Technical Note on Prediction of Songs' Spotify Popularity

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1 Introduction

This document contains figures and explanations of methodology not conducive to an engaging presentation, but very relevant to our work and results. Thank you for taking the time to read it.

2 Confusion Matrices

The following are the confusion matrices resulting from the gradient boosting machine model with optimal hyperparameters. Overall it performs well in both but classes 3 and 8 were somewhat inaccurate. We therefore recommend to use the 4 class model initially and use the 8 class model to infer what half of the class of the popularity bracket resulting from the 4 class model a given song may be in.

3 Partial dependence plots

3.1 Summary

Partial dependence plots work by allowing one feature to vary whilst holding the others constant. This allows valuable insights into how each feature individually affects the predicted outcome. A higher partial dependence implies a higher outcome [1], in this case popularity. We found plots for each of the nine important features, ran for both 4 bins and 8 bins. Our analysis aimed to find patterns and trends that withstood the different binning methods, to provide the most robust advice possible.

(a) 4 classes

$$\begin{bmatrix} 665 & 137 & 14 & 2 \\ 1 & 128 & 55 & 5 \\ 0 & 16 & 671 & 224 \\ 0 & 0 & 51 & 428 \end{bmatrix}$$

(b) 8 classes

$$\begin{bmatrix} 334 & 63 & 33 & 4 & 0 & 0 & 0 & 0 \\ 29 & 215 & 94 & 23 & 11 & 4 & 2 & 0 \\ 1 & 2 & 6 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 4 & 125 & 50 & 12 & 2 & 3 \\ 0 & 0 & 1 & 11 & 147 & 97 & 31 & 9 \\ 0 & 0 & 0 & 0 & 144 & 340 & 172 & 21 \\ 0 & 0 & 0 & 0 & 2 & 32 & 208 & 98 \\ 0 & 0 & 0 & 0 & 0 & 2 & 28 & 35 \end{bmatrix}$$

Figure 1: Confusion Matrices for Gradient Boosting Machine with 4 and 8 classes

3.2 Song length

Song length correlated positively with partial dependence peaking at 230,000ms and 275,000ms for 8 and 4 bins respectively. With four classes, song length had another peak at 150,000ms which is also a very common length or songs, but this wasn't matched in the eight class predictor.

3.3 Acousticness

Higher acousticness appeared to increase popularity, until levels past 0.8. This indicates that it is possible to overdo the acoustic elements of a song.

3.4 Danceability

Surprisingly, danceability correlated negatively with popularity. We hypothesised that it could be because incredibly danceable music is less repeatable because of it's specific emotional and energetic requirements.

3.5 Energy

A high energy level was most optimal of around 0.83-0.84. This seemingly contradictory profile in comparison to danceability could be because energetic music replenishes energy whereas dancing music requires it.

3.6 Liveness

Low livenesses (0.1-0.2) were preferred by our model, so listeners are clearly listening more to the original, studio versions of songs rather than their 'recorded live' counterparts.

3.7 Loudness

Loudness closer to zero, on a range of 0db to -60db showed better results from the plots, although there were some differences between how close to zero our ideal should be. We thought this could also link to repeatability and palletability for higher streams.

3.8 Speechiness

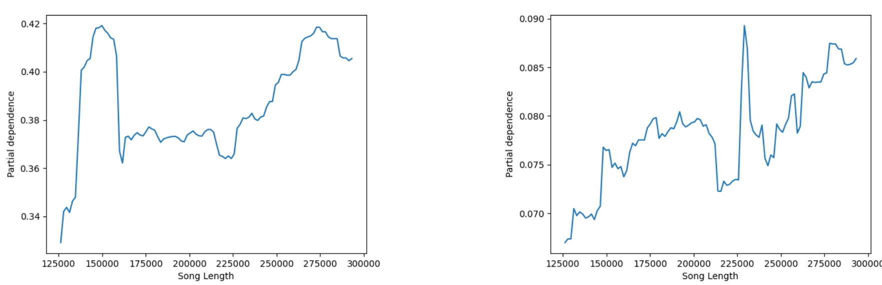
Values of around 0.35 performed amongst the highest for both four and eight classes. As such we made the recommendation to create songs with a little speech, as 0.33 is the cusp for a song having music and speech included. However, for eight classes, the best value was less than 0.05. This shows that highly instrumental music can be very popular too.

3.9 Tempo

We found overlap between the ideal regions of both classes at around 130-145 bpm, so this was our recommendation. Too low bpm drags and too high is hardly suitable for casual listening, decreasing streams dramatically.

3.10 Valence

High valence showed the highest popularity- happy music is clearly on trend. This makes sense when we think about the themes of repeatability and palletability of before.



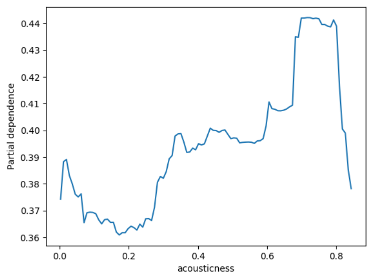
(a) Song length- 4 classes

(b) Song length- 8 classes

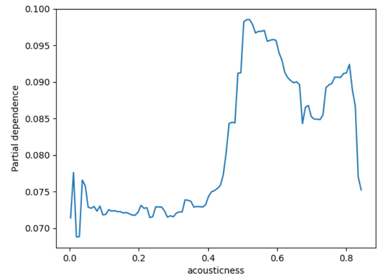
Figure 2: Song length

References

[1] Scikit-Learn. Partial dependence plots, 2023. Accessed: 25 April 2024.

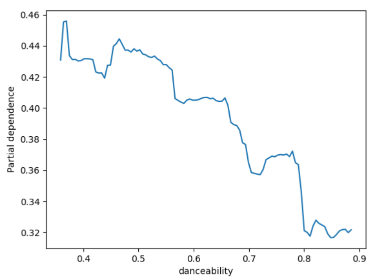


(a) Acousticness- 4 classes

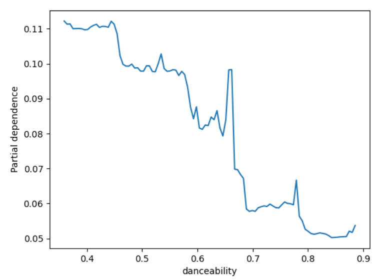


(b) Acousticness- 8 classes

Figure 3: Acousticness

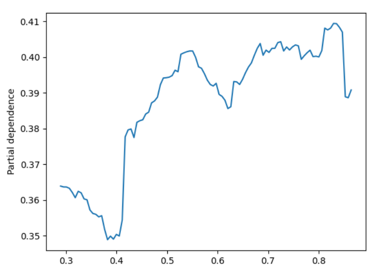


(a) Danceability- 4 classes

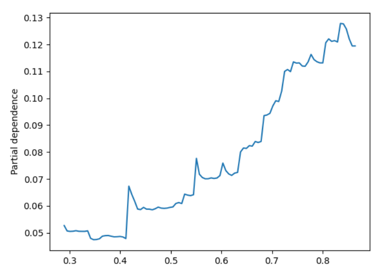


(b) Danceability- 8 classes

Figure 4: Danceability

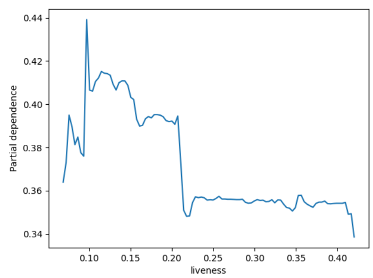


(a) Energy- 4 classes

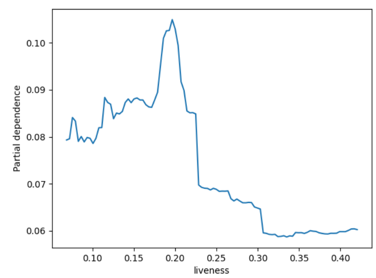


(b) Energy- 8 classes

Figure 5: Energy

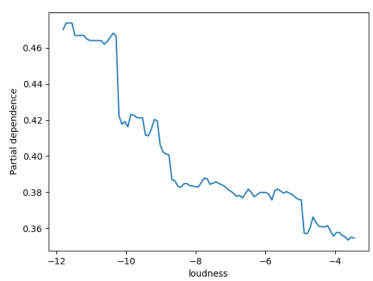


(a) Liveness- 4 classes

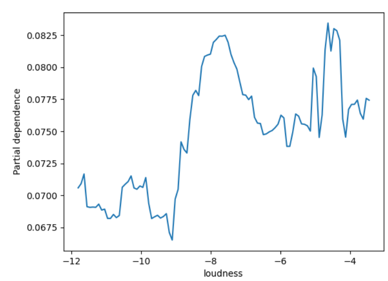


(b) Liveness- 8 classes

Figure 6: Liveness

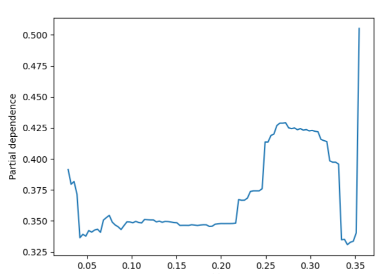


(a) Loudness- 4 classes

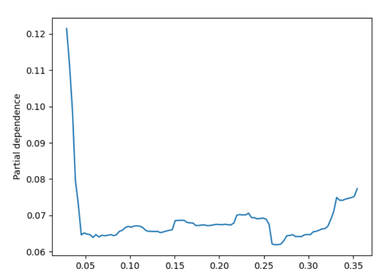


(b) Loudness- 8 classes

Figure 7: Loudness

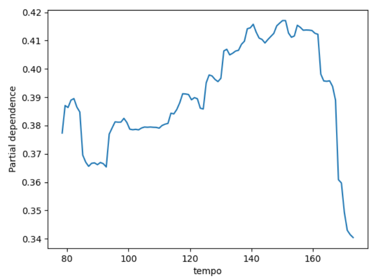


(a) Speechiness- 4 classes

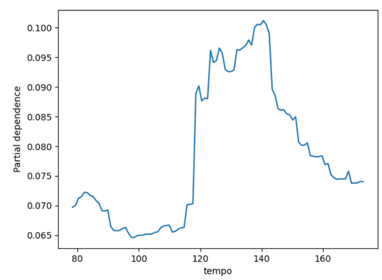


(b) Speechiness- 8 classes

Figure 8: Speechiness

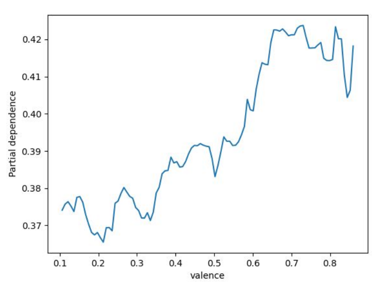


(a) Tempo- 4 classes

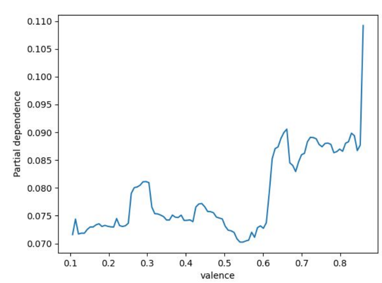


(b) Tempo- 8 classes

Figure 9: Tempo



(a) Valence- 4 classes



(b) Valence- 8 classes

Figure 10: Valence