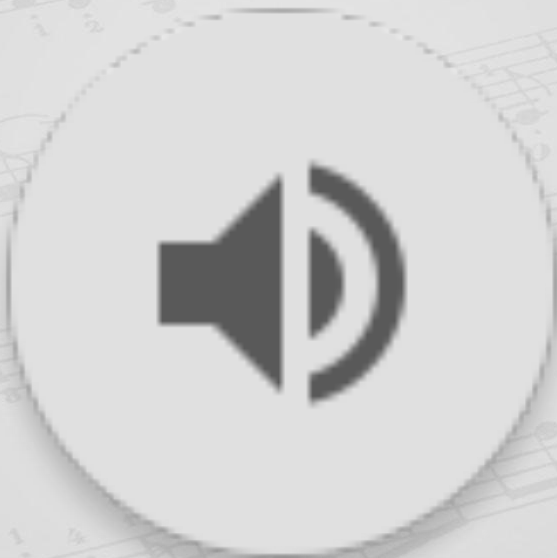
## **Why is predicting hit songs valuable?**

- Artists
- Listeners
- Labels
- Streaming Platforms
- Marketing

## **What “hit” means in your project?**

- Popularity, from Spotify API  $\geq 45$  cutoff

Guess whether it's a hit or miss!



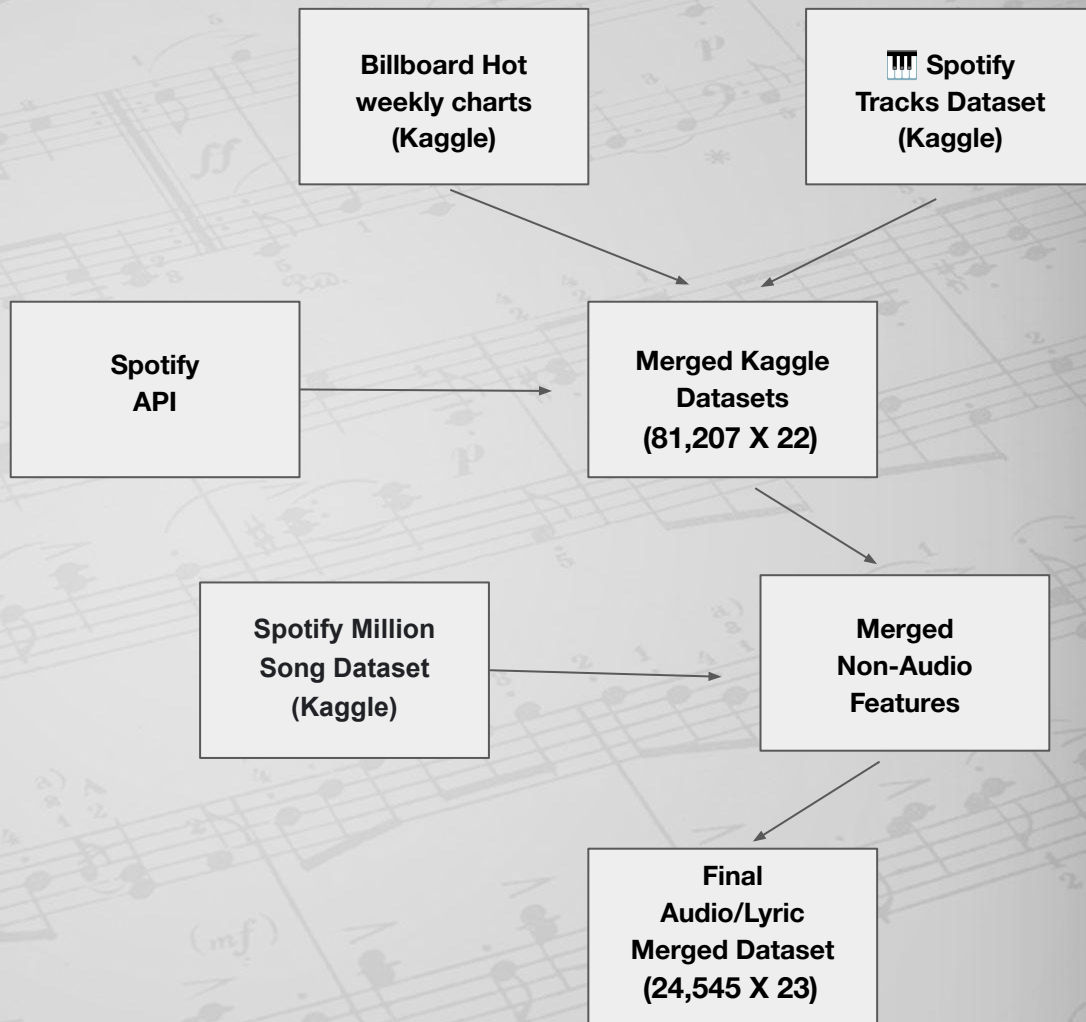
# Dataset & Features

## Numeric Features:

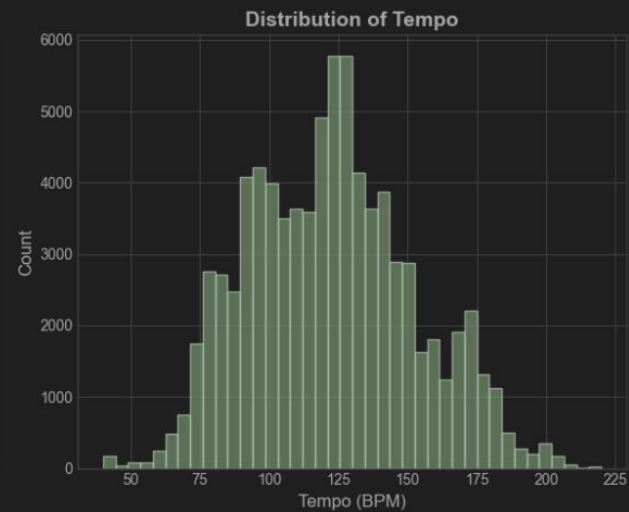
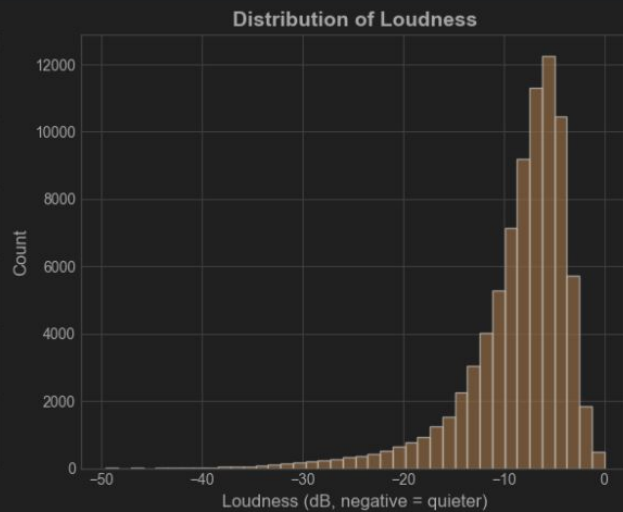
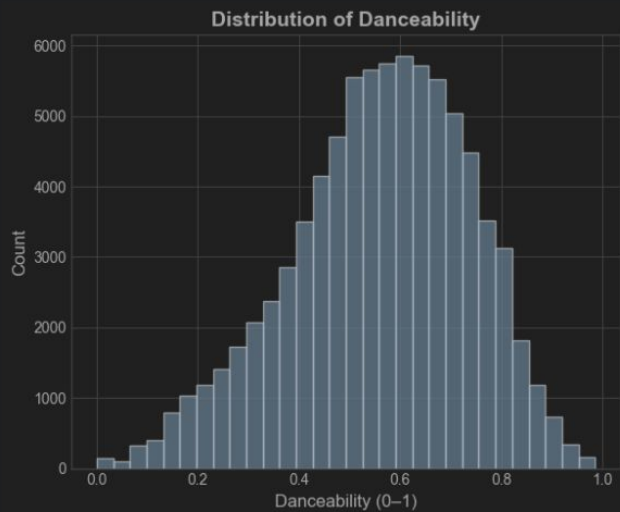
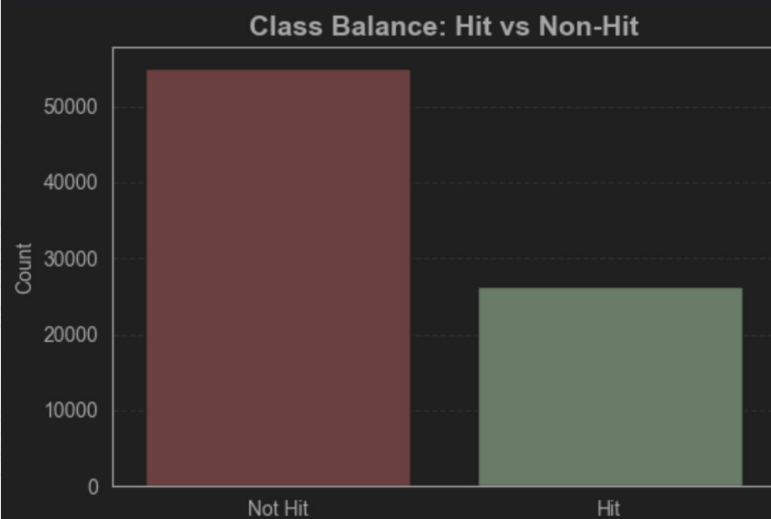
- **Audio:**  
Danceability, Energy, Speechiness, Tempo, Liveness, Loudness, Instrumentalness, Valence
- **Non-Audio:**  
Tracks in Album, Artist Popularity, Artist Followers

## Categorical Features:

- Explicit, Mode, Album Type, Label Group, Artist Genre, Track Genre, Lyrics



# Exploratory Data Analysis



# Challenges and Featured Engineering

## Challenges in the Data

- Missing values
- Inconsistent formats in Genres and Labels
- Key stored as numbers, instead of musical notes
- Imbalanced target: only ~19% of songs are “hits”

## Feature Engineering Solutions

- Extracted release\_year, release\_month, added flags
- Simplified genres and grouped labels into groups
- Log transforms
- Interaction of features

BEFORE (original features)

	duration_ms	tempo	loudness	energy	valence	danceability
0	230666.0	87.917	-6.746	0.461	0.715	0.676

AFTER (engineered features added)

	log_duration	log_tempo	log_loudness	energy_valence	dance_tempo
0	12.34873	4.487703	2.047177	0.329615	59.431892

# Methods

## Modeling Approach

- Train/test split (80/20, stratified).
- Models tested: Logistic Regression, Random Forest, LightGBM, CatBoost, **XGBoost (tuned)**.
- Evaluation metrics: Accuracy, Precision, Recall, F1, ROC-AUC.



# Model Comparison

Model	Accuracy (%)
<b>Tuned XGBoost</b>	<b>88.2%</b>
LightGBM	88%
XGBoost (default)	87%
Random Forest	84%
Logistic Regression	82%

Tuned XGBoost (threshold=0.50)

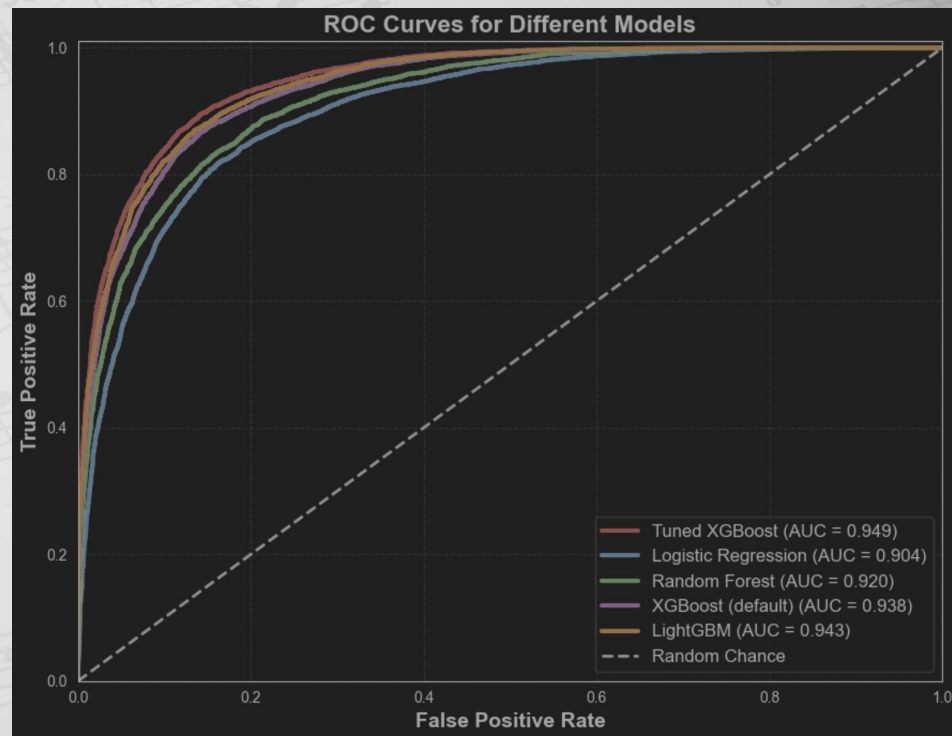
	precision	recall	f1-score
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0	0.909	0.918	0.913
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1	0.824	0.807	0.815
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accuracy	0.882
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# ROC-AUC Comparison





## Methods pt. 2

### **Lyrical Analysis**

- Standardized lyrics
- Converted lyrics into numeric features using term frequency-inverse document frequency (TF-IDF)
- Split and run logistic regression
- Extract top words
- WordCloud

The song was....

A HIT



## Top 25 most common hit lyrics



# Reflection

## **Positive:**

- Importance of non-audio features
- Learned TF-IDF

## **Negative:**

- Remove duplicates
- Limitations of Spotify API

# Any questions?

