DATA MINING

GENRE CLASSIFICATION USING SONG LYRICS

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03.12.20

AGENDA

- Project Intro
- Data Exploration
- Data Preparation
- Modeling
- Evaluation
- Deployment
- Conclusion

PROJECT SCOPE

PROJECT OBJECTIVE

Explore the feasibility of predicting genres through song lyrics

TACTICS

Use data mining techniques to clean, prepare, model, and evaluate results (NLP).

DATA SOURCE

Lyrics.com - 50K songs | Kaggle
Genres from Spotify API

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WHAT DOES SUCCESS LOOK LIKE?

Find a relationship between lyrics and genre

DATA EXPLORATION

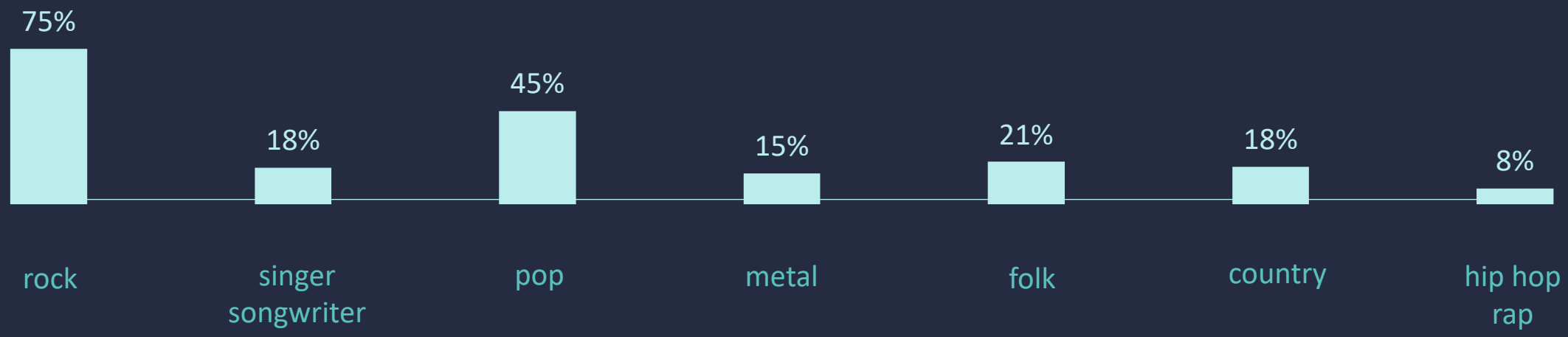
An initial look at our data.

MOST LIKE THE OTHER

- Singer-songwriter and Folk
- Singer-songwriter and Country
- Folk and Rock

MOST UNLIKE THE OTHER

- Hip-Hop/Rap and Rock
- Metal and Pop
- Rock and Pop
- Country and Pop



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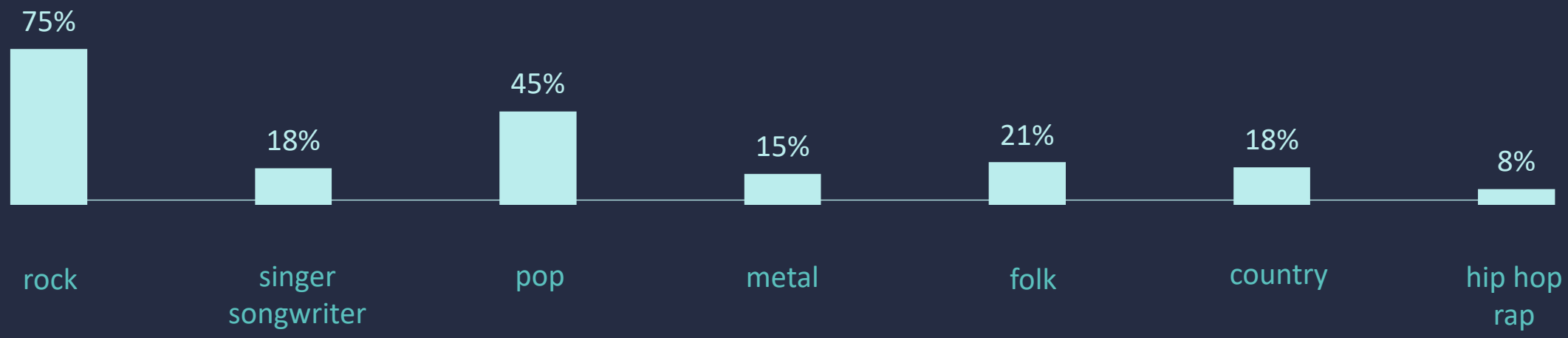
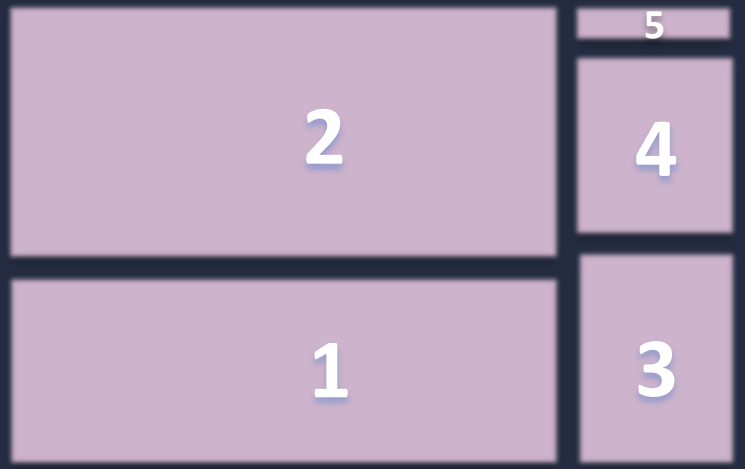
SONG GENRES ARE NOT MUTUALLY EXCLUSIVE

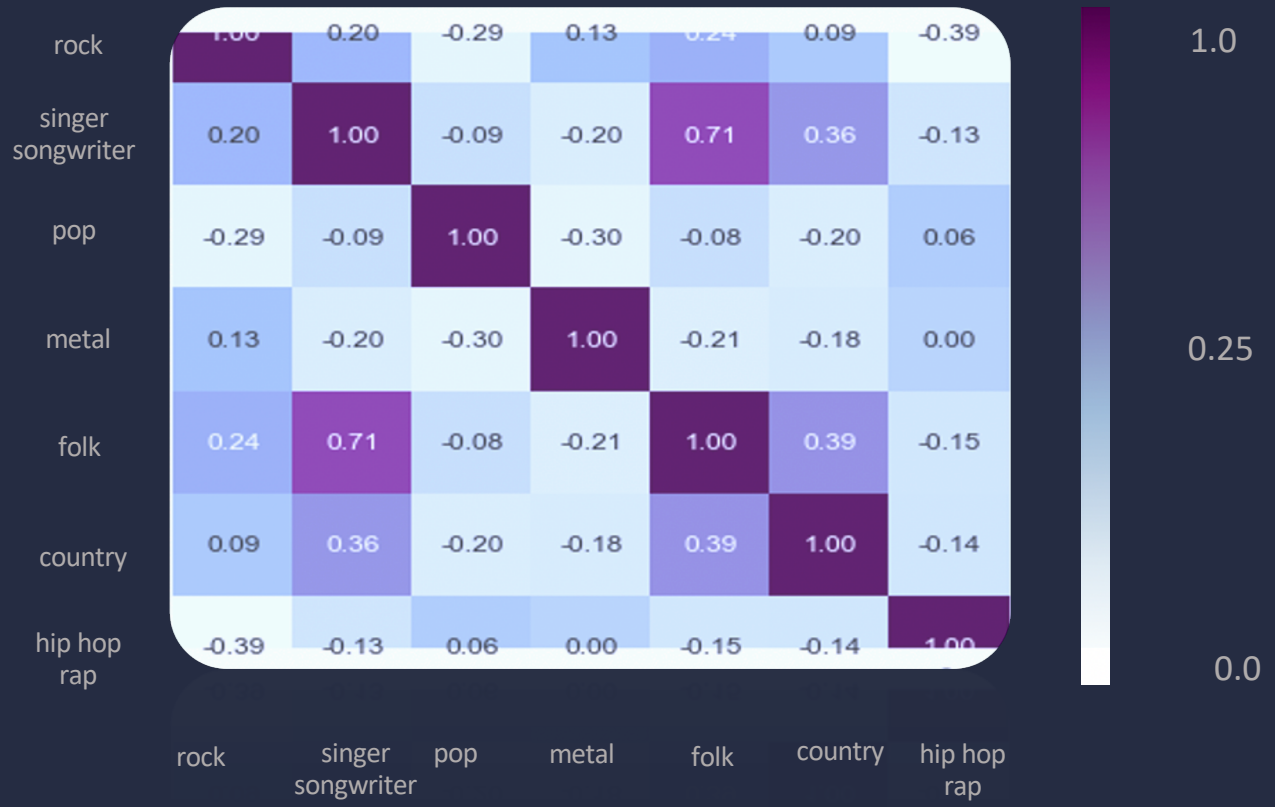


An initial look at our data.

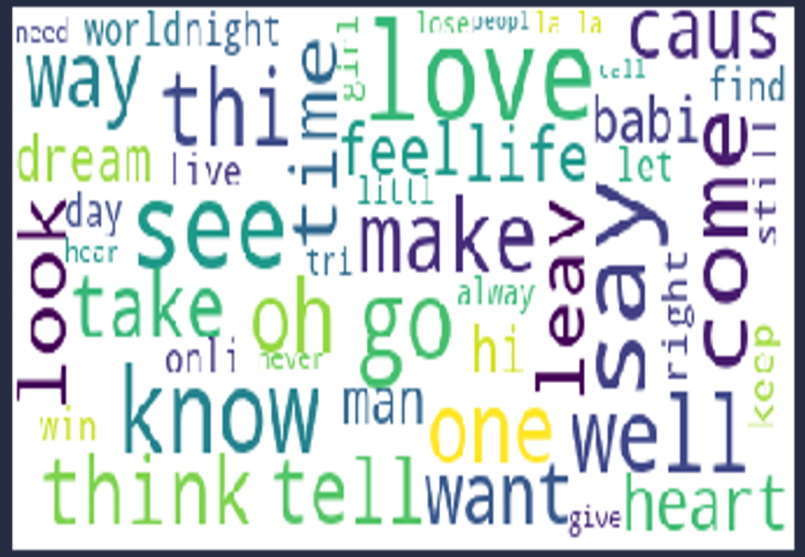
Songs with multiple genres



Correlation

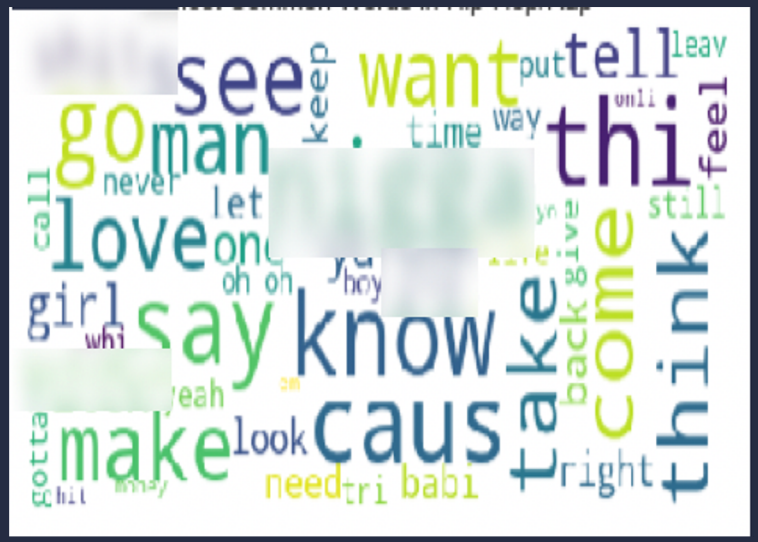


Words By Genre



SINGER-SONGWRITER

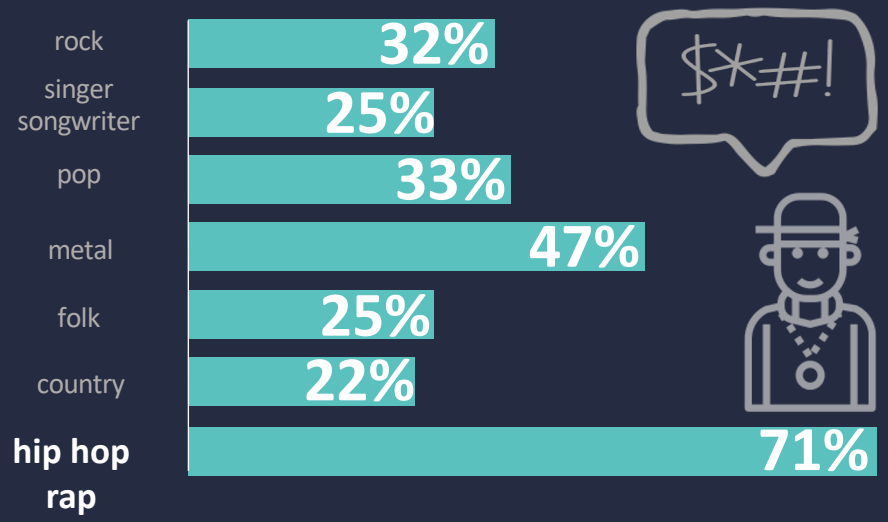
POP



HIP-HOP

Potential Future Exploration

Profanity by genre



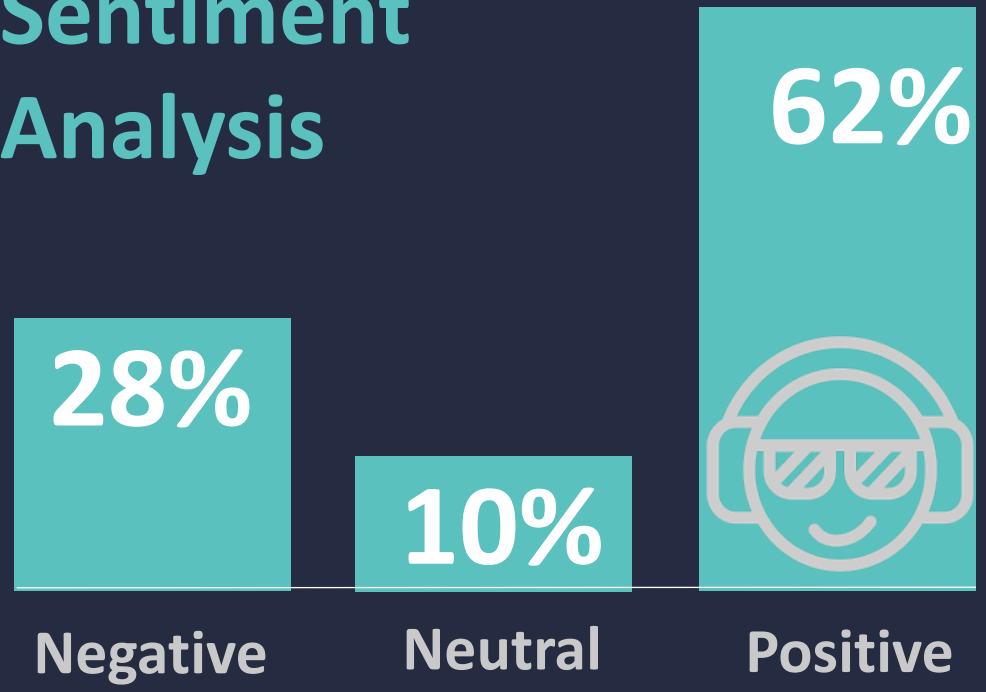
predict and predict_prob from profanity_check

Potential Future Exploration

Profanity by genre

predict and predict_prob from profanity_check

Sentiment Analysis



SentimentIntensityAnalyzer()
'vader_lexicon' from nltk

DATA CLEANING

Cleaning
Pre-Processing

TEXT FORMATTING

- Non-lyric text line breaks
- Square brackets vs. parenthesis

LANGUAGE

- Non-English lyrics
- Probability of English lyrics
- langdetect

A hero is someone who understands the responsibility that comes with his freedom.

-Bob Dylan

Cleaning Pre-Processing

PRE-PROCESSING DATA

- Text formatting
- Tokenization
- simple_preprocess
- gensim.utils

LEMMATIZATION

- WordNetLemmatizer
- nltk.stem

REMOVING STOP WORDS

- stopwords nltk.corpus

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REMOVING STOP WORDS

- stopwords nltk.corpus

"Take a silver dollar and put it in your pocket, \nNever let it slip away. \nAlways be a man, not a boy gone astray. \nWhen ya get half cra-zy from the August hear

"'take', 'silver', 'dollar', 'put', 'pocket', 'never', 'let', 'slip', 'away', 'alway', 'man', 'boy', 'go', 'astray', 'ya', 'get', 'half', 'craz', 'august', 'heat', '

Word2Vec

The word2vec objective function causes the words that occur in similar contexts to have similar embeddings.

What is it?

- A two layer neural network to generate word embeddings (mapping of words) given a text corpus

Why use it?

- Preserve relationships between words
- Deals with addition of new words in the vocabulary
- Better results in lots of deep learning

"Woman"
0.73
0.89
-1.67
1.32
0.36
-1.49
2.71

"Man"
0.52
0.76
1.21
0.22
-1.36
0.49
-3.69

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An Example

The kid said he would grow up to be superman.
The child said he would grow up to be superman.

Thus the words kid and child will have similar word vectors due to a similar context

Doc2Vec

What is Doc2Vec?

- An unsupervised algorithm that learns fixed-length feature representations from variable-length pieces of texts, such as sentences, paragraphs, and documents.

Why Doc2Vec?

- We need a vector representation for each lyric, which is a group of words(Paragraph)
- Doc2Vec usually outperforms simple-averaging of Word2Vec vectors

"'take', 'silver', 'dollar', 'put', 'pocket', 'never', 'let', 'slip', 'away', 'alway', 'man', 'boy', 'go', 'astray', 'ya', 'get', 'half', 'craz', 'august', 'heat', 'freez', 'rot', 'road', 'one', 'complain', 'achin', 'feet', 'gonna', 'walk', 'endless', 'highway', 'walk', 'high', 'way', 'till', 'die', 'children', 'goin', 'way', 'better', 'tell', 'home', 'life', 'sweet', 'goodby', 'see', 'detour', 'ahead'...''

[0.80030984, -1.8968158 , -0.20183174, 2.038949 , 0.6700128 ,
0.80359936, -0.26136535, 0.8038724 , -0.01780331, 1.6143647 ,
-0.66266567, -1.3268974 , 1.4345216 , 1.2054638 , 0.06268109,
-0.29674092, 0.84357643, -0.9477247 , 0.10439444, 0.8167453 ,
-0.02420871, -0.0391538 , 0.11021158, 1.4326952 , 0.01581643,
1.0310534 , -0.2578711 , -0.6832181 , 1.2554826 , 0.5251921 ,
0.09430447, -0.37911037, 1.4898267 , -0.3236018 , 0.9216325 , …]

MODELING

Understanding the nuances between Multi-label and Multi-class are crucial to identifying the right model.

MULTI-CLASS

More than 2 Classes

Sample is assigned only one class

Classes **ARE** mutually exclusive

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movie rating

PG-13

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MULTI-LABEL

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Samples may be assigned more than one class

Classes ARE NOT mutually exclusive

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movie rating

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movie genres

Action, Adventure, Drama

There are a three ways to handle multi-label classification.

1) PROBLEM TRANSFORMATION

2) ADAPTED ALGORITHMS

3) ENSEMBLE METHODS

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PROBLEM TRANSFORMATION

Transforms multi-label task into several single-label tasks.

BinaryRelevance()

SONGS	GENRES
X_1	pop folk rap
X_2	rock
X_3	pop
X_4	rock rap
X_5	rap

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HOW IT WORKS

Learns one binary classifier for each label

Outputs the union of their predictions

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pop		rock		folk		rap	
x_1	1	x_1	0	x_1	1	x_1	1
x_2	0	x_2	1	x_2	0	x_2	0
x_3	1	x_3	0	x_3	0	x_3	0
x_4	0	x_4	1	x_4	0	x_4	1
x_5	0	x_5	0	x_5	0	x_5	1

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- **Learns one binary classifier for each label**
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☺ **SIMPLEST WAY**
WIDELY ACCEPTED

☹ **IGNORES RELATIONSHIPS**
BETWEEN LABELS

SONGS	GENRES
X_1	pop folk rap
X_2	rock
X_3	pop
X_4	rock rap
X_5	rap

pop		rock		folk		rap	
X_1	1	X_1	0	X_1	1	X_1	1
X_2	0	X_2	1	X_2	0	X_2	0
X_3	1	X_3	0	X_3	0	X_3	0
X_4	0	X_4	1	X_4	0	X_4	1
X_5	0	X_5	0	X_5	0	X_5	1

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ADAPTED ALGORITHMS

Adapts the algorithm to directly perform multi-label classification.

MLkNN() MULTI-LABEL K- NEAREST NEIGHBORS

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Identifies k nearest neighbor from the training set
Learns info about these neighbors
Determines label

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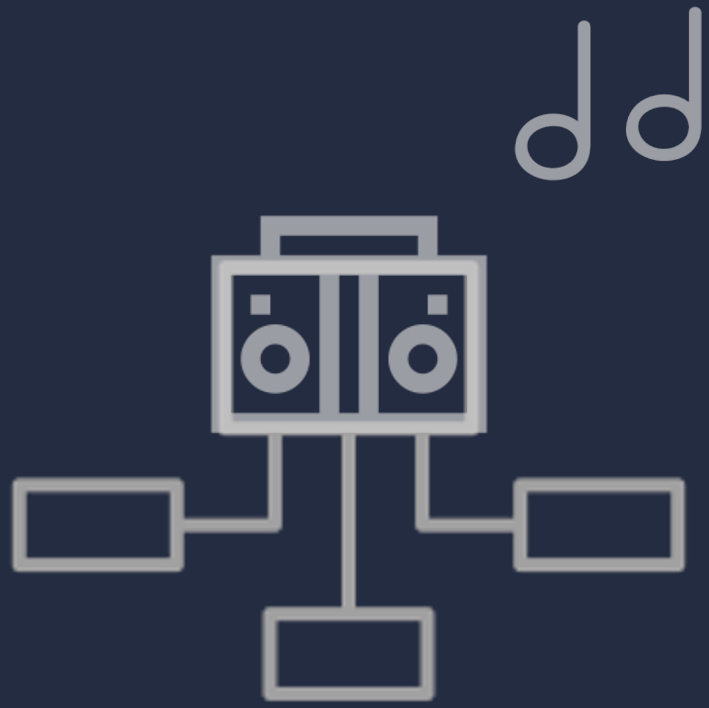
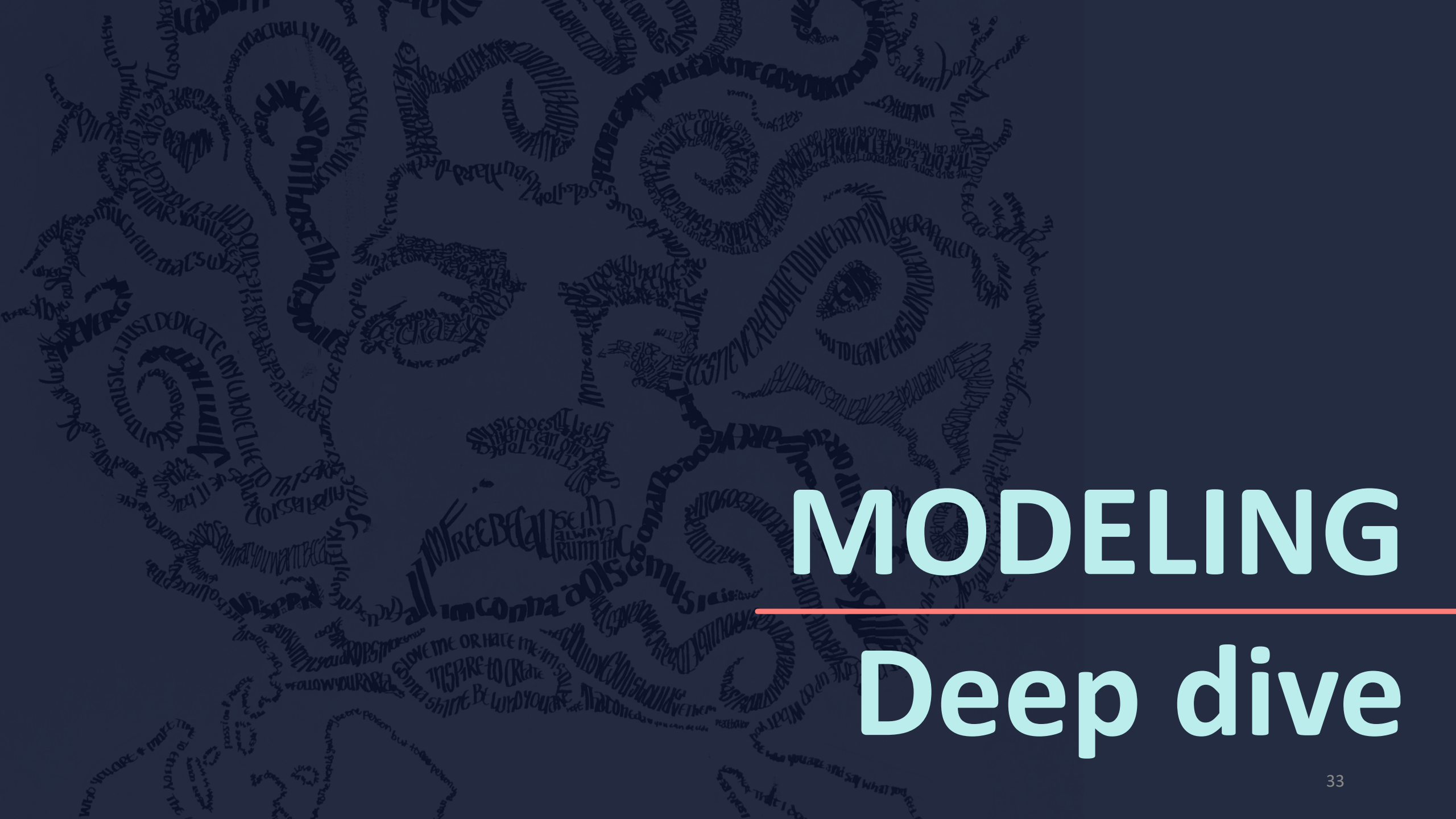
ACCEPTS MULTI-LABEL CLASSIFICATION AS IS

HATERS WILL SAY THIS METHOD IS LAZY

Not all models are suited for multi-label classification.

RidgeClassifier()
Binary Relevance()
MLkNN()
GradientBoostingClassifier()
RandomForestClassifier()
LogisticRegression()

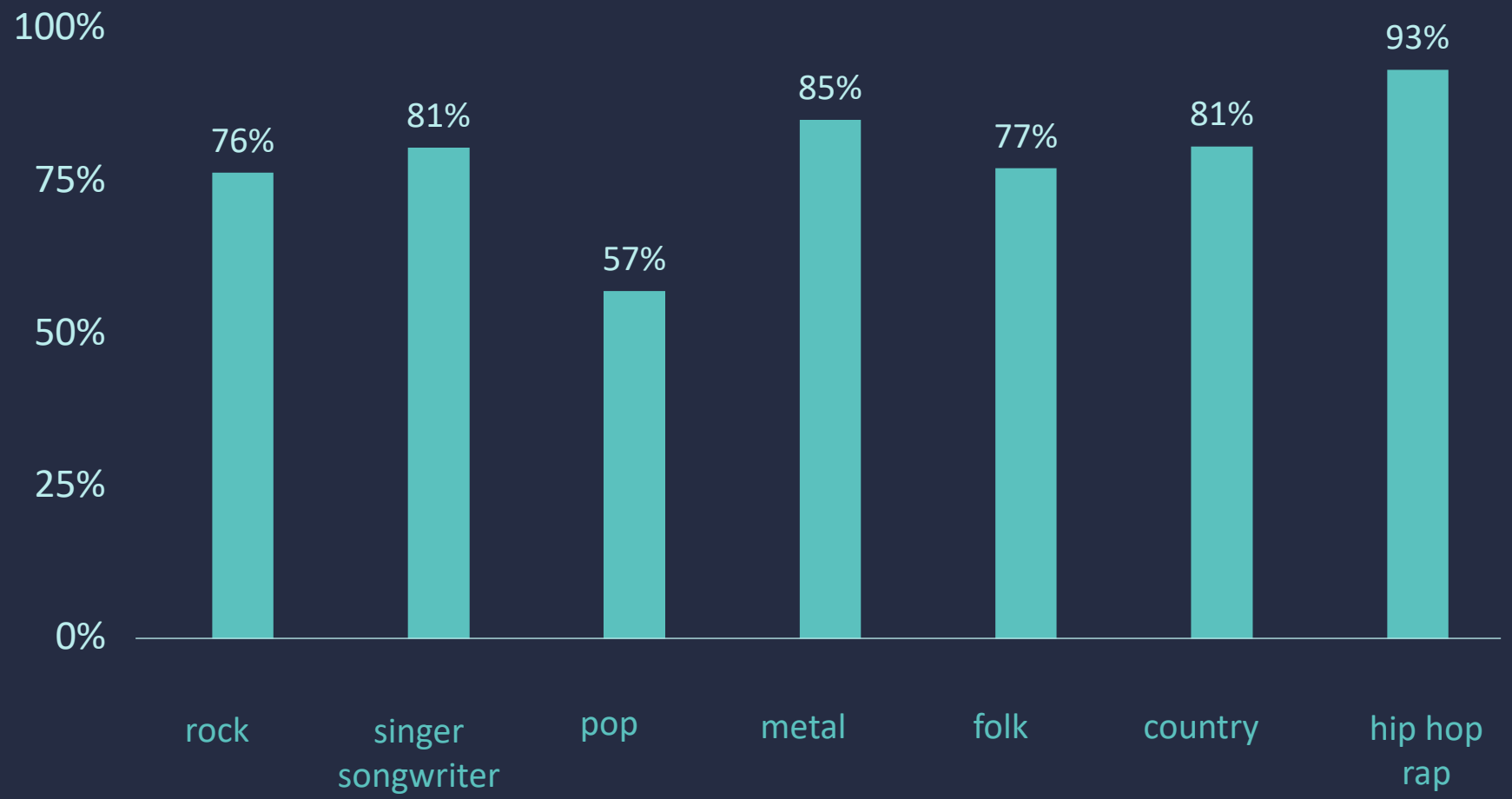




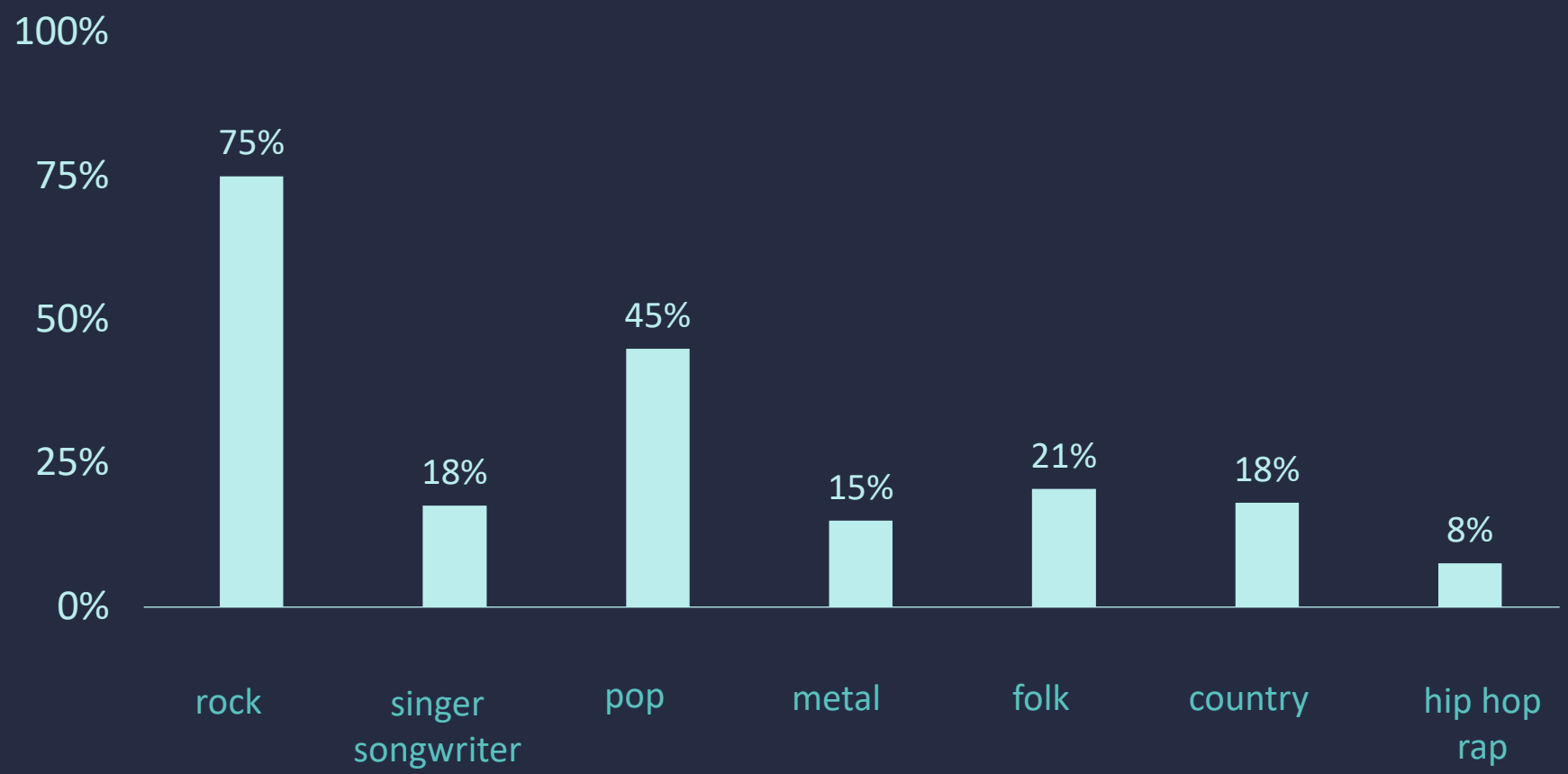
MODELING
Deep dive

Initial prediction accuracy

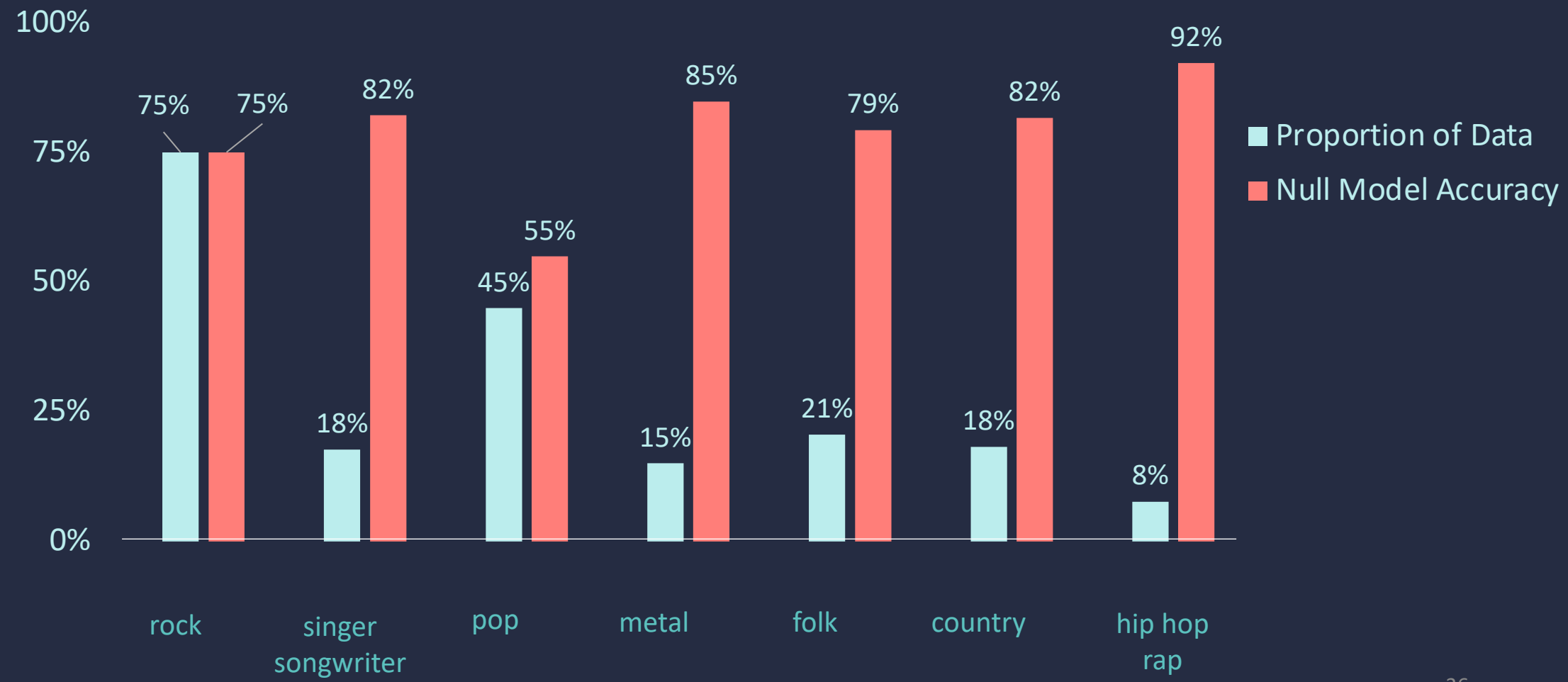
Gradient Boosting



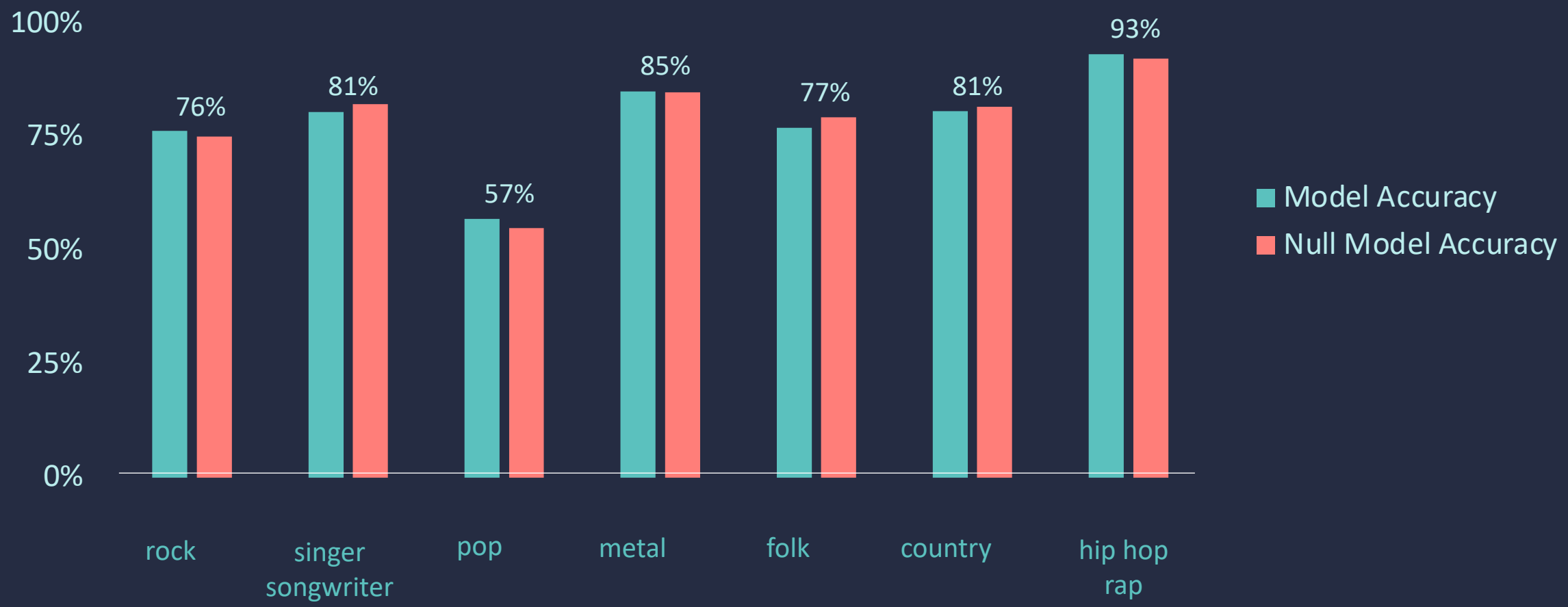
Proportion of songs in each genre



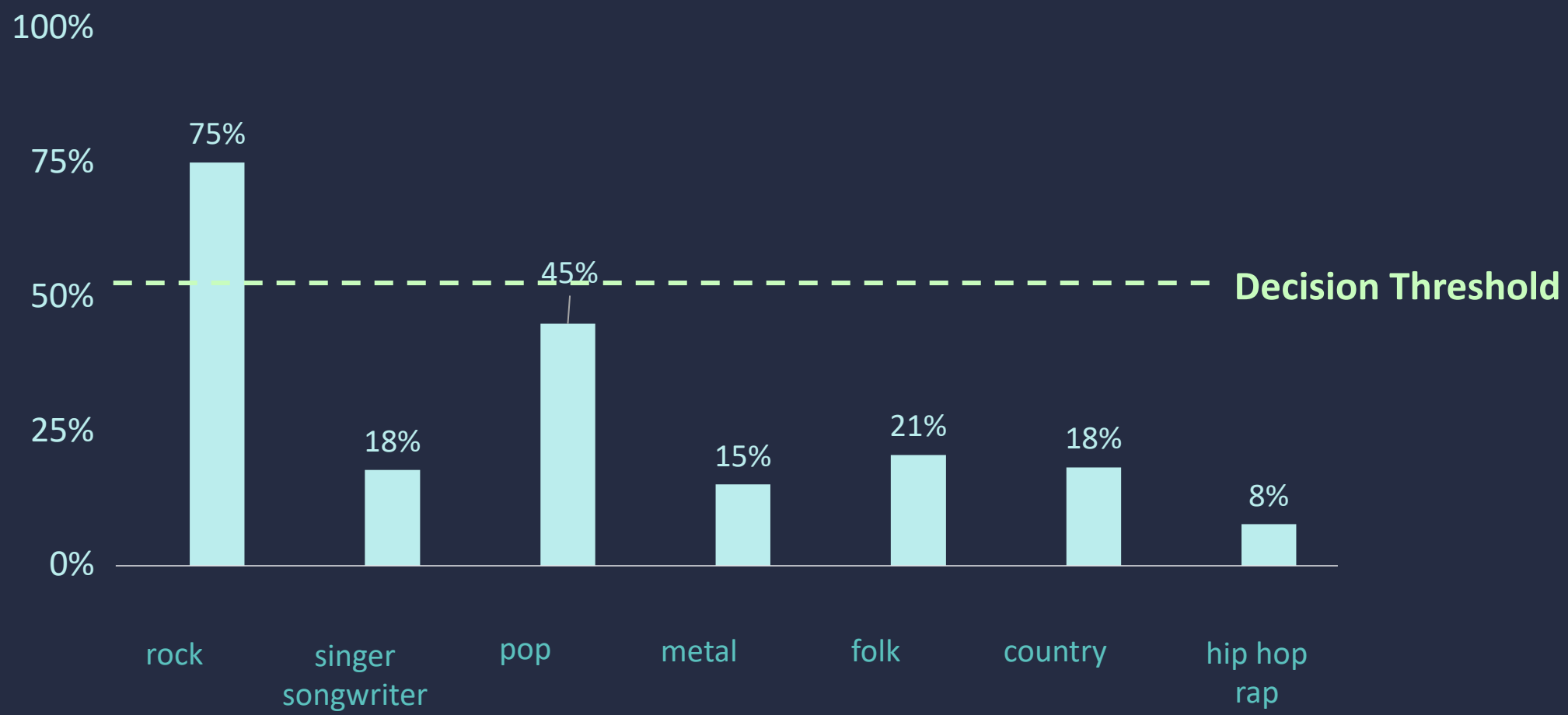
Null Model


100%
75%
50%
25%
0%
75%
75%
18%
82%
45%
55%
15%
85%
21%
79%
18%
82%
8%
92%
rock
singer songwriter
pop
metal
folk
country
hip hop rap
Proportion of Data
Null Model Accuracy

Null Model vs Gradient Boosting

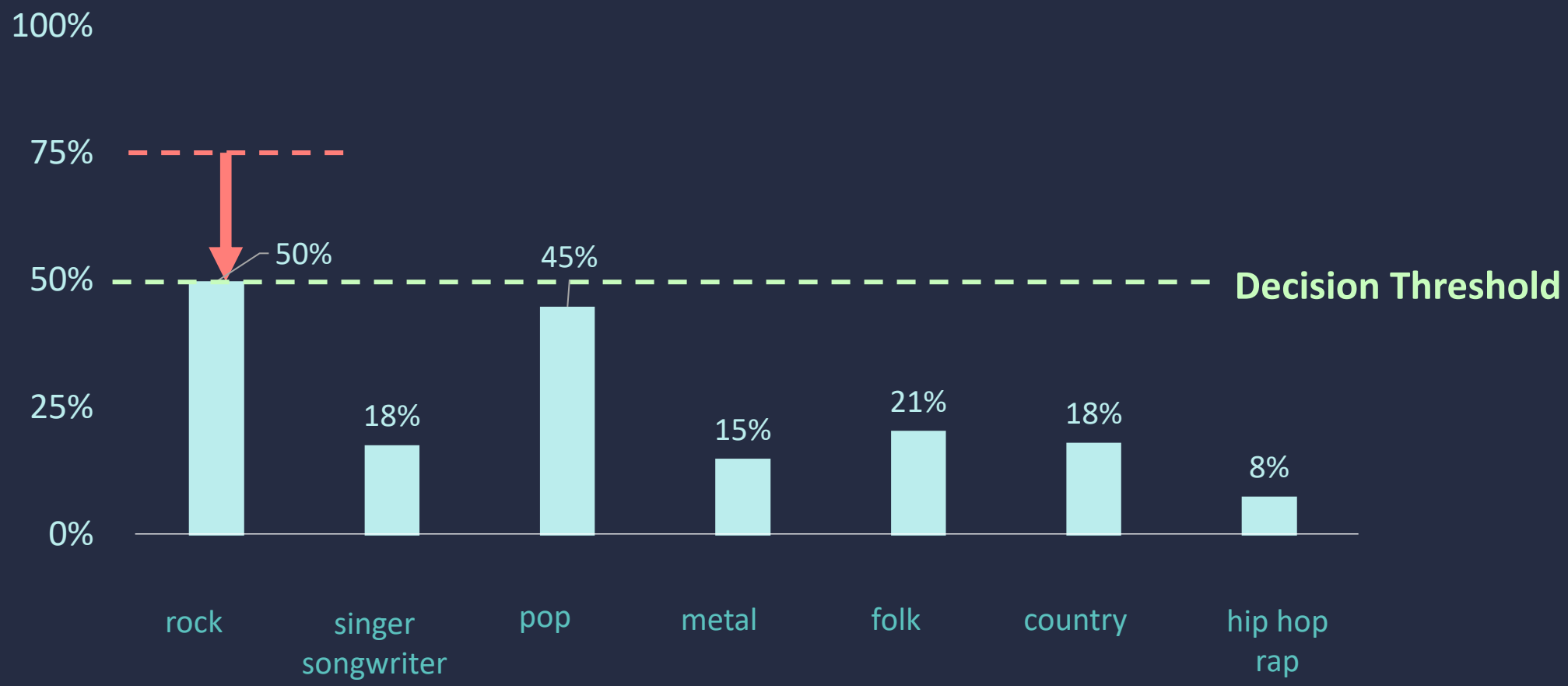


Proportion of songs in each genre



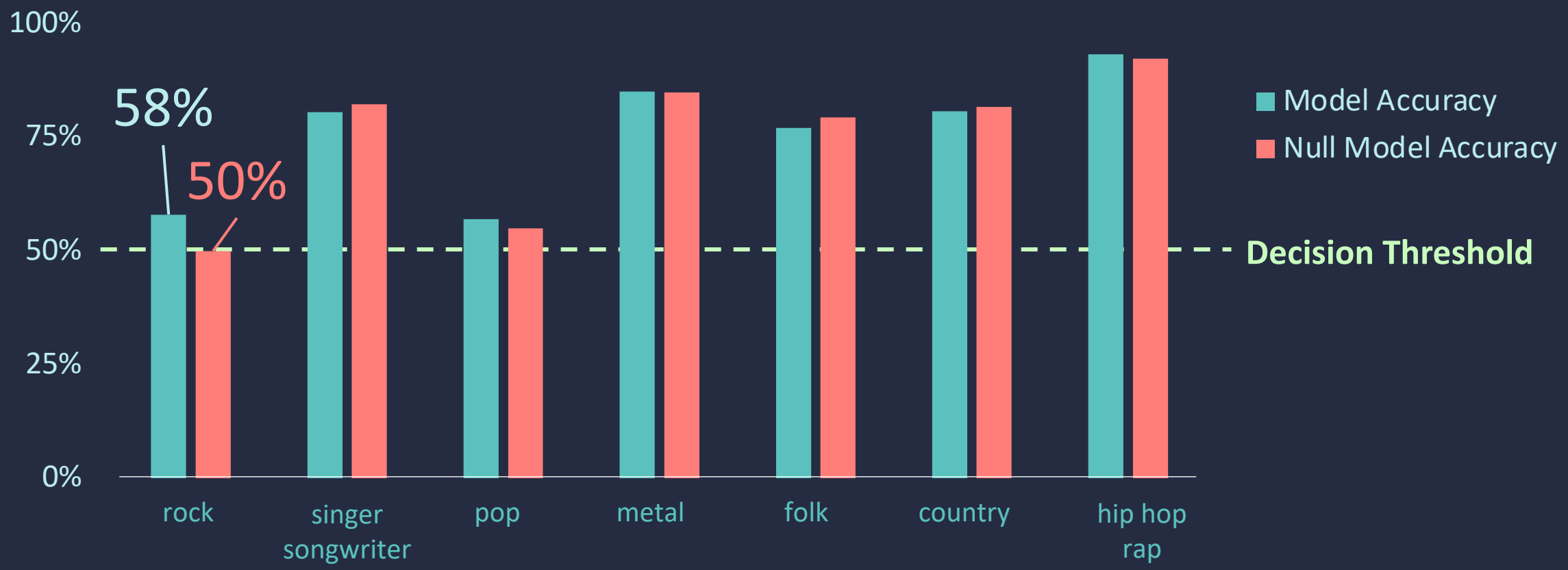
Proportion of songs in each genre

Randomly Undersampling Rock



Null Model vs Gradient Boosting

Randomly Undersampling Rock



EVALUATION

Evaluation Metrics

ACCURACY
PRECISION
RECALL
F1-SCORE
AUC
MATTHEWS CORRELATION COEFFICIENT(MCC)

The MCC is in essence a correlation coefficient between the observed and predicted binary classifications

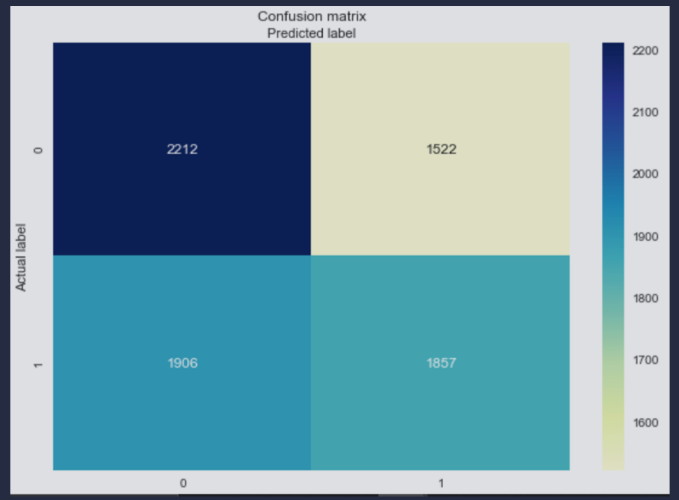
It returns a value between −1 and +1.

A coefficient of +1 represents a perfect prediction, 0 no better than random prediction and −1 indicates total disagreement between prediction and observation.

MCC is a useful measure even when the two classes are of very different sizes.

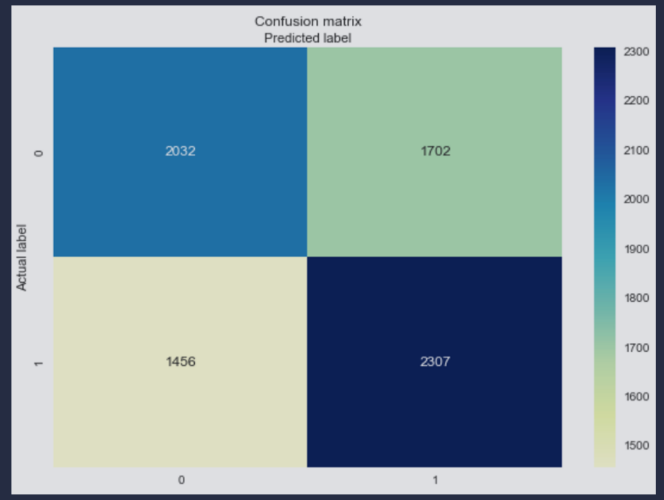
Model Performance Comparison

Random Forest



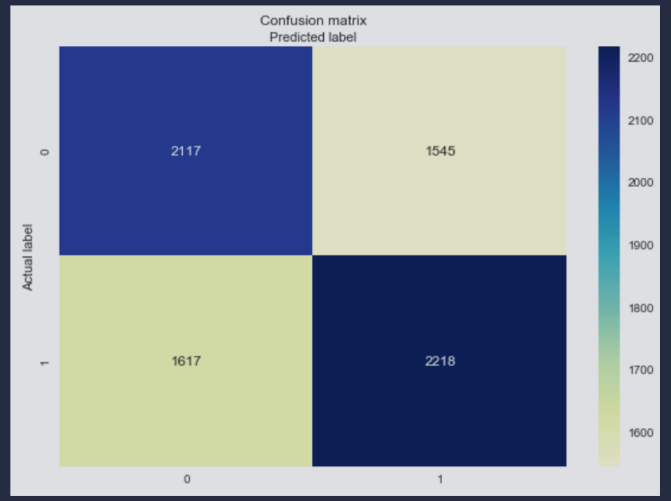
	precision	recall	f1-score
0	0.54	0.59	0.56
1	0.55	0.49	0.52
accuracy			0.54
macro avg	0.54	0.54	0.54
weighted avg	0.54	0.54	0.54

Gradient Boost



	precision	recall	f1-score
0	0.58	0.54	0.56
1	0.58	0.61	0.59
accuracy			0.58
macro avg	0.58	0.58	0.58
weighted avg	0.58	0.58	0.58

Ridge Classification



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Model Performance Comparison

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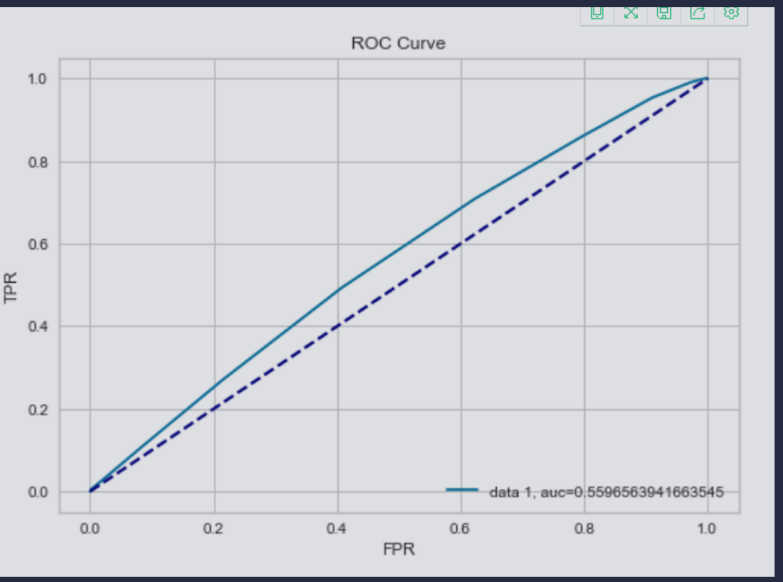
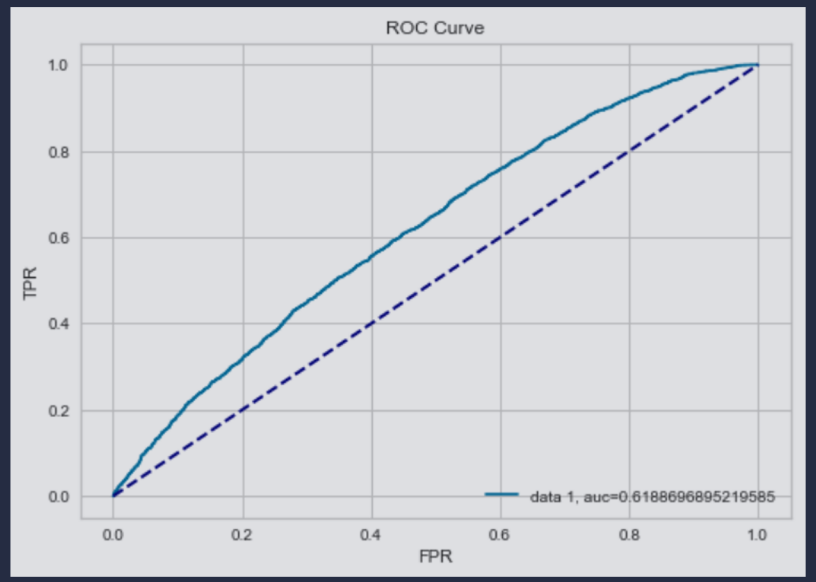


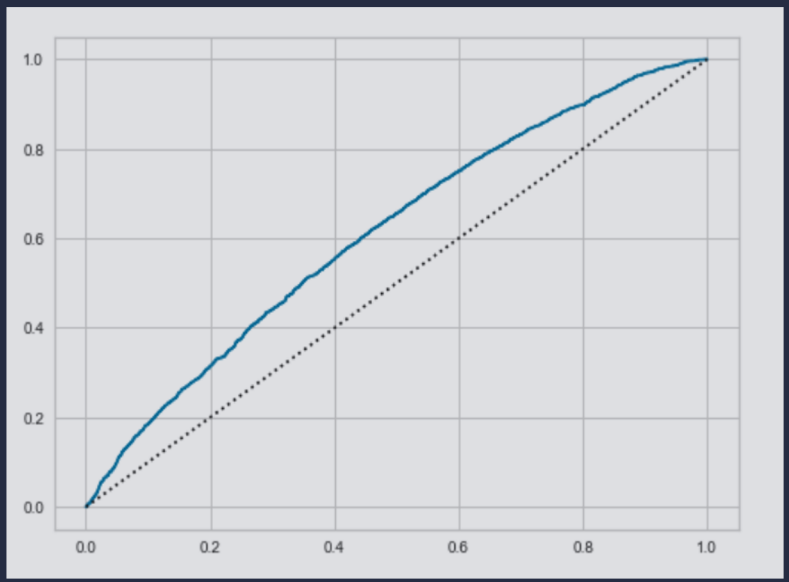
Accuracy: 0.54
AUC: 0.56
MCC: 0.086

Gradient Boost



Accuracy: 0.58
AUC: 0.62
MCC: 0.158

Ridge Classification



Accuracy: 0.58
AUC: 0.58
MCC: 0.156

Testing our Models on New Data

Data: 3,800 lyrics from MetroLyrics with song title, artist name, and genre already

- cleaned , preprocessed and applied doc2vec

Dropped all songs with genres not in our genre set

Testing our Models on New Data

- Ran on Gradient Boost Model to predict “Rock” Genre

- Accuracy: 0.52
- f1-score: 0.62
- Precision: 0.58
- Recall: 0.67

Confusion Matrix	Actual Rock	Actual Not Rock
Predicted Rock	700	352
Predicted Not Rock	497	230

CONCLUSION

Balancing Multi-label Data is an unresolved problem in the industry.

CHALLENGE

Common balancing techniques handle single labels

Labels are not independent

Balance within/between labels

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SOLUTION

REMEDIAL - a decoupling and resampling algorithm

SCUMBLE - a measure of dependence between labels

Cleanliness is a virtue – Data Cleanliness is a necessity.

CHALLENGE

Weighting words by occurrence

Stopword selection

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CHALLENGE

Weighting words by occurrence

Stopword selection

SOLUTION

Compare with alternative feature extraction methods

Refine stopwords

Additional Learnings

Understanding multi-class versus multi-label

Scaling the amount of available data

Understand metrics of model success

With a few improvements, our model has potential for many business use cases.

BUSINESS USE CASES

Music streaming services

additional metrics for recommendation

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BUSINESS USE CASES

Music streaming services

additional metrics for recommendation

New artists

identify potential new demographics

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BUSINESS USE CASES

Music streaming services
additional metrics for recommendation

New artists
identify potential new demographics

Media production
algorithmic song generation


SOY IN REPETITION THE DREAM
CONTROVERSY
EROTICA
DELIRIOUS
PURPLE RAIN
BABY I'M A STAR
TAKE ME WITH YOU

THANK YOU