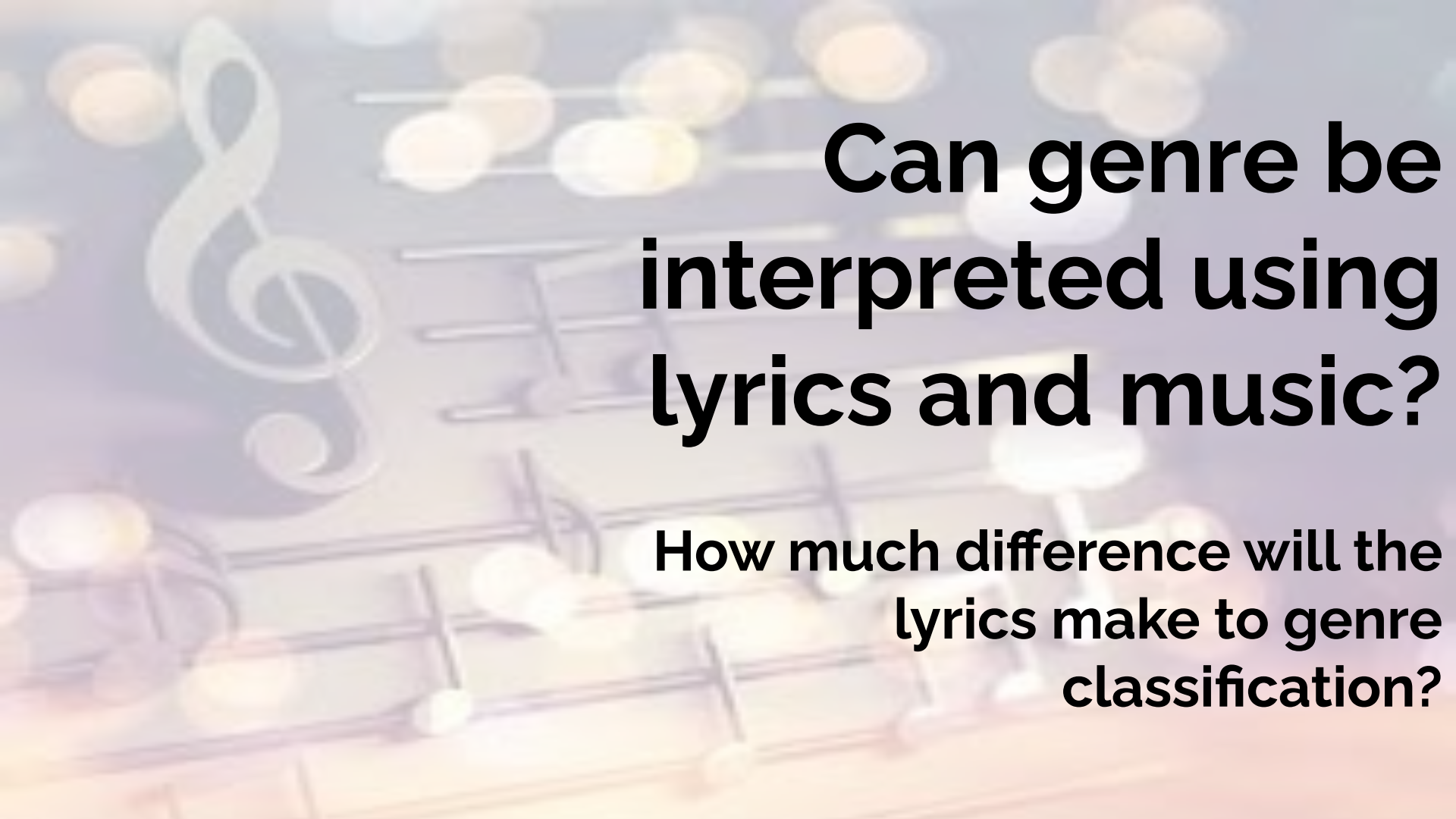


A dark silhouette of a human head in profile, facing left. The interior of the head is filled with a dense, chaotic arrangement of various musical notes, including eighth, sixteenth, and quarter notes, as well as treble and bass clefs. Some notes are larger and more prominent than others. The background is white, and the musical notes appear to be floating out from the head, creating a sense of sound and rhythm. The overall composition is artistic and thematic, representing the concept of music interpretation.

# **Interpreting Music Genres**

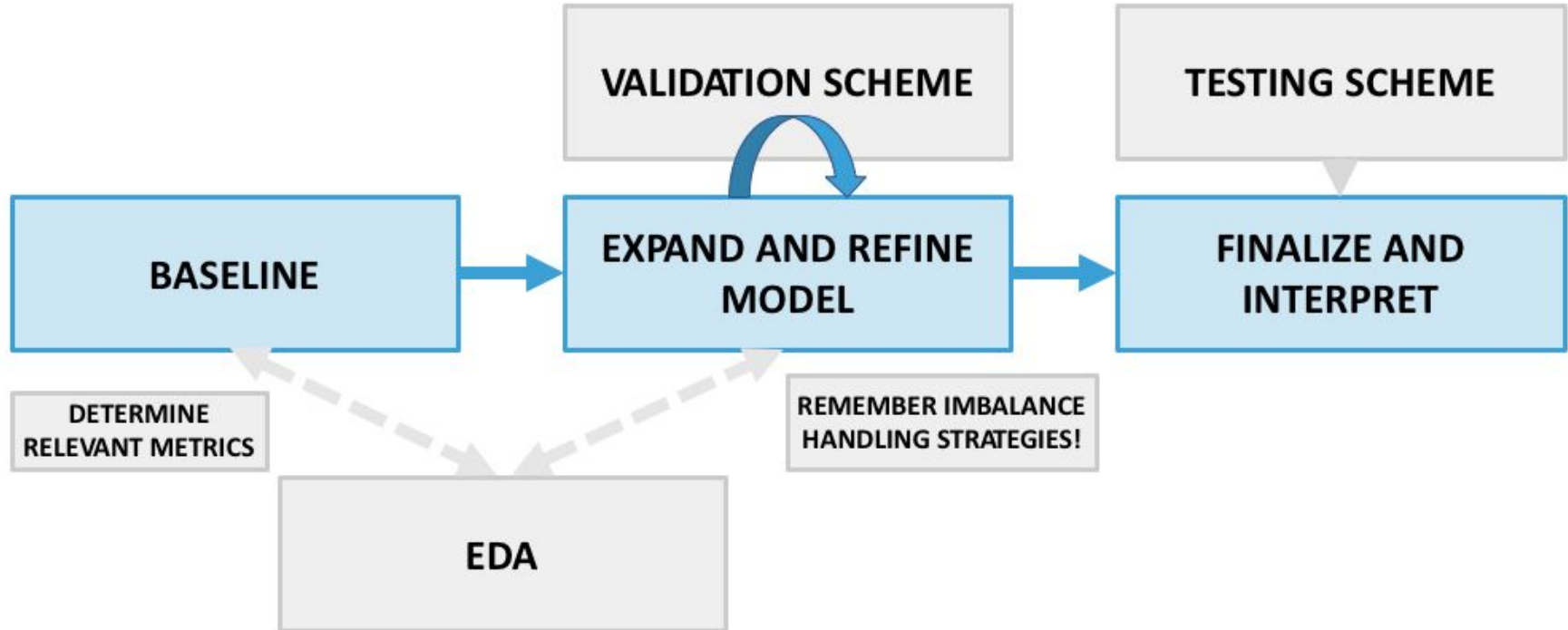
**Using Song Lyrics and  
Audio Metadata**



**Can genre be  
interpreted using  
lyrics and music?**

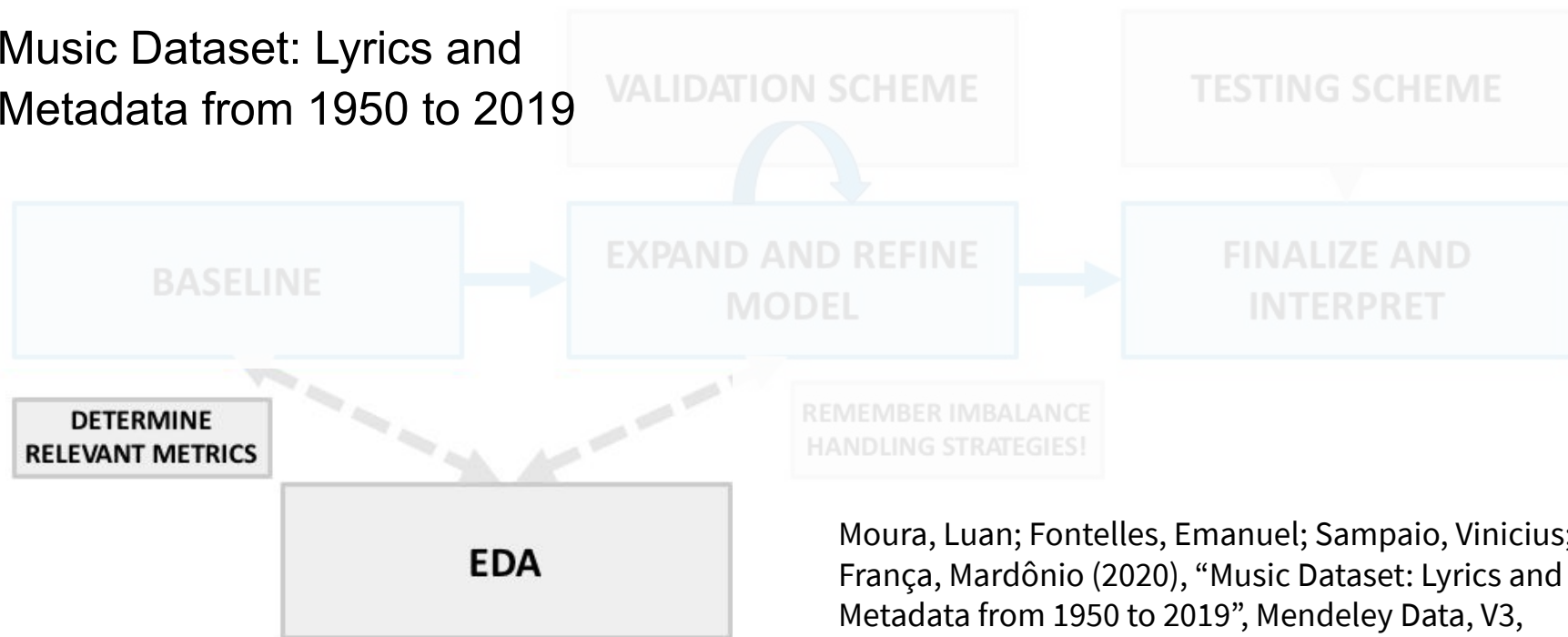
**How much difference will the  
lyrics make to genre  
classification?**

# Methodology: Classification Workflow



# EDA and Metrics

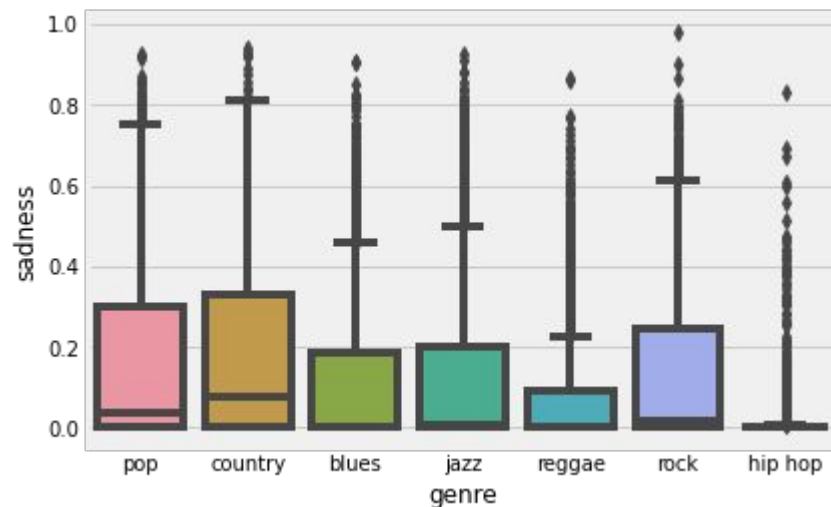
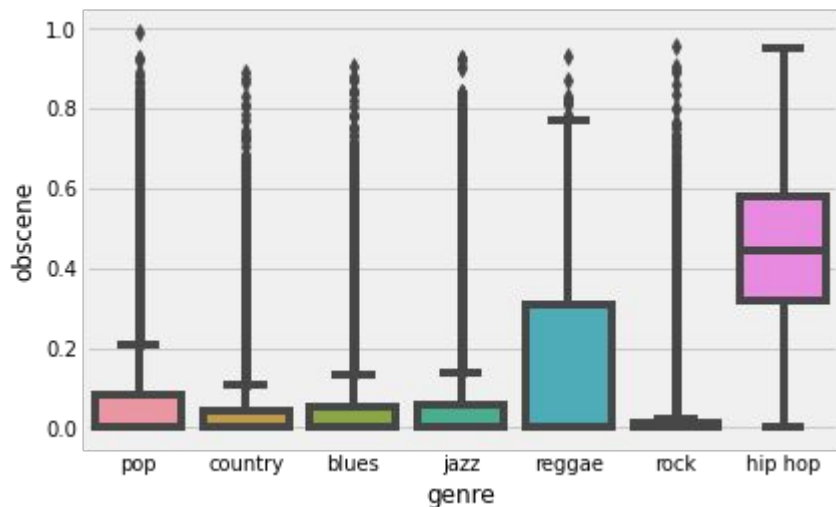
Music Dataset: Lyrics and Metadata from 1950 to 2019



Moura, Luan; Fontelles, Emanuel; Sampaio, Vinicius; França, Mardônio (2020), "Music Dataset: Lyrics and Metadata from 1950 to 2019", Mendeley Data, V3, doi: 10.17632/3t9vbwxgr5.3

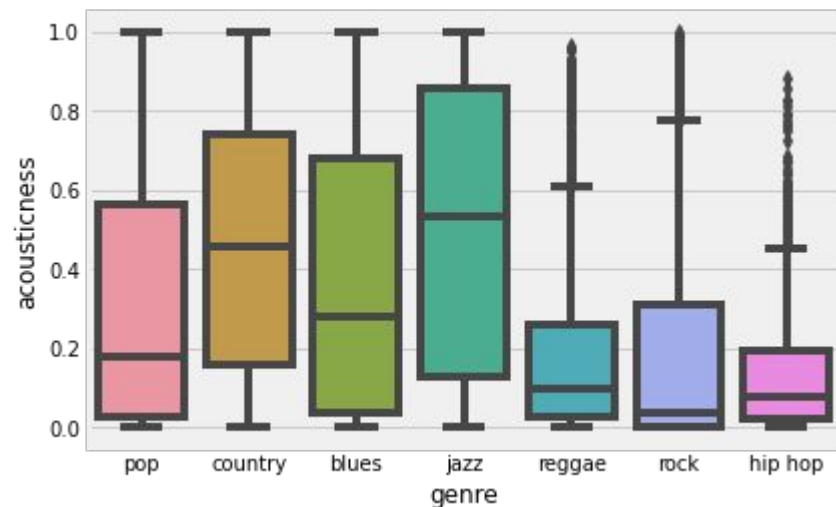
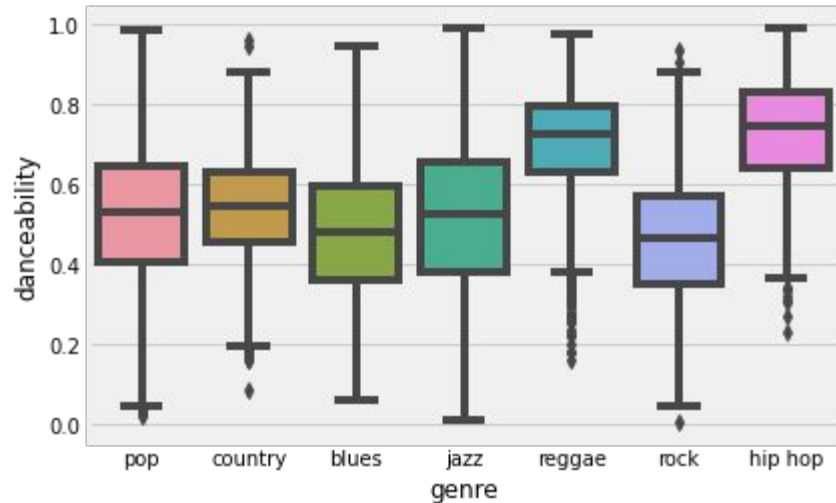
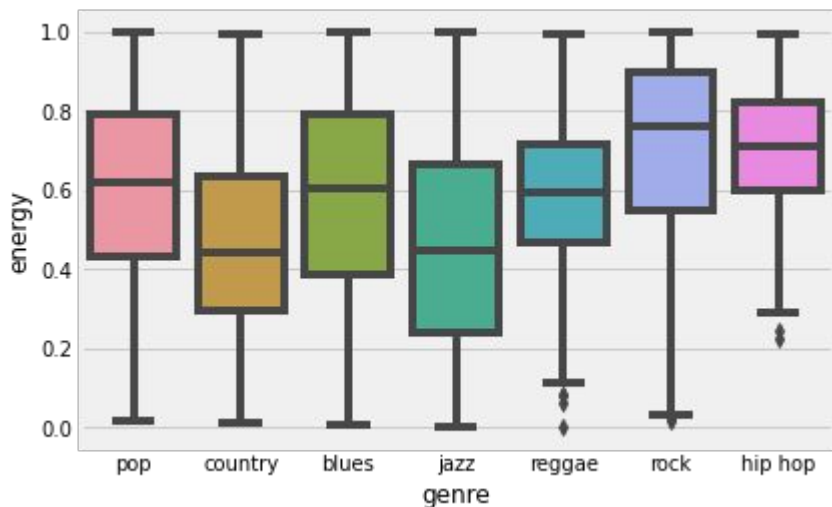
# EDA and Metrics

Lyrics: Topic modeling via Natural Language Processing



# EDA and Metrics

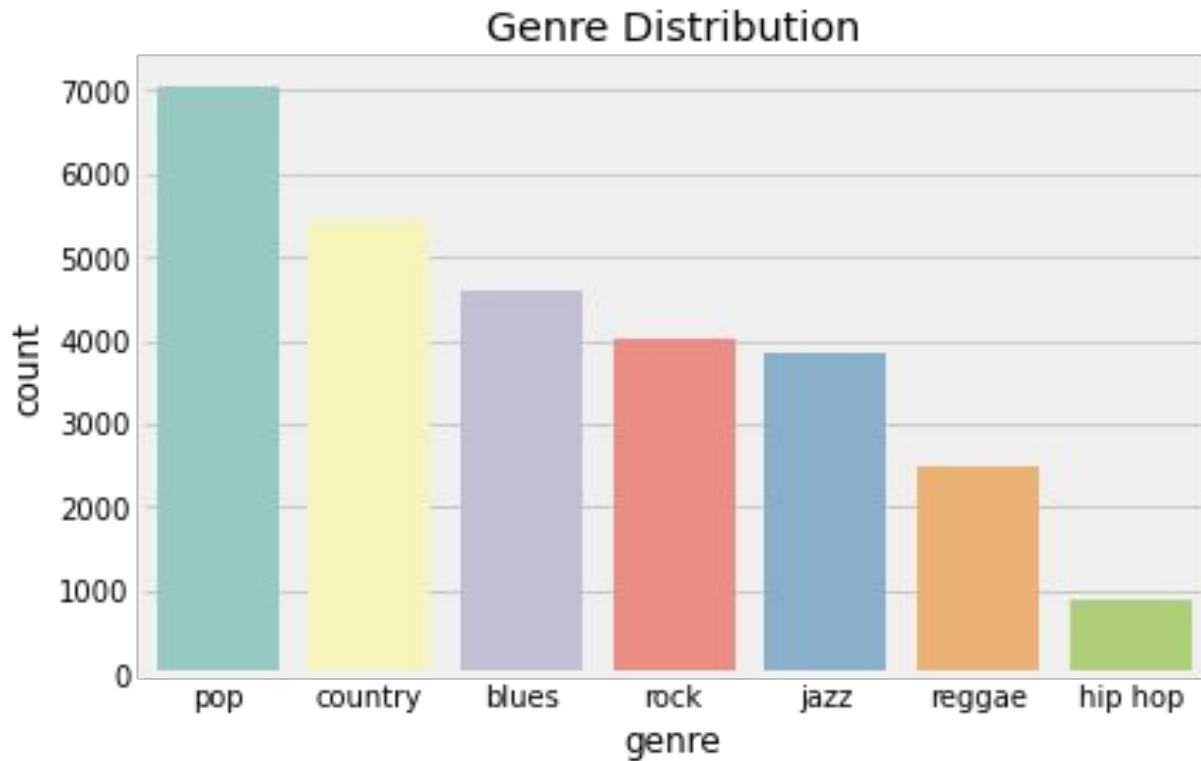
Audio metadata: features from Spotify



# EDA and Metrics

## Accuracy:

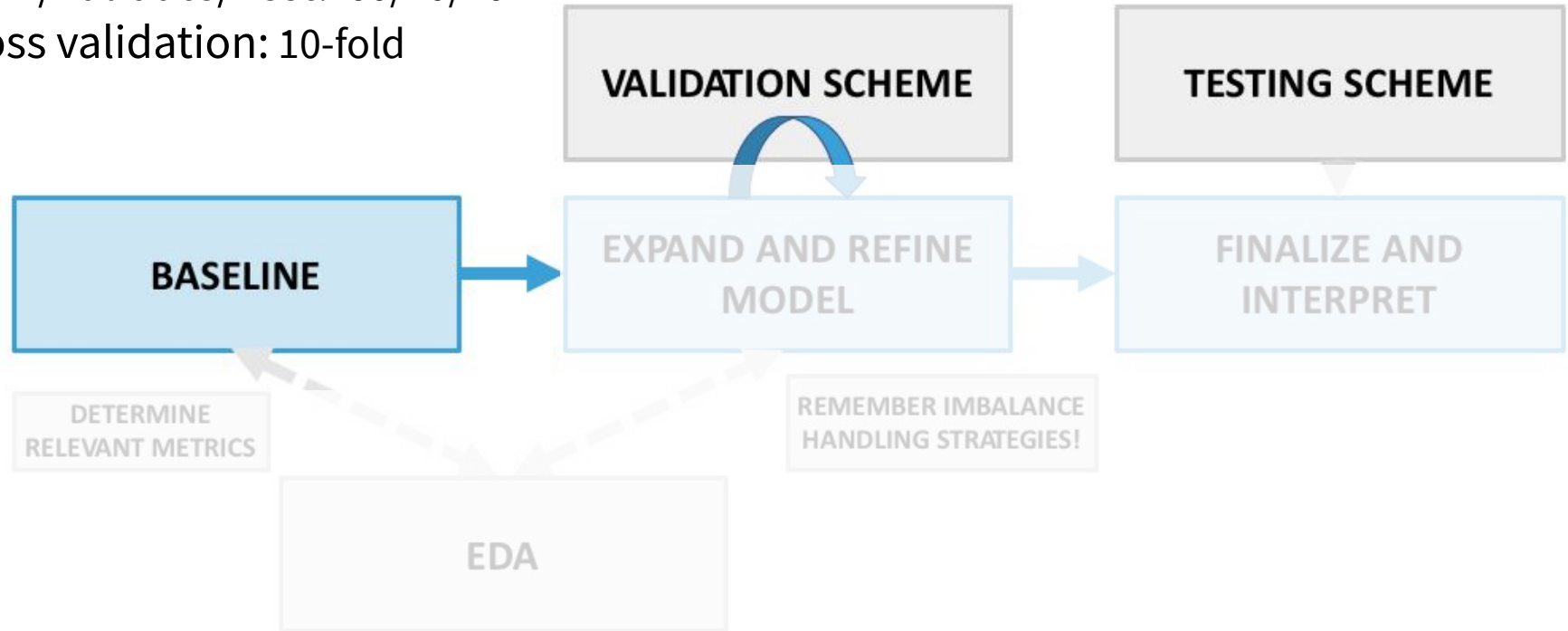
How well can the model predict 1 of 7 genres using topics and audio features?



# Establish Baseline and Validation/Testing Scheme

Train/Validate/Test: 60/20/20

Cross validation: 10-fold





# Baseline and Establish Validation/Testing Scheme

**BASELINE**

Model	Score
• kNN	→ 32.16%
• Multinomial Logistic Regression	→ 37.20%
• Random Forest	→ 41.12%
• Naive Bayes	→ 32.03%

# Expand and Refine Model

Feature engineering using  
feature/target attributes  
and musical knowledge

VALIDATION SCHEME

TESTING SCHEME

BASELINE

**EXPAND AND REFINE  
MODEL**

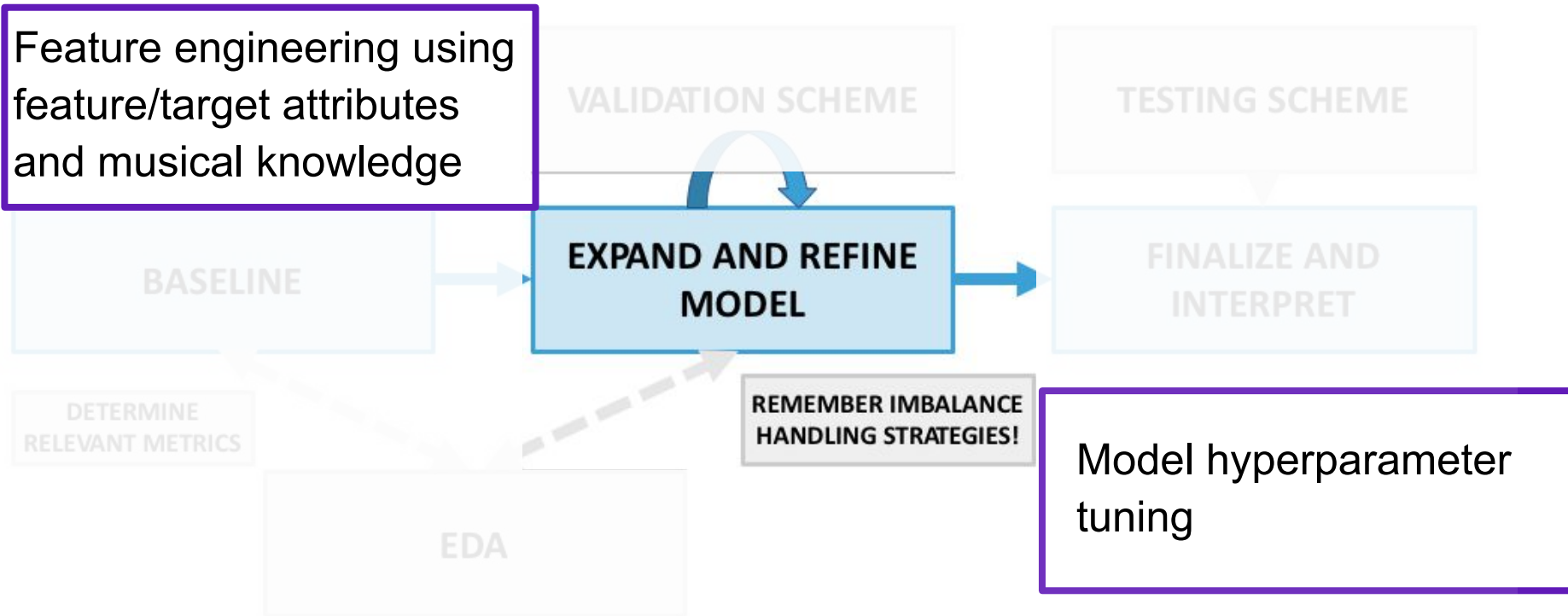
FINALIZE AND  
INTERPRET

DETERMINE  
RELEVANT METRICS

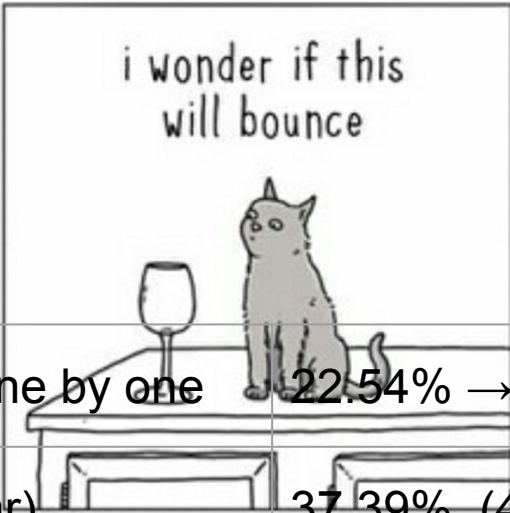
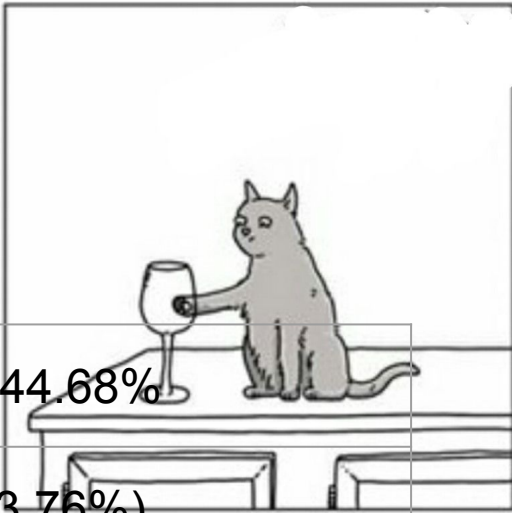
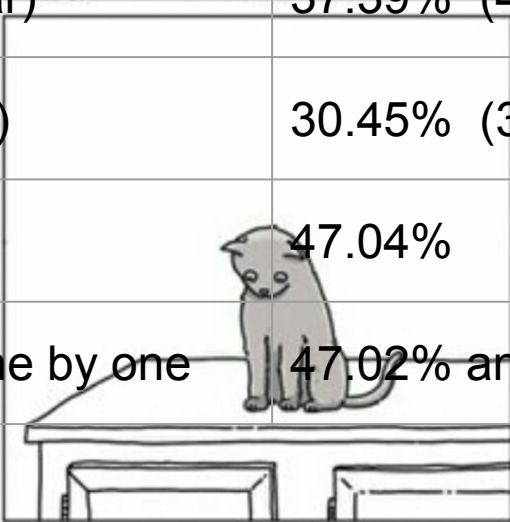
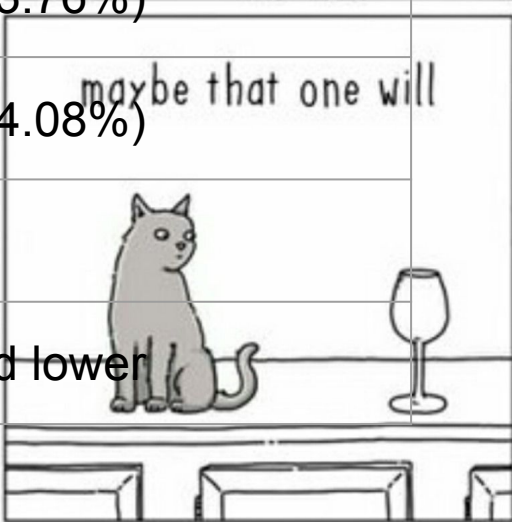
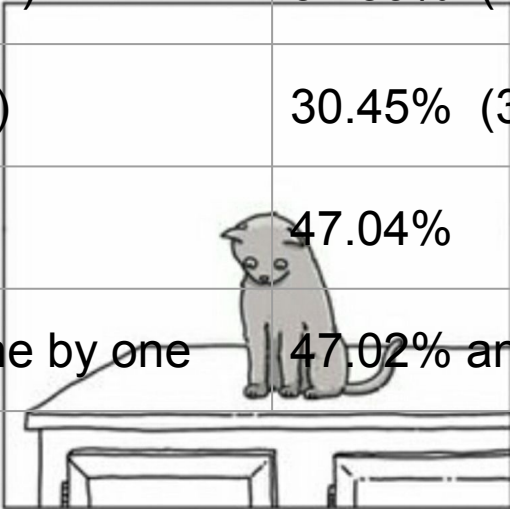
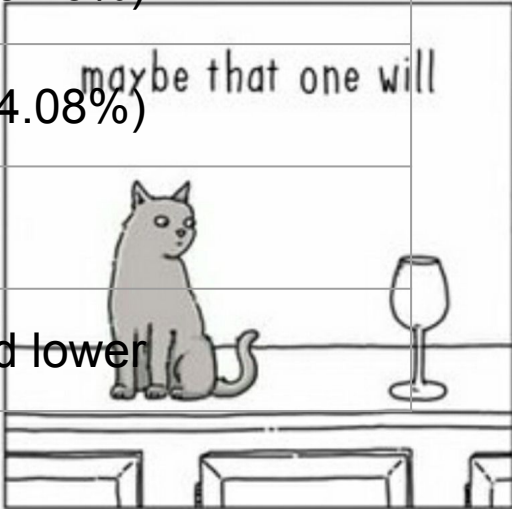
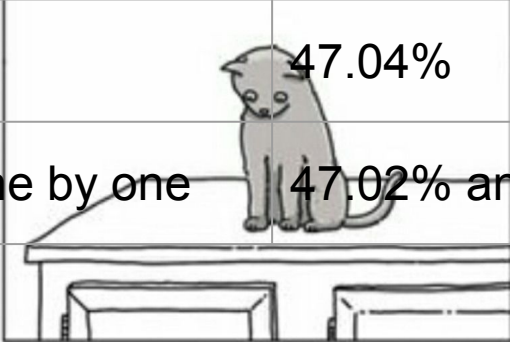


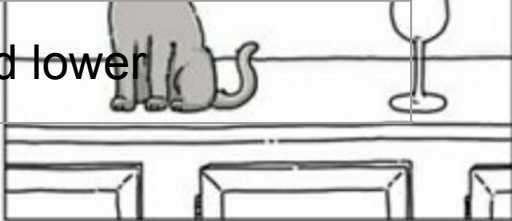
EDA

REMEMBER IMBALANCE  
HANDLING STRATEGIES!

Model hyperparameter  
tuning



# Feature Engineering

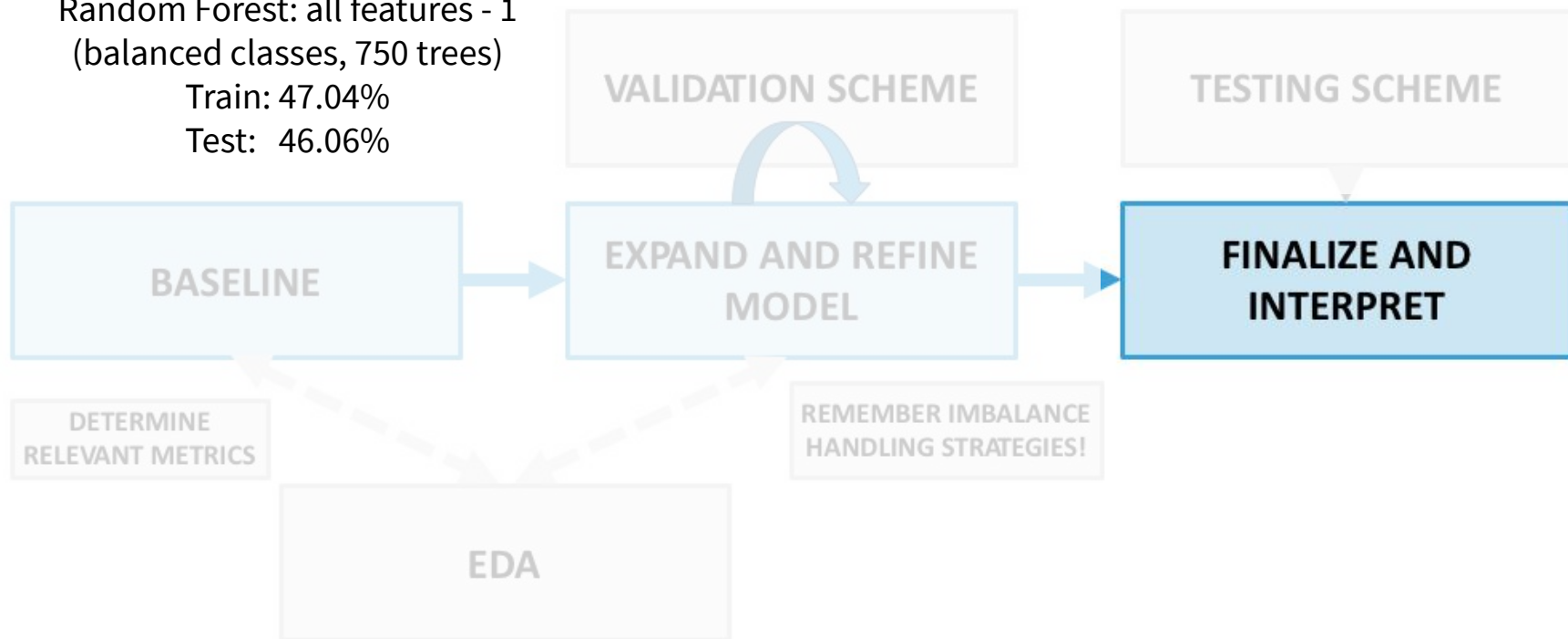
Adding 8 most important features one by one	22.54% → 44.68%		
Model only audio features (plus year)	37.39% (43.76%)		
Model only LDA features (plus year)	30.45% (34.08%)		
Model with all features	47.04%		
Remove least important features one by one	47.02% and lower		

# Conclusions

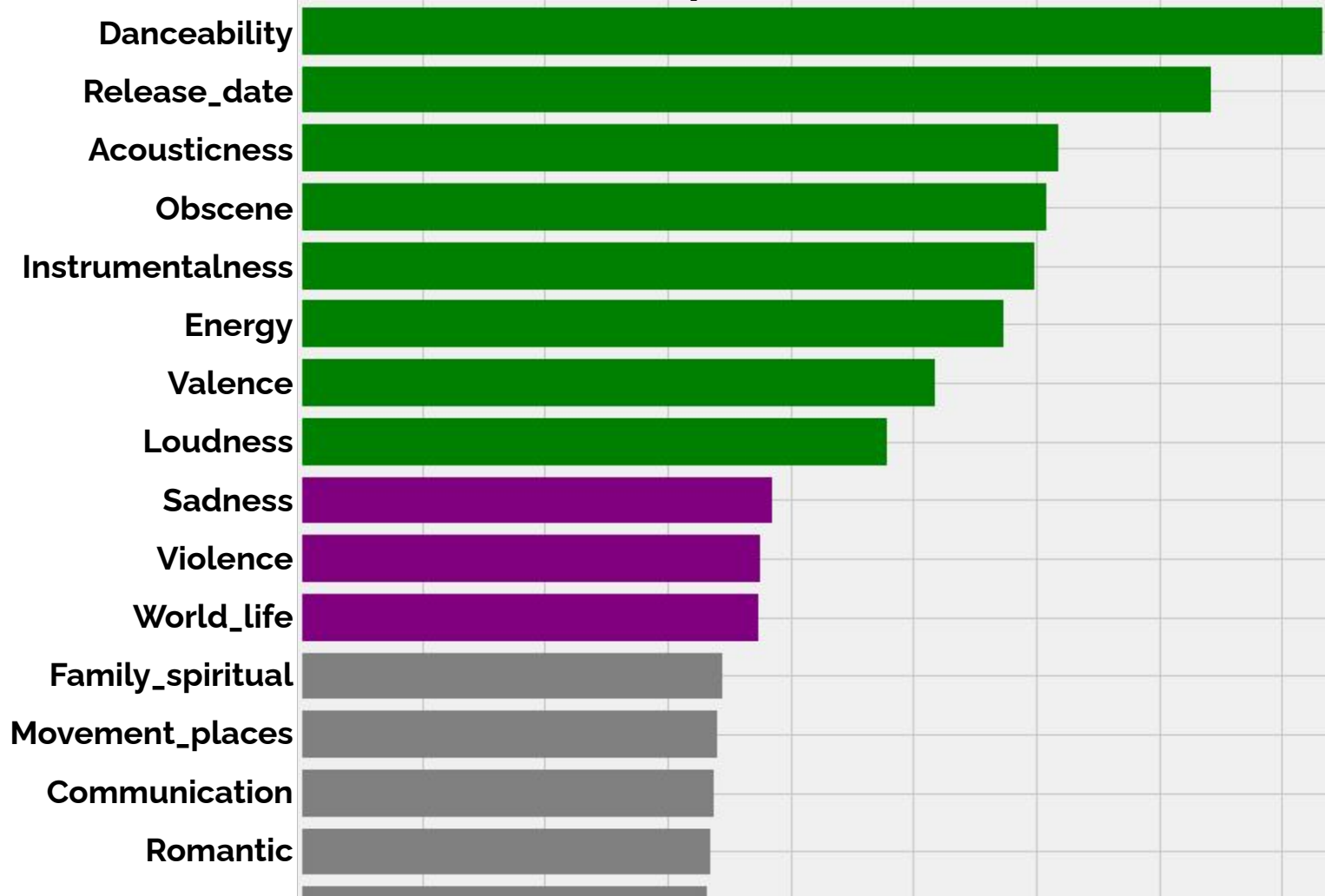
Random Forest: all features - 1  
(balanced classes, 750 trees)

Train: 47.04%

Test: 46.06%



## Feature importance



# Conclusions

- ❖ Intuition good - most features I picked as important actually were
- ❖ Lyrics do add value to the genre prediction
- ❖ Genres are tricky - lots of crossover
- ❖ Given the features and correlated genres, model result isn't horrible at 46%

Genre	Precision	Recall	F1-score
<b>Blues</b>	0.48	0.30	0.37
<b>Country</b>	0.47	0.60	0.53
<b>Hip Hop</b>	<b>0.65</b>	0.48	0.55
<b>Jazz</b>	<b>0.55</b>	0.41	0.47
<b>Pop</b>	0.40	0.56	0.46
<b>Reggae</b>	<b>0.52</b>	0.48	0.50
<b>Rock</b>	0.46	0.32	0.38

## Future considerations

- Use a different type of topic modelling for lyrics
- Add more audio features using Spotify API
- Try XGBoost
- Try a different set of songs with different genres

# Appendix