



# MUSIC GENRE CLASSIFICATION

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# Problem Statement

# PROBLEM STATEMENT

Using features derived from an audio source, can a classification model predict the genre of a 30-second audio clip with high enough accuracy to organize songs into their respective genres automatically?

# WHO CARES?

Classifying genre is important for music **distribution** and **streaming platforms**. Automating the process would save time and money.

Assigning genre properly allows **listeners** to find new artists they might like, and, in turn, helps **musicians** connect with new audiences via genre-based playlists. Everyone's happy, everyone wins!



# The Dataset

# 9365 Songs

⊗ 30-second audio samples pulled from Spotify.

⊗ Spotify API gives access to:

- ⦿ General song metadata
- ⦿ Pre-engineered features



## Issues with the data?

- ⊗ Genre connected to **artist** instead of song
- ⊗ One song could have **multiple** genres
- ⊗ Some songs have **no 30-sec** preview
- ⊗ Some track names contain **non-English** characters
- ⊗ Unbalanced classes



# 10 Genres

- ⊗ Bootstrapped 500 songs per genre
- ⊗ Some genres are closely related
- ⊗ Created a subset of 5 general genres



# What are the genres?

## 5-genre set

- ⊗ Classical
- ⊗ Rock
- ⊗ Rap
- ⊗ R&B
- ⊗ Progressive Bluegrass

## 10-genre set (orig. 5 plus)

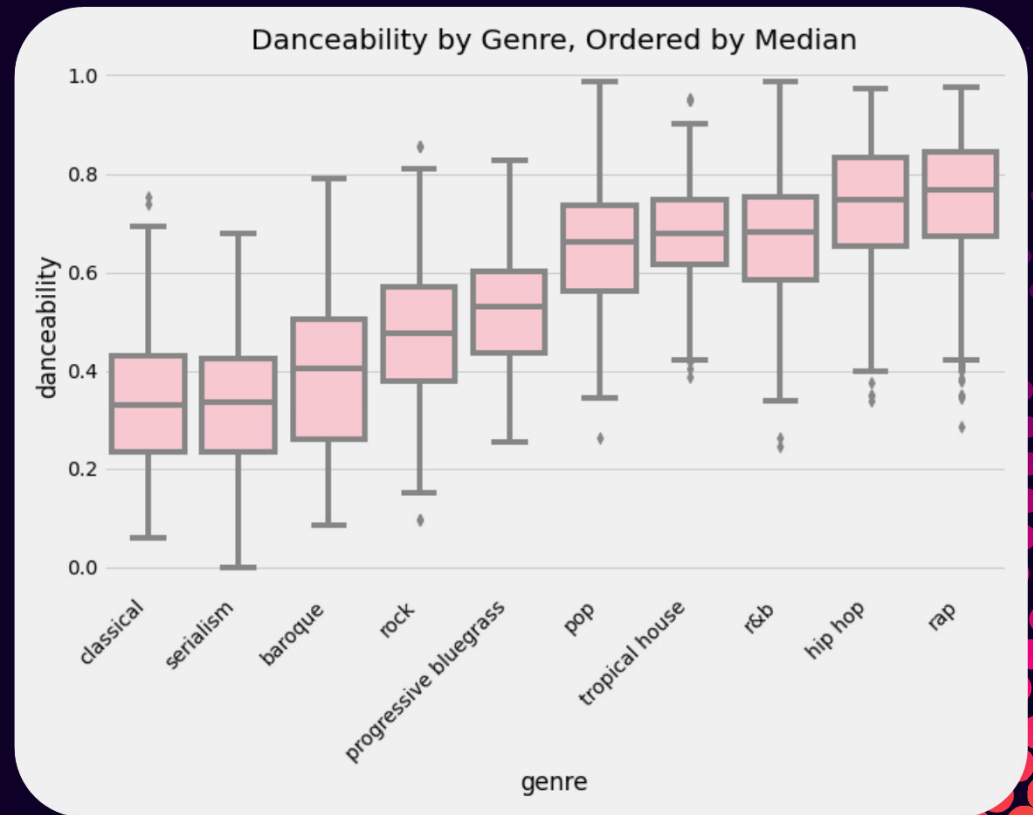
- ⊗ Baroque
- ⊗ Serialism
- ⊗ Hip Hop
- ⊗ Pop
- ⊗ Tropical House



EDA

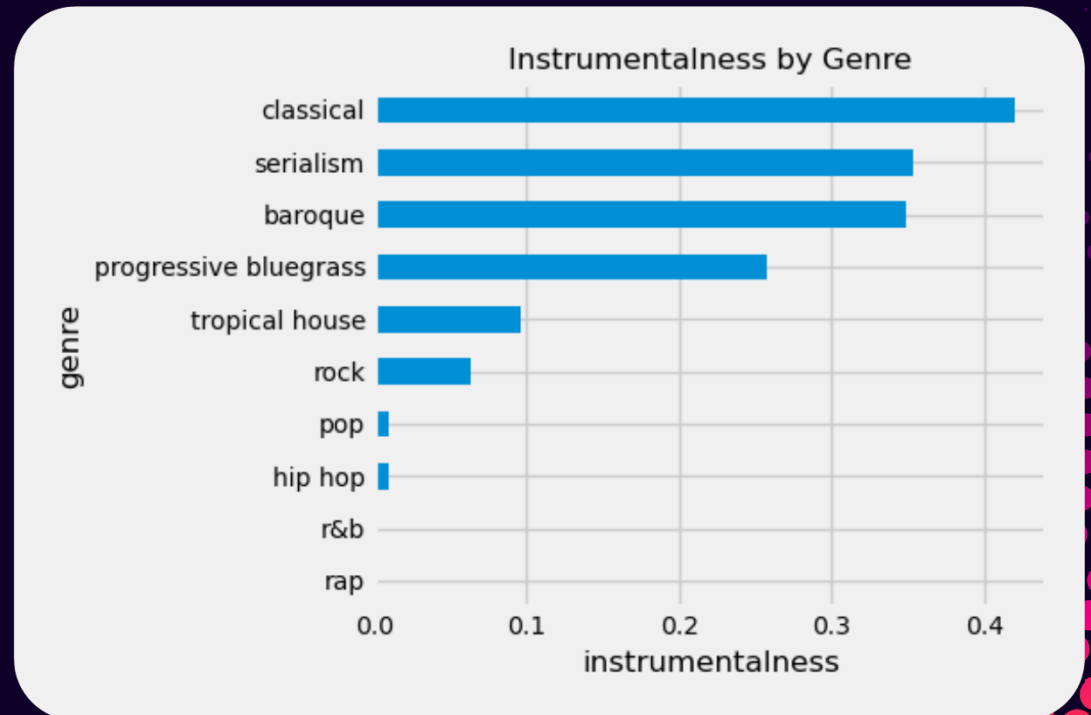
# Danceability

Pre-made feature from Spotify combining many different rhythmic aspects of a song.



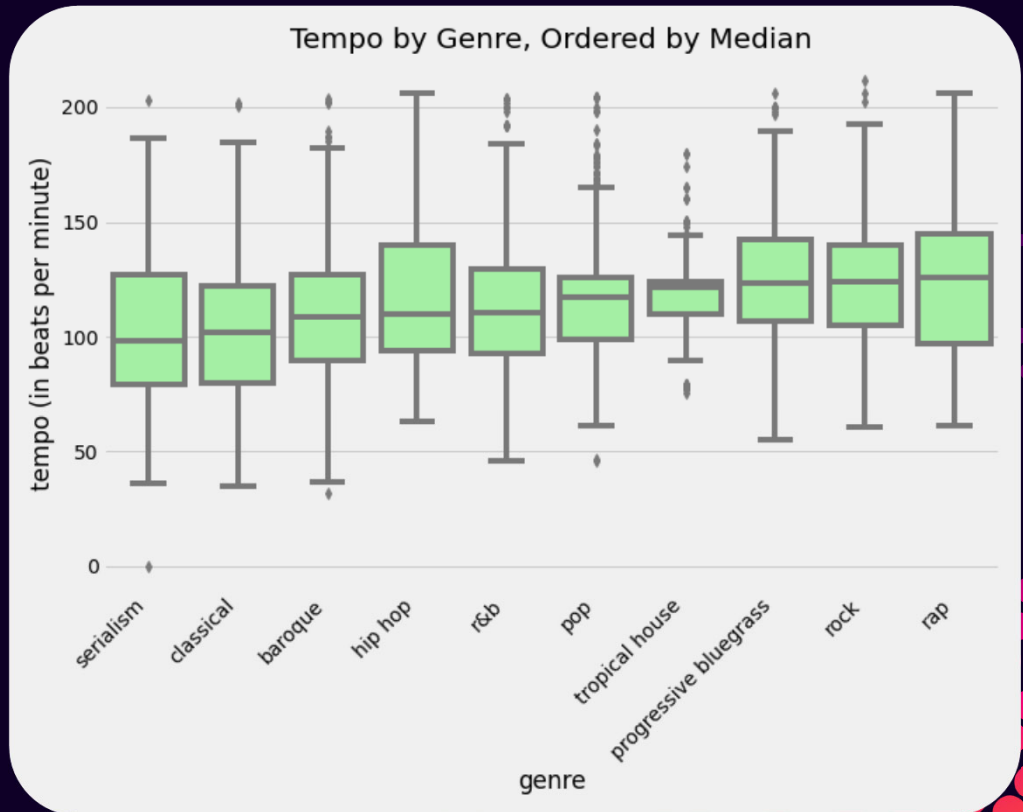
# Instrumentalness

Pre-made feature from Spotify rating how much of the song is purely instrumental.

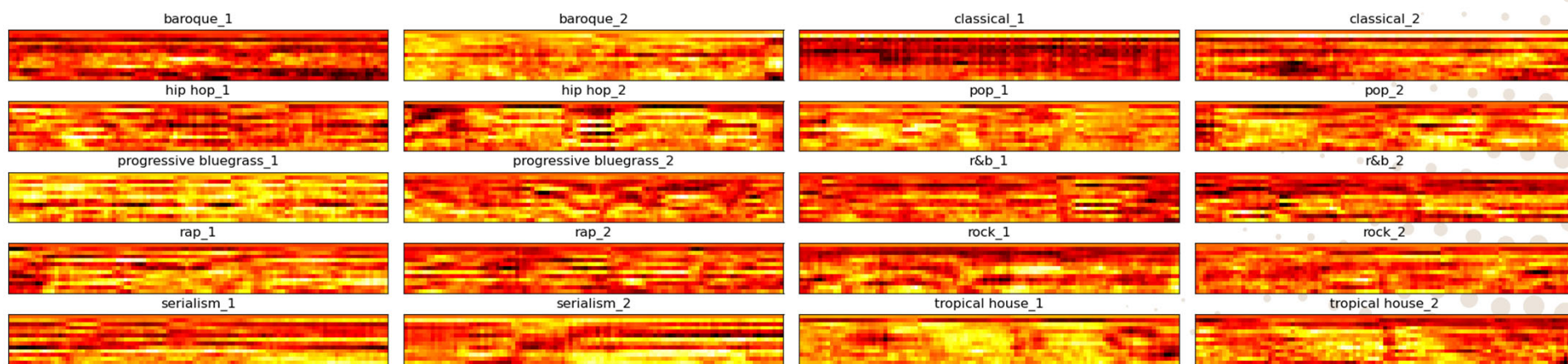


# Tempo

Pre-made feature from Spotify showing the speed of the song.



# Mel Frequency Cepstral Coefficient (MFCC)



# Modeling



# Metrics and Baseline Model

## Metric

⊗ Accuracy

## Baseline Model

- ⊗ 5-genres: 20% Accuracy
- ⊗ 10-genres: 10% Accuracy

# A Tale of Two Feature Sets

## Model #1

Trained on **Spotify's** pre-made features only

## Model #2

Trained on **my own** extracted features only

# What features did we create?

- ⊗ Volume/Loudness
  - ⊙ Energy
  - ⊙ Root Mean Squared Energy
- ⊗ Power across frequency spectrum
  - ⊙ MFCC

# What models did we consider?

## SVC

- ⊗ Good training/testing accuracy
- ⊗ Takes seconds to fit model
- ⊗ CON: Does not scale well to large datasets

## Convolutional Neural Net

- ⊗ Similar training/testing accuracy as SVC
- ⊗ Large dataset (>3 GB)
- ⊗ CON: Can't compare Spotify features to newly-extracted features.

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## SVC

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Large dataset (>3 GB)

CON: Can't compare Spotify features to newly-extracted features.

## Model Comparison: Spotify features vs. my features

| # of Genres | Acc (Spotify features) | Acc (my features) |
|-------------|------------------------|-------------------|
| 5           | 78.4%                  | 84.2%             |
| 10          | 50.6%                  | 56.5%             |

# 5.85%

Mean Improvement when compared to model trained on Spotify features

## 10-Genre Classifier Breakdown

### Pop

Genre predicted correctly *least often* by both models (Spotify: 14.4%, Extracted: 17.6%)

### Progressive Bluegrass

Genre predicted correctly *most often* by both models (Spotify: 77.6%, Extracted: 84%)



# Pop Quiz

(or maybe Tropical House Quiz)



## Digging in - why is our model confused?

- ⊗ What genre would you classify this as?
  - ⊙ Pop
  - ⊙ Classical
  - ⊙ Tropical House



## Digging in - why is our model confused?

- ⊗ What genre would you classify this as?
  - ⊙ Pop → Predicted Genre
  - ⊙ Classical
  - ⊙ Tropical House → Correct Genre!

*Drums not as heavy as other  
Tropical House tracks?*

## Digging in - why is our model confused?

- ⊗ What genre would you classify this as?
  - ⊙ Rock
  - ⊙ Progressive Bluegrass
  - ⊙ Tropical House



## Digging in - why is our model confused?

- ⊗ What genre would you classify this as?
  - ⊙ Rock → Correct Genre!
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  - ⊙ Tropical House → Predicted Genre

*Dynamic Contrast and "Drops" in  
Tropical House Music*

## Digging in - why is our model confused?

- ⊗ What genre would you classify this as?
  - ⊙ Rap
  - ⊙ Tropical House
  - ⊙ Hip Hop



## Digging in - why is our model confused?

- ⊗ What genre would you classify this as?
  - ⊙ Rap → Correct Genre!
  - ⊙ Tropical House → Predicted Genre
  - ⊙ Hip Hop

*Bad 30-second draw, the hook of this Rap song seems to be inspired by Tropical House genre*



# Conclusions

# CONCLUSIONS

## Good things

Our extracted-features model is **outperforming the baseline** as well as a similar model trained on Spotify's features.

When predicting wrong, the models **tend to predict related genres**.

## Bad things

~56% accuracy is **not good enough to automatically assign genre at a large scale**. We'd wind up with a lot of misclassified genres and confused listeners.

## What I learned

**Sub-genres are not very well defined at the sonic level**. There are likely other factors that go into the creation of sub-genre. (Artist location, lyrical content, time period, instrumentation)



## Future Steps

- ⊗ Manually assign genres per song
- ⊗ Instrument extraction
- ⊗ Unsupervised learning for more accurate genres



# SOURCES

⊗ Presentation template by [SlidesCarnival](#)

⊗ Photographs by [Unsplash](#)

1. <https://musicinformationretrieval.com/energy.html>

2. <https://musicinformationretrieval.com/mfcc.html>

3. Sahidullah, Md.; Saha, Goutam (May 2012). "Design, analysis and experimental evaluation of block-based transformation in MFCC computation for speaker recognition". *Speech Communication*. 54 (4): 543–565.  
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4. Adams, Seth. "DSP Background – Deep Learning for Audio Classification".  
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# THANKS!

Any questions?

