**Introduction and Motivation**

While our original intent was focused around the association between music genre popularity and culture at large, we felt that its challenge was outside the scope of this project, and shifted gears towards what determines the popularity of songs

**Data Description**

We are using [this](https://data.world/typhon/billboard-hot-100-songs-2000-2018-w-spotify-data-lyrics) data set, compiled by Michael Tauberg.

How the data was collected:

* Starting from the year 2000 onward, each week's archived Hot 100 was added to the data set, with their rank
* When a song is collected again, on a subsequent week, the original entry is removed with its rank updated and its previous value put into "last\_pos"
* If the rank is higher than the previous week and the recorded peak position, the peak position is updated
* The song is then cross referenced with Spotify's API to acquire information about the song, such as characteristics, lyrics, and its spotify link.

While containing lots of useful information such as titles, genres, and lyrics, we really focused on the (spotify) musical characteristic combined with Peak Billboard Rank and year of release.

Mood: Danceability, Valence (Happiness), Energy, Tempo

Properties: Loudness, Speechiness, Instrumentalness

Context: Liveness, Acousticness

Segments: Key, Mode, Time Signature, Duration

**Pre-Processing and Cleaning**

Having loaded in the raw .csv with headers, converted it into a dataframe, and then took relevant columns and loaded them into a standalone data frame,w e made sure every column was numeric data, and as the data set had a significant amount of messing data, omitted incomplete rows.

**Exploratory Data Analysis**

We just plotted basic relationships between intuitive predictors and responses,

* Rank vs (Duration or Danceability or Energy)
* Year vs Danceability

Using the former, we discovered that the way that the data was collected -- removing the last time a song appeared from the data-set, to prevent duplicates, made "rank" unreliable, as songs would rarely exit the Hot 100 when they were still in the Top 40. Because of this, we opted for Peak Position, which was a lot more randomly distributed.

Once we accounted for this, we found clear -- albeit limited -- relationships between different musical characteristics, peak position, and year, and preceded with model selection.

**Data Science Model**

Our first model was a linear model. We used a cross validated LASSO approach to select our features.

cv.lasso <- cv.glmnet(x, y, family = "gaussian", alpha = .5, parallel = TRUE, standardize = TRUE, type.measure = "mse")

coef(cv.lasso, s=cv.lasso$lambda.1se)

And then wrote the generalized linear model

fit <- glm(peak\_pos ~ danceability + year + duration\_ms + valence, data = df1)

As we saw room for improvement, we decided to form a polynomial regression model

poly <- glm(peak\_pos ~ poly(energy, 2) + poly(liveness, 3) + poly(tempo,1)+ poly(acousticness,2) + poly(instrumentalness,3) + poly(time\_signature,3)+ poly(danceability,2) + poly(duration\_ms,3)+ poly(loudness,1)+ poly(valence,1), data = df1)

We then converted that into a Generalized Additive Model:

gam <- gam(peak\_pos ~ s(energy, 2) + s(liveness, 3) + s(tempo,1)+ s(acousticness,2) + s(instrumentalness,3) + s(time\_signature,3)+ s(danceability,2) + s(duration\_ms,3)+ s(loudness,1)+ s(valence,1), data = df1)

And using backward stepwise feature selection, our GAM was simplified down to:

gam3 <- gam(peak\_pos ~ s(liveness, 3) + s(tempo,1) + s(instrumentalness,3) + s(danceability,2) + s(duration\_ms,3)+ s(loudness,1)+ s(valence,1), data = df1) summary(gam3)

**Model Evaluation**

To evaluate the performance of our different models, we put them through 1016-fold cross validation to measure each Mean Standard Error

|  |  |
| --- | --- |
| Model | MSE |
| Linear Model with all features | 889.13 |
| Linear Model with removed features | 887.68 |
| Polynomial Model with all features | 885.83 |
| GAM with all features | 885.58 |
| GAM with removed features | 888.60 |

With this information, we deemed that while not very different; our most complex model (GAM with all features) had the most accurate predictive power of all the models.

**Results**

With our model, we learned that the musical qualities of a popular song is simply not an accurate indicator of where it will peak on the Hot 100 chart. Unsurprisingly, other characteristics may matter more -- such as artist popularity or marketing success among other things.

For perspective, here are some of 2018's #1 hits run through the linear model (which did not measure 2018):

|  |  |  |
| --- | --- | --- |
| Artist | Song | Predicted Peak Position |
| Drake | God’s Plan | 52 |
| Ed Sheeran | Perfect | 52 |
| Childish Gambino | This is America | 47 |
| Cardi B | Bodak Yellow | 48 |
| Ed Sheeran | Shape of You | 46 |

Two of these songs had a higher predicted peak position than the median and mean peak position of all of the songs in our data set.

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