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Spotify DATA Analysis

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Meet Our Team!



Nicho Lin



Ethan Liu



Hanwei Chang



Jewel Ling



Katherine Wang



Camilla Zhao

Dataset





A dataset spanning 2010-2020 of ~26,000 rows of 'popular' and 'unpopular' songs released up to March 2020; the target variable is "popular"













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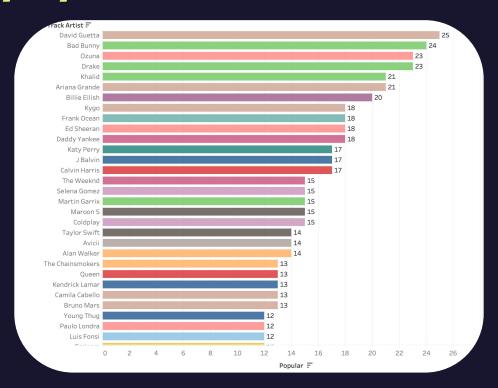






Popularity by Artists







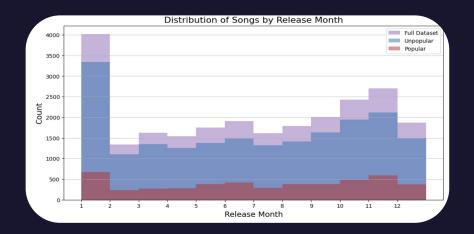


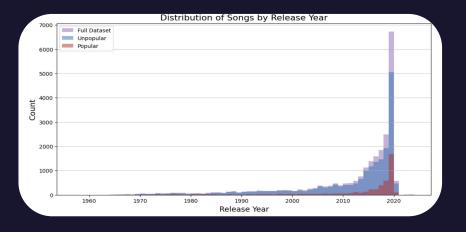




Popularity by Release Month & Year















Popularity by Genre

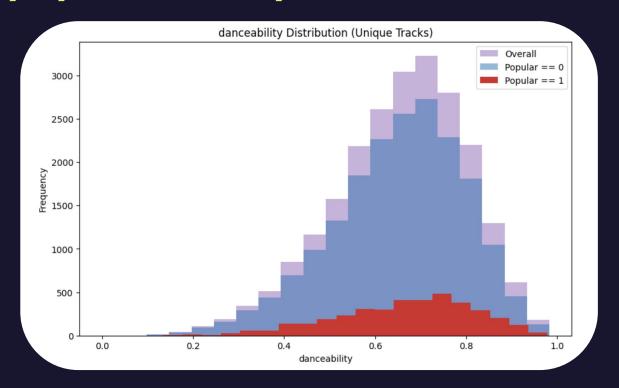


Genre	Total	Popular	Unpopular	Popular Ratio
Рор	4099	1124	2975	27.42%
Latin	3756	911	2845	24.25%
R&B	4098	804	3294	19.62%
Rock	3567	693	2874	19.43%
Rap	4415	723	3692	16.38%
EDM	4434	455	3979	10.26%



Popularity by Danceability



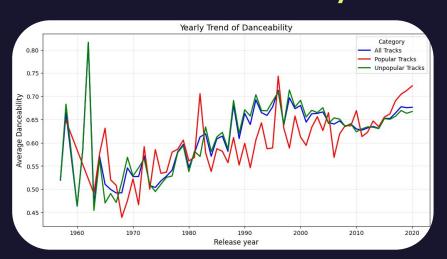




Other Exploration



Trend of Danceability



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Trend of Speechiness

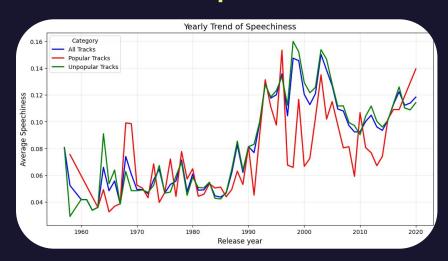








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Data Cleaning



Duplicate Tracks_id

• Observation: Songs with multiple genres represented as individual rows.

Release Year Errors

- Observation: Large chunk of data set to 1905 and a well has value 0
- Likely Explanation: a placeholder for missing release years or data error.

Release Month Anomalies

- Observation: Disproportionate concentration in January.
- Likely Explanation: Placeholder for missing month data.

Other Missing Values

Minimal single-digit missing values in a few columns.

	count
elease_yea	r
0	21
1905	1360
1957	1
1958	1
1961	1











Data Cleaning

Correcting Data with Spotify API

- Identify Errors: Flag invalid info (e.g. release years == 1905)
- **Set Up API:** Create Spotify Developer account. Authenticate using Spotify API credentials (client_id and client_secret).
- Fetch Data: Query track info via track_id or search by track name
 and artist.
- Validate Matches: Ensure track and artist names align between API and dataset.
- Update Dataset: Correct release_year and release_month using
 API results.
- **Save Results:** Export corrected data to a CSV to prevent redundant API calls.













Data Cleaning

Create New Columns

Combine Year and Month into a New Column (date)

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 Purpose: Enables time-series analysis to identify trends, such as popularity during specific periods.

Create a New Column (key_mode)

- Combines key and mode columns.
- In music theory, a key in a specific mode conveys unique meaning (e.g., C Major vs. C Minor), making it logical to combine them into a single entity.











Logistic Model Performance





Logistic Regression as a baseline model

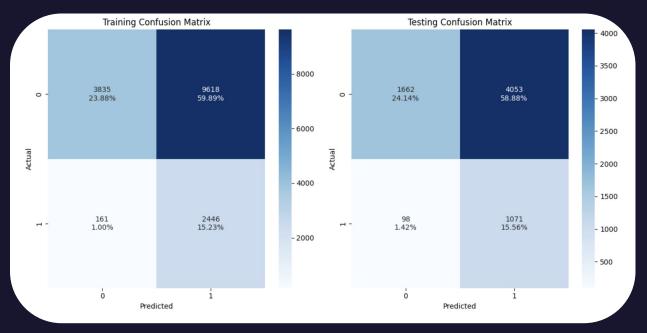
The highest profit, **\$87,990,000** was achieved at a cutoff of 0.07, where accuracy = 39.70%, precision = 20.90%, and recall = 91.62%

The graph pattern suggests that **recall** is the key metric we should be focusing on.



Logistic - Confusion Matrix





Confusion Matrix at 0.07 cutoff









Model Summary



Model	Cutoff	Accuracy	Precision	Recall	Profit	
Logistic Regression	0.07	0.397008	0.209016	0.916168	87990000	
Decision Tree	0	0.169814	0.169814	1	83130000	
Random Forest	0.09	0.425189	0.217356	0.917023	90040000	
Bagging	0.05	0.344858	0.200788	0.958939	89900000	
XGBoost	0.08	0.429256	0.220195	0.928999	91860000	
Neural Network	0.06	0.444073	0.219739	0.89136	88040000	







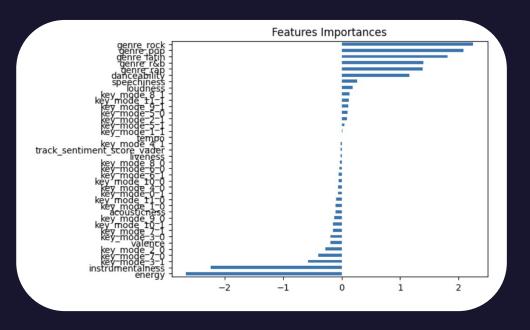




^{*}Performance was obtained with optimal hyperparameters after tuning

Logistic - Inspecting the Features





Some prominent features: genres, danceability, energy, instrumentalness

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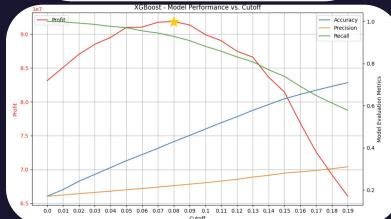
Best Final Model: XGBoost

XGBoost stands out as the best final model, delivering optimal financial outcomes with balanced metrics.

Why?

- Feature Handling: Captured complex relationships in Spotify's dataset.
- Optimized Threshold (0.08): Balanced recall and precision, ensuring popular tracks were promoted while minimizing wasted resources.
- **Scalability:** Efficiently processed large data, optimizing predictions for financial outcomes.
- **Cost-Effective:** High recall avoided missing hit tracks, and precision ensured focused investments.

			for XGBoos				
	Cutoff	Accuracy	Precision	Recall	AUC_ROC	Confusion Matrix	Prof
0	0.00	0.169814	0.169814	1.000000	0.738699	[[0, 5715], [0, 1169]]	831300
1	0.01	0.201191	0.175120	0.998289	0.738699	[[218, 5497], [2, 1167]]	850700
2	0.02	0.240558	0.181847	0.992301	0.738699	[[496, 5219], [9, 1160]]	870100
3	0.03	0.273242	0.187785	0.986313	0.738699	[[728, 4987], [16, 1153]]	884900
4	0.04	0.305491	0.193691	0.976903	0.738699	[[961, 4754], [27, 1142]]	895000
5	0.05	0.338175	0.200636	0.970915	0.738699	[[1193, 4522], [34, 1135]]	909800
6	0.06	0.367664	0.206165	0.955518	0.738699	[[1414, 4301], [52, 1117]]	910300
7	0.07	0.397298	0.212909	0.945252	0.738699	[[1630, 4085], [64, 1105]]	917500
8	0.08	0.429256	0.220195	0.928999	0.738699	[[1869, 3846], [83, 1086]]	918600
9	0.09	0.458600	0.226943	0.909324	0.738699	[[2094, 3621], [106, 1063]]	913500
10	0.10	0.488960	0.233734	0.881950	0.738699	[[2335, 3380], [138, 1031]]	899200
11	0.11	0.519030	0.241928	0.858854	0.738699	[[2569, 3146], [165, 1004]]	890200
12	0.12	0.547647	0.249936	0.831480	0.738699	[[2798, 2917], [197, 972]]	874700
13	0.13	0.578007	0.260618	0.808383	0.738699	[[3034, 2681], [224, 945]]	865900
14	0.14	0.605462	0.269036	0.770744	0.738699	[[3267, 2448], [268, 901]]	836400
15	0.15	0.632481	0.279702	0.739093	0.738699	[[3490, 2225], [305, 864]]	814300
16	0.16	0.653835	0.285664	0.692044	0.738699	[[3692, 2023], [360, 809]]	768500
17	0.17	0.673591	0.292213	0.648417	0.738699	[[3879, 1836], [411, 758]]	7260



Question 2b



Old Profit Formula = (\$120K * TP) - (\$10K * FP)

What if a 20% chance of unpopular songs get popular after we promote it?

- What songs to promote?
 - FPs, because they were relatively more likely to be popular than the rest of the songs (i.e. songs classified as unpopular)

If Promotion Cost < \$16K:

Lower cutoff to include more songs as expected return for each promoted FP would be positive.

Else if Promotion Cost >= \$16K:

Raise the cutoff with caution to avoid losses and optimize profit.









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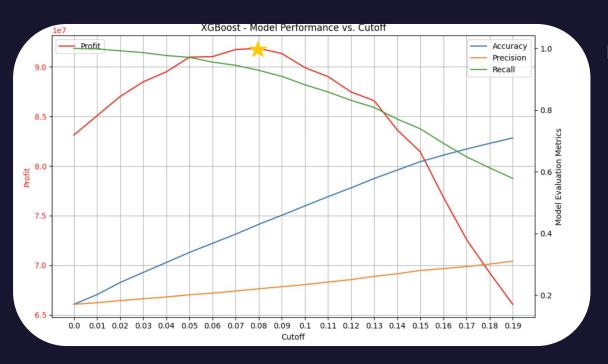


Recommendations



Recommendations Based on XGBoost Model





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Real-Life Implementation for UMG

- Feature-Based Predictions: Use more comprehensive data like streaming metrics, fan engagement, and sentiment analysis to predict hit tracks.
- Targeted Promotion: Prioritize marketing for tracks predicted to succeed (e.g., regional campaigns for Olivia Rodrigo in emerging markets).
- Resource Optimization: Allocate higher budgets to high-probability hits, avoiding overpromotion of low-potential tracks.
- Collaboration Strategy: Identify data-backed artist pairings (e.g., emerging talent with top performers like Billie Eilish)









Recommendations for Universal Music





Data-Driven Music Production

Employing the XGBoost model during the music creation process to **strategically balance song features**, maximizing the likelihood of producing hits.



Strategic Playlist Curation

Using the XGBoost model to predict the popularity and profitability of various bundled songs is an ideal approach for optimizing curated playlists.



Optimized Song Promotion

Prioritize tracks with high predicted **popularity** probabilities for promotional efforts;
Use **genre and feature** insights to design tailored campaigns.



Collaboration Strategies

Identify **artist collaborations** based on complementary styles or shared audience demographics.







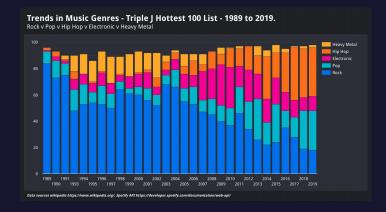






Limitations & Mitigations





01 Dynamic Market Trends

The model relies on historical Spotify data, which may not fully capture rapidly changing audience preferences.

Mitigation: Regularly retrain the model with new data to reflect evolving trends.

02 Limited Creativity

While data can guide production, artistic creativity and experimentation remain vital for breakthrough success.

Mitigation: Use insights as a supplement, not a substitute, for artistic intuition.



"What Was I Made For?" Bongo Cat Cover "Meow" ver. Became a hit









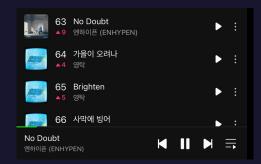




Incorporate Real-Time Metrics



03 Feedback Loop



Next Steps

Regional Customization













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Thank you!







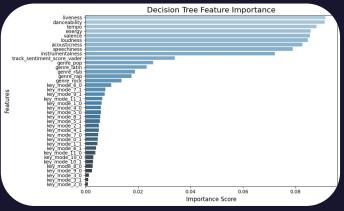


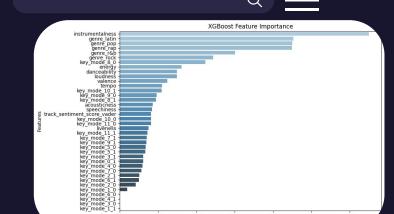
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Feature Importance





0.04

0.06

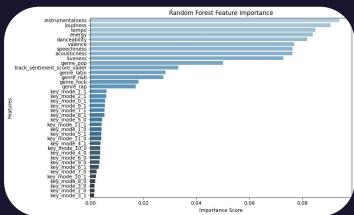
Importance Score

0.08

0.10

0.12

0.02



Main takeaway: Key_mode combination has minimal predictive power on a song's popularity.