Exploring Feature Importance in Predicting Music Preference

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Outline

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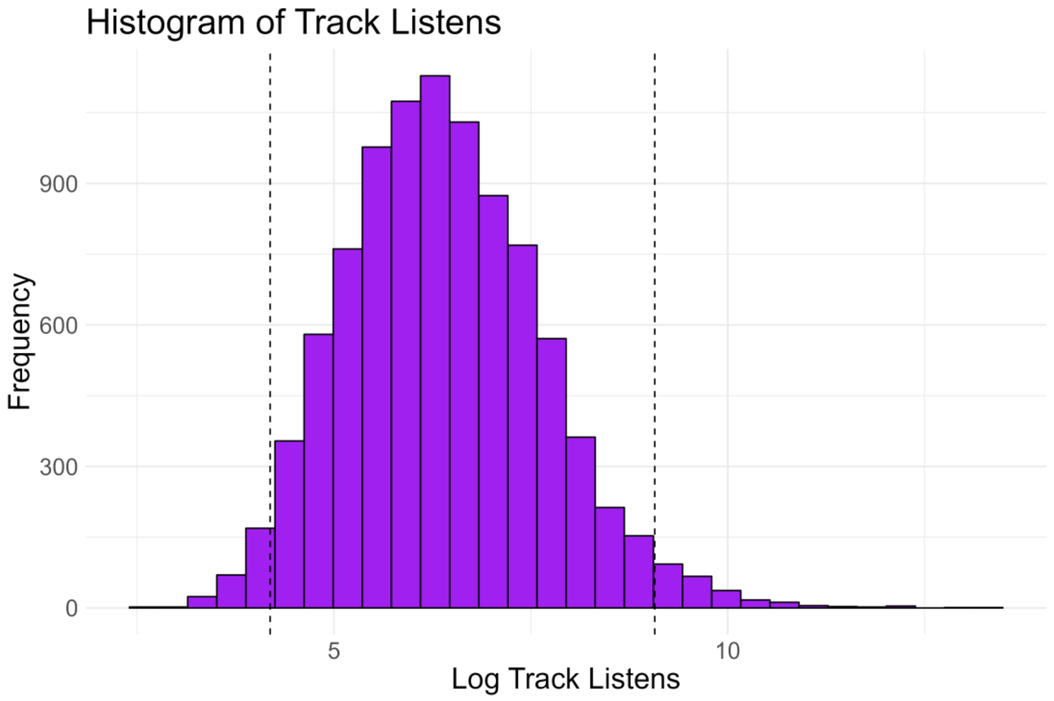
Introduction + Motivation

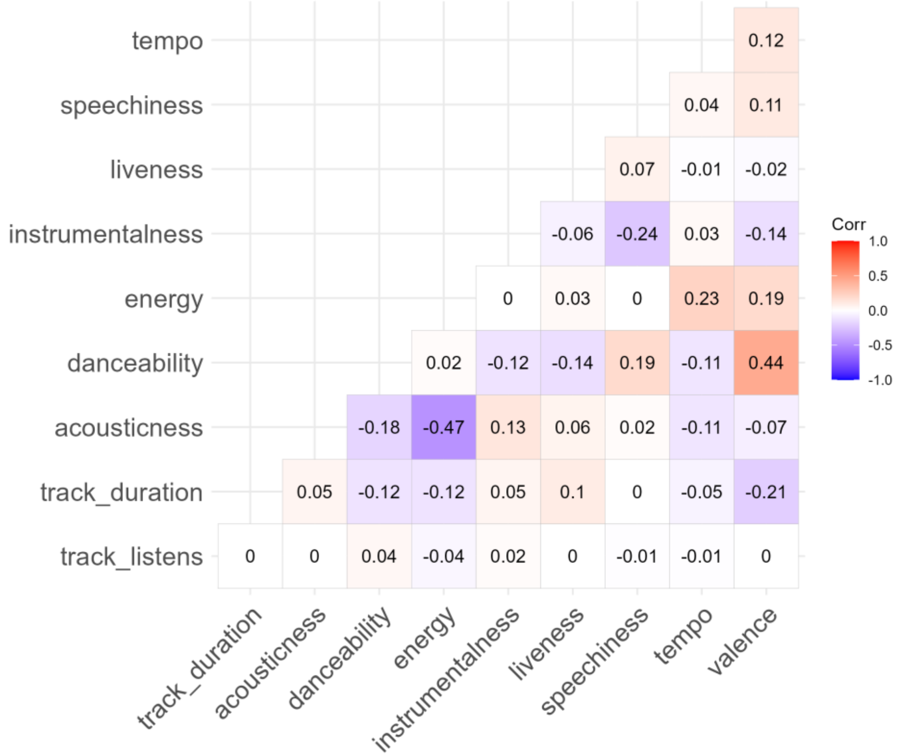
- Music popularity is influenced by a complex interplay of factors
    - Artist recognition, marketing, etc.
    - Qualities and acoustic features of music
- By analyzing acoustic features, we can determine specific musical features that predict the popularity and success of the song
- Further implications include identifying key features to prioritize for music recommendation, improving listener engagements

Data: Free Music Archive

- The Free Music Archive (FMA) dataset is a publicly available collection of over 106,000 tracks, each annotated with metadata
  - Popularity/success determined by the number of listens per track
  - Bottom and top 2.5% removed

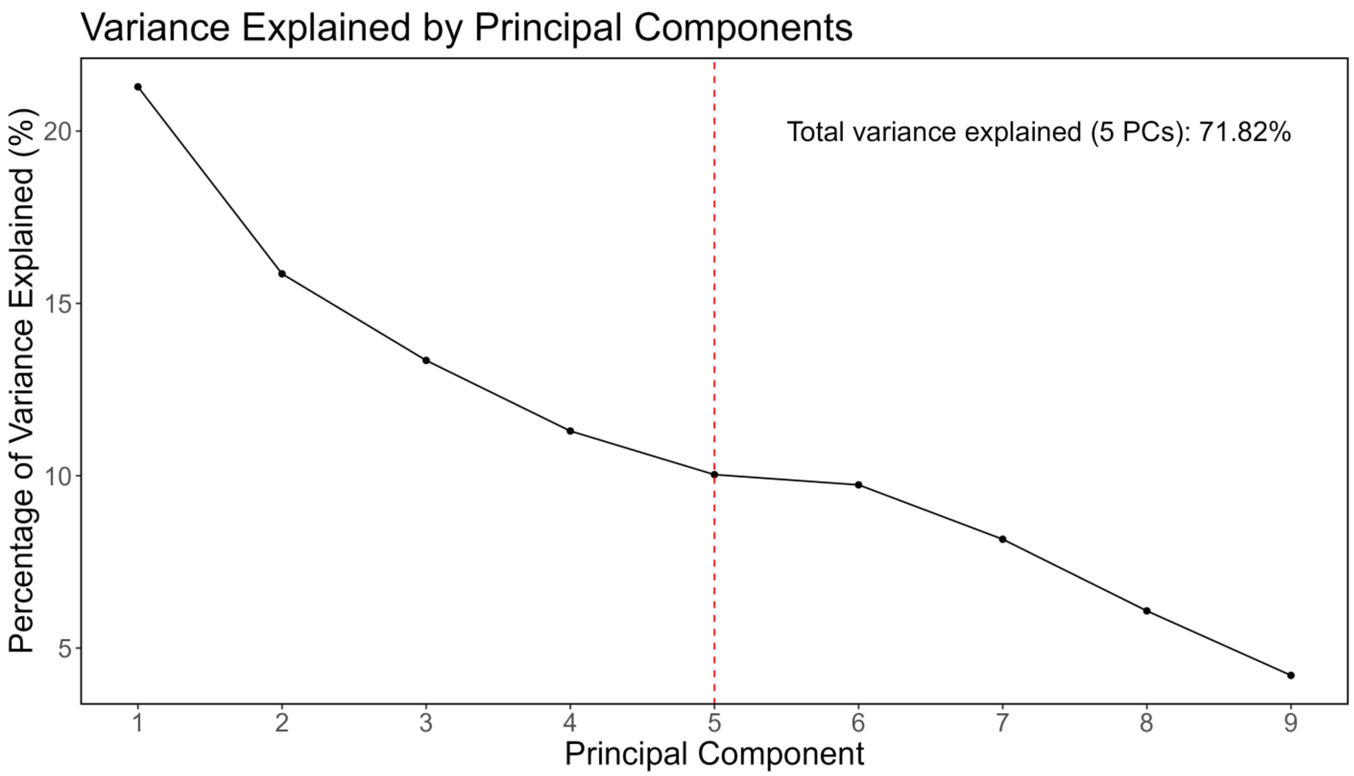


- ~9000 tracks included audio features extracted by Echo nest (Spotify's music AI platform)



Methods: PCA

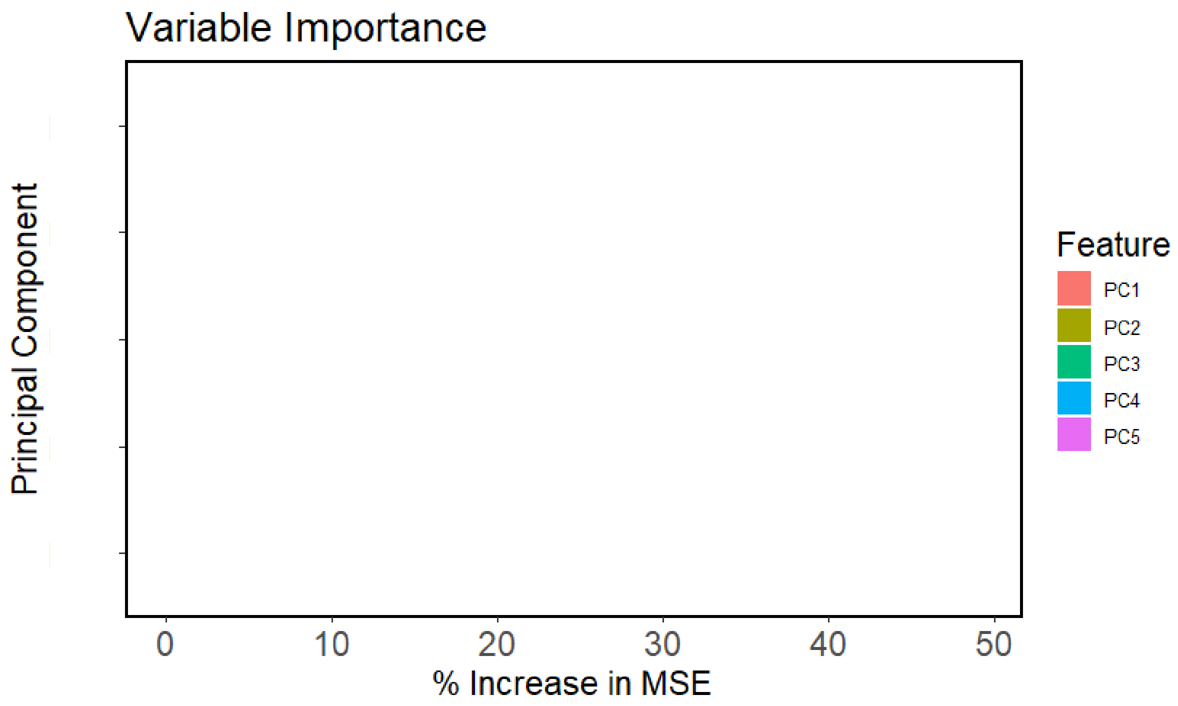
- Principal Components Analysis used for dimensionality reduction
- Used first 5 PCs as they explain ~72% of the total variance
  - log_track_listens ~ PC1 + PC2 + PC3 + PC4 + PC5



Methods: Models

Exploring the predictive power of PCs on music popularity using regression models

- 80% for Training and 20% for Testing
- Model Evaluation using
  - Feature (PC) Importance
  - RMSE and R-squared



Random Forest Regression

- Random Forest Parameter Tuning:
  - 500 Trees
  - mtry = 1

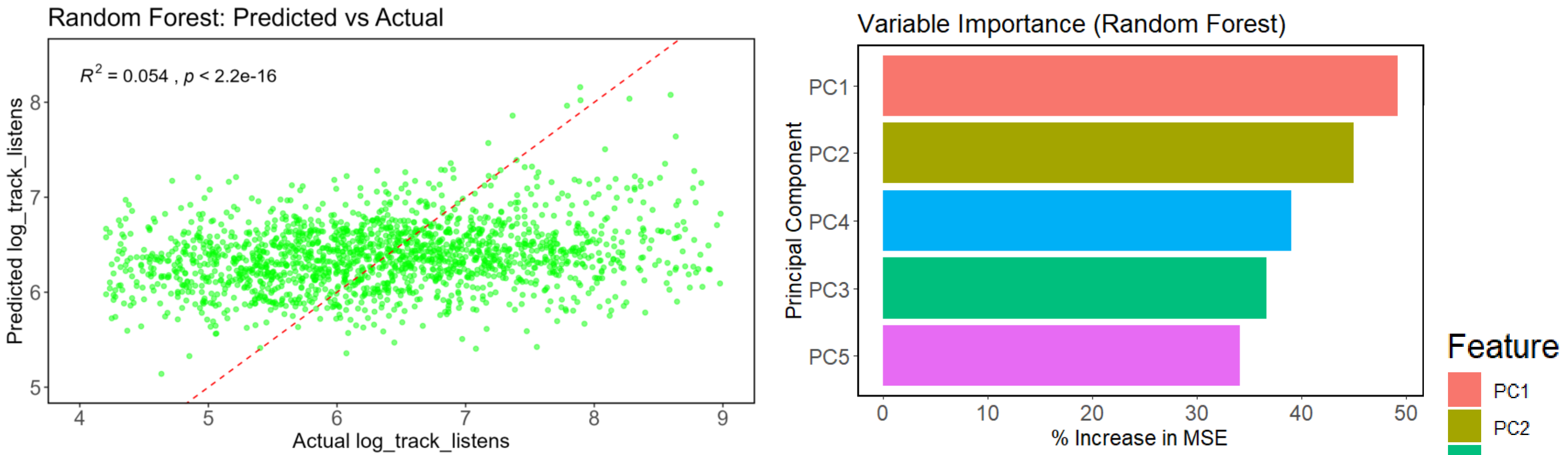
Regression with Boosting

- XGBoost Parameter Tuning:
  - 200 Trees (rounds of boosting)
  - Tested depth from 1-5
  - Minimizing test RMSE while using the lowest max_depth: depth of 3 at boost iteration 137

Results: Model Comparison & PCA Loadings

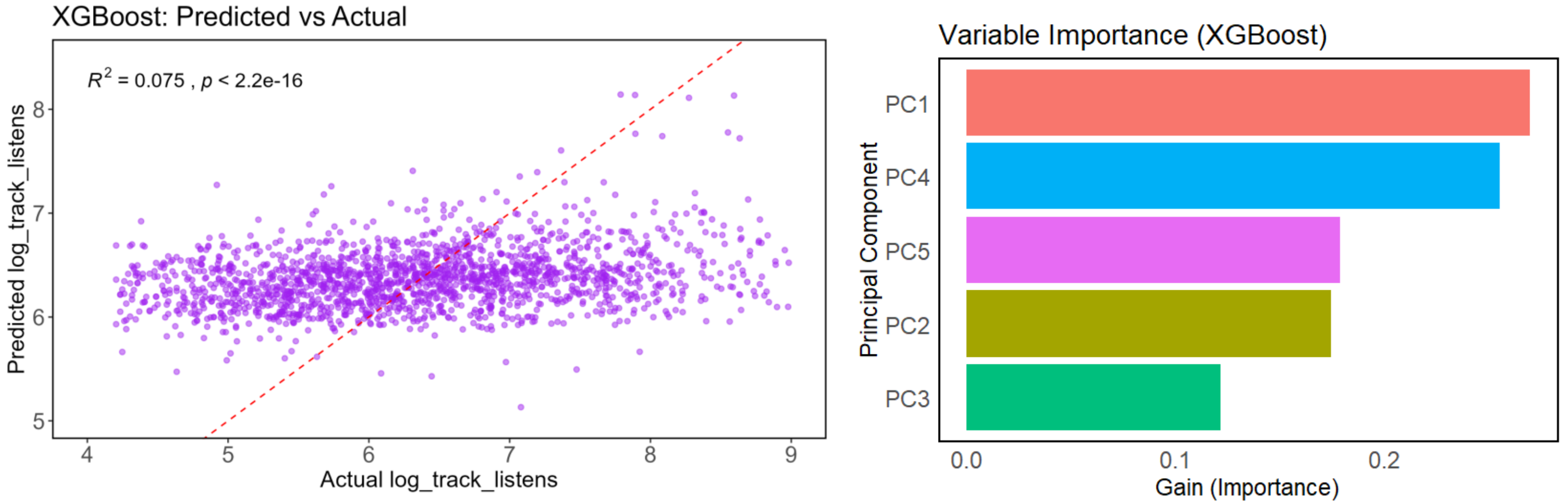
Random Forest Regression

- RMSE: 1.043
- R-squared = 0.054***
- Most Important: PC1, PC2



Regression with Boosting

- RMSE: 1.026
- R-squared = 0.075***
- Most Important: PC1, PC4



Discussion: PC and Feature Loadings

High RMSEs suggest that **acoustic features alone cannot predict** much variance in music preference, however, there was still a **small significant association** with the first 5 PCs on the number of listens the piece had in both models

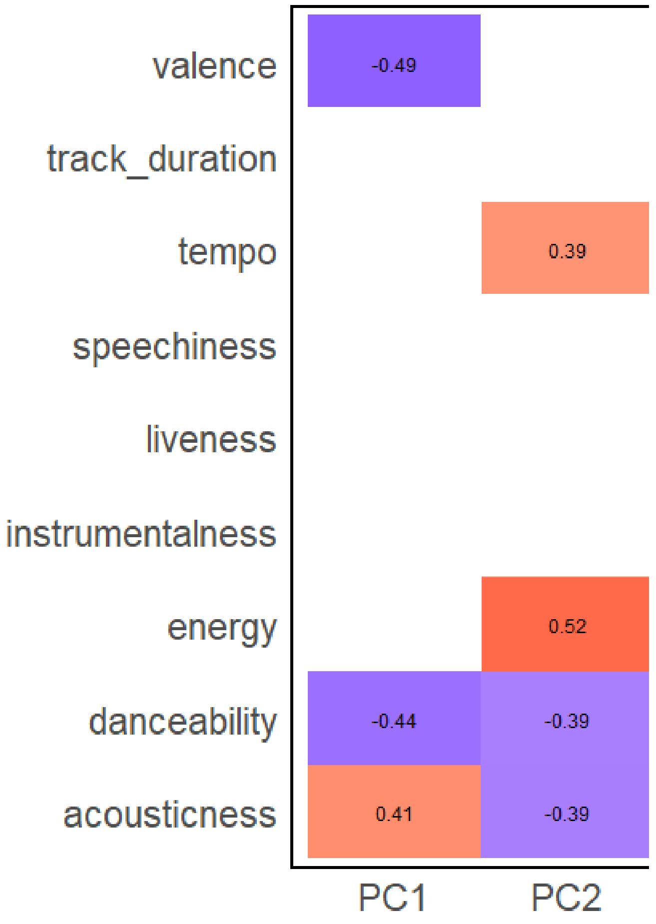
Random Forest Regression

- **PC1:** Low valence, low danceability, high acousticness
  - *Sad, slow, acoustic music*
- **PC2:** High energy & fast tempo, low danceability, low acousticness
  - *Fast, energetic, electronic music*

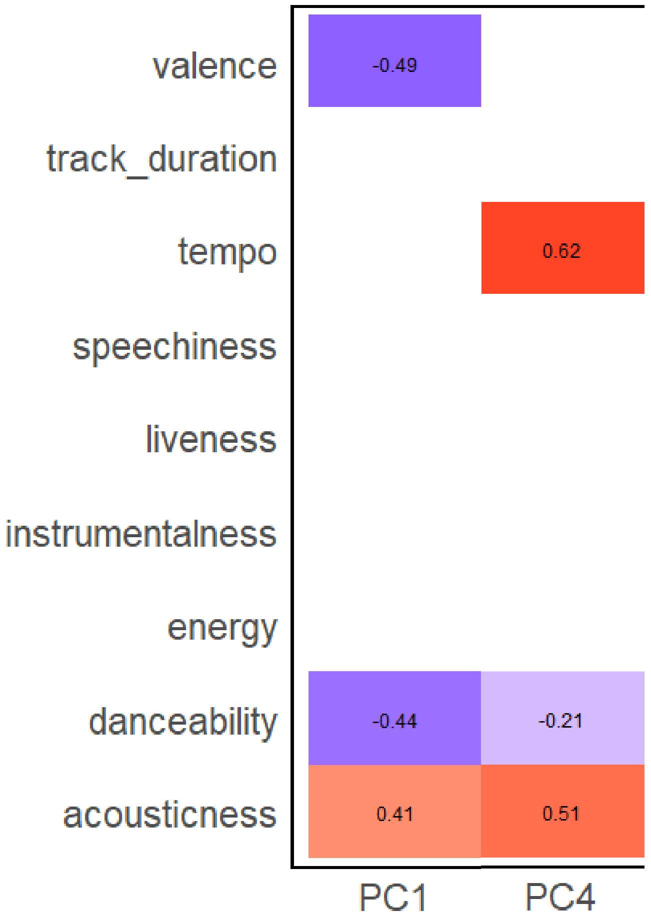
Regression with Boosting

- **PC1:** *Sad, slow, acoustic music*
- **PC4:** Fast tempo, high acousticness, short duration
  - *Short, upbeat, acoustic music*

Random Forest Regression



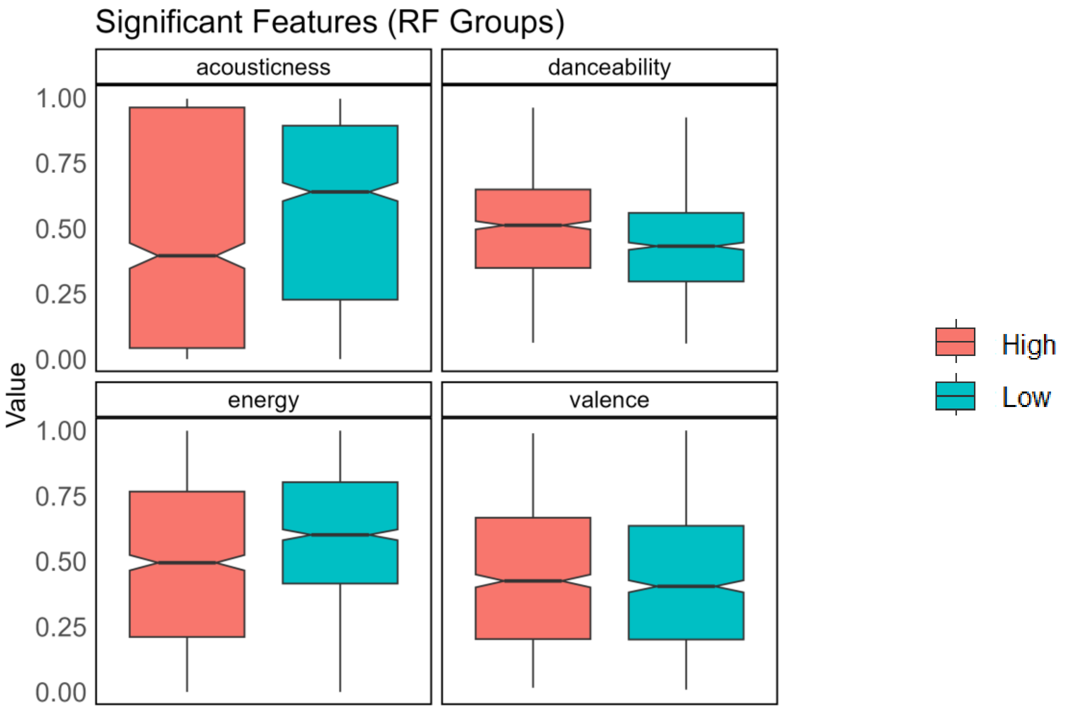
Regression with Boosting



Discussion: PC and Feature Loadings

Random Forest Regression

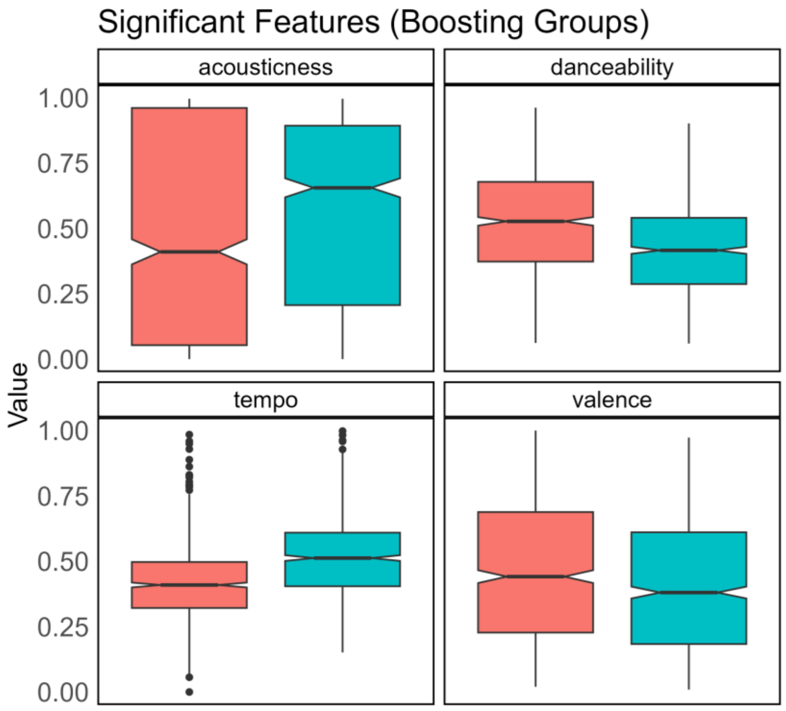
- Valence, Energy, Danceability, Acousticness



According to the RF regression model, listeners prefer music with less acoustics, more danceable, moderate to low energy, and slightly more positive valence.

Regression with Boosting

- Valence, Tempo, Danceability, Acousticness



According to the boosting regression model, listeners prefer music with less acoustics, more danceable, moderate to slower tempo, and positive valence.

Thank you!

Questions?

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