Optimal song properties for popularity

Group 3

December 4th, 2024

List your group members, including their student numbers, here:

- Justin Lee (169085217)
- Raiyan Junaid (169099497)
- Dylan Plut (169083130)
- Seamus Chai (169091540)

Introduction

Every year, Spotify users receive a summary of their year in music, nicknamed "wrapped" as it comes out before Christmas. As any artist, it can be said that appearing on Spotify users wrapped summaries is a very respectable achievement, and since many users post their wrapped data on social media, it is also good for artist growth. Furthermore, artists partner with Spotify to make videos for their top listeners (people with the most minutes streamed). For artists that did not make users wrapped's this year, they will likely be wondering what it was about their songs, if anything, that prevented them from being relevant.

Goals

The goal of this analysis will be to compare key metrics for Spotify's songs via their API (Application Programming Interface) to see if songs with certain attributes perform better than others. To do this, we will graph various different attributes against each other and measure it relative to popularity to see correlation. If meaningful correlation is found then we will create models for the data so that future artists can optimize their songs.

Libraries

```r
library(tidyverse)
library(tidymodels)
library(devtools)
library(ggrepel)
library(neuralnet)
library(ranger)
library(data.table)
```

```r
folder_path <- "Raw Data Files"
csv_files <- list.files(path = folder_path, pattern = "\\.csv$", full.names = TRUE)
data_list <- lapply(csv_files, fread)

big_dataset <- read_csv("tracks_features.csv")
```

Tidying Data

```r
# Joining the datasets
read_and_convert <- function(file) {
  df <- read_csv(file, col_types = cols(.default = "c"))
  df |> mutate(across(everything(), as.character))
}

all_data <- map(csv_files, read_and_convert)
combined_data <- bind_rows(all_data)

numeric_cols <- c("Duration (ms)", "Popularity", "Danceability", "Energy", "Key", "Loudness",
                  "Mode", "Speechiness", "Acousticness", "Instrumentalness", "Liveness",
                  "Valence", "Tempo", "Time Signature")

combined_data <- combined_data |>
  mutate(across(all_of(numeric_cols), as.numeric),
         `Release Date` = as.POSIXct(`Release Date`, format = "%Y-%m-%d")) |>
  select(Popularity, `Artist Name(s)`, `Track Name`, `Duration (ms)`, `Track ID`)

# Creating the decades column
big_set <- big_dataset |>
  mutate(release_date = as.POSIXct(release_date, format = "%Y-%m-%d")) |>
  mutate(Decade = case_when(
    year >= 2020 ~ "2020+",
    year >= 2010 & year < 2020 ~ "2010 - 2020",
    year >= 2000 & year < 2010 ~ "2000 - 2010",
    year >= 1990 & year < 2000 ~ "1990 - 2000",
    year >= 1980 & year < 1990 ~ "1980 - 1990",
    year >= 1970 & year < 1980 ~ "1970 - 1980",
    year >= 1960 & year < 1970 ~ "1960 - 1970",
    year >= 1950 & year < 1960 ~ "1950 - 1960",
    year < 1950 ~ "1950-",
  ))

# Fixing the duration column to not be in ms but instead in seconds. Also matching the "name" column fo
combined_data <- combined_data |>
  mutate(`Duration (sec)` = `Duration (ms)` / 1000) |>
  rename(
    `artists` = `Artist Name(s)`,
    `id` = `Track ID`,
    `name` = `Track Name`
    )
#combined_data
```

```r
# Fixing artists names in "big_set" to be more similar to strings instead of lists/arrays
big_set$artists <- gsub("\\[|\\]|'", "", big_set$artists)

# Matching the formatting of the new artists column in combined_data to the one in big_set.
# This line adds a space after every comma...
combined_data$artists <- gsub(",([^ ])", ", \\1", combined_data$artists) #...idek man this is built on

# Adding popularity to the big dataset from our limited dataset
complete_set <- big_set |>
  inner_join(
    combined_data,
    by = join_by(id, artists)
  ) |>
  select(-duration_ms) |> # Extra duration column from "big_set"
  # Getting rid of duplicates
  unique() |>
  arrange(artists)
# Modifying the popularity set to be an effective factor variable set (that has ranges)
complete_set <- complete_set |>
  mutate(pop_scale = case_when(
    Popularity <= 10 ~ "0-10",
    Popularity > 10 & Popularity <= 20 ~ "11-20",
    Popularity > 20 & Popularity <= 30 ~ "21-30",
    Popularity > 30 & Popularity <= 40 ~ "31-40",
    Popularity > 40 & Popularity <= 50 ~ "41-50",
    Popularity > 50 & Popularity <= 60 ~ "51-60",
    Popularity > 60 & Popularity <= 70 ~ "61-70",
    Popularity > 70 & Popularity <= 80 ~ "71-80",
    Popularity > 80 & Popularity <= 90 ~ "81-90",
    Popularity > 90 & Popularity <= 100 ~ "91-100"
  ),
    pop_scale = as.factor(pop_scale)
    )
# Creating the artist_count column
complete_set$artist_count <- numeric(nrow(complete_set))
for (i in 1:nrow(complete_set)) {
  count <- 1  # Start with 1 because there's always at least one name
  artist_string <- complete_set$artists[i]

  for (char in strsplit(artist_string, "")[[1]]) {
    if (char == ",") {
      count <- count + 1
    }
  }
  complete_set$artist_count[i] <- count
}

complete_set_split <- initial_validation_split(complete_set, prop = c(0.6, 0.2), strata = Decade)
complete_set_split
```

Tidying explanation

We start the data processing flow by reading the CSV files and converting them into a consistent format. The function reads and ensures all columns are then combines into a single combined_data table. In this table, there are numeric columns such as "Duration (ms)" and "Popularity" which are converted from character to numeric. The "Release Date" is also formatted as a date from a string. The columns such as Popularity, Artist Names, and Track Name are kept in the dataset for further analysis because they are important.

Next, the big_set dataset is enriched by adding a Decade column. When categorizing each track it helps to sort by decade ranges such as "2010 - 2020" or "2000 - 2010". This assists in understanding trends across different eras of music. The data was then standardized by converting the track durations from millisends to second and then renaming columns to align with the big_set structure. Artist names were cleaned for consistency. This allowed other datasets to be compatible for merging. The 2 datasets are merged using an inner join based on the ID and Artists columns. After clearing out duplicate entries and sorting the data by artist names, the final complete_set is created with information about each track.

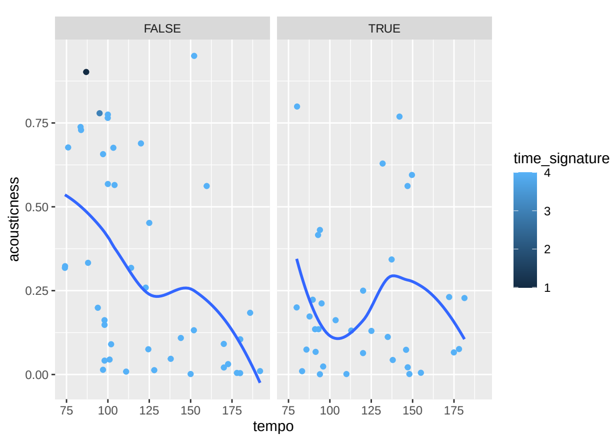
To make the analysis easier to model, we transformed some features into factor variables, enabling us to categorize data into meaningful groups or ranges for better interpretation and comparison. The popularity score is categorzied into factor ranges, "0-10" and "11-20" for the decades. This is to facilitate better interpretation of popularity distributions. An artist_count column is also added, which counts the number of artists collaborating on each track by identifying the commas in the Artists field. Finally, the cleaned and changed dataset is split into training, validaiton, and test sets using a stratified approach based on the Decade column. This ensures each decade is proportionally represented, creating balanced dataset for future modelling and analysis potential.

Overall, this process creates a structured and well-prepared dataset that is ready for further exploration, such as analyzing trends in music popularity over time or building predictive models based on track attributes.

Visualizations

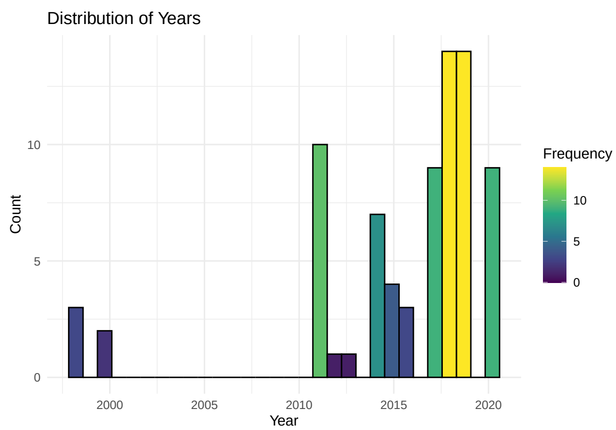
Exploratory Plots - Acousticness vs Tempo and Explicity

```
Acous_vs_temp_plot <- training(complete_set_split) |> ggplot(aes(y = acousticness, x = tempo)) +
  geom_point(aes(colour = time_signature)) +
  geom_smooth(se = FALSE) +
  facet_wrap(~explicit)
Acous_vs_temp_plot
```



The graph above showcases how different song compositions tend to have a more general pattern, as shown by the graph when the song is not explicit there is an inverse correlation between the acousticness and the tempo of the song. This differs from the graph of the songs which are explicit as the slope is almost flat with there being close to no correlation. With this we can imply the composition of a song based on the factors of tempo and the explicitness. It is important to note that with these conclusions they can be biased based on the small sample size. (see limitations)

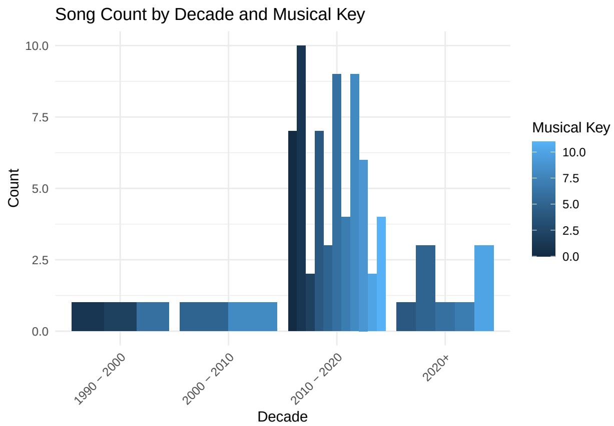
```
plot_year_histogram <- training(complete_set_split) |>
  ggplot(aes(x = year, fill = after_stat(count))) +
  geom_histogram( color = "black") +
  scale_fill_viridis_c() +
  labs(title = "Distribution of Years",
       x = "Year",
       y = "Count",
       fill = "Frequency") +
  theme_minimal()
plot_year_histogram
```



The graph shown above demonstrates one of the measure we took to circumvent the downfalls of our data. This problem we had to solve was that the popularity value found on the Spotify api is more a score of relevancy with parts of its calculations being based on recent listens, this posed difficulty with songs as an older mor popular song would have a lower popularity score. To circumvent this issue we decided to pull the majority of data based in recent years as shown by the graph. This also caused some issue but that is also found in the limitations.

With this information something that we would like to improve on the future of the project is to increase the quantity of data collected and potentially to find a better variable to judge popularity by such as total Listeners or albums sales of older songs.

```
plot_bar <- training(complete_set_split) |>
  ggplot(aes(x = Decade, group = key, fill = key)) +
  geom_bar(position = "dodge") +
  labs(title = "Song Count by Decade and Musical Key",
       x = "Decade",
       y = "Count",
       fill = "Musical Key") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
plot_bar
```



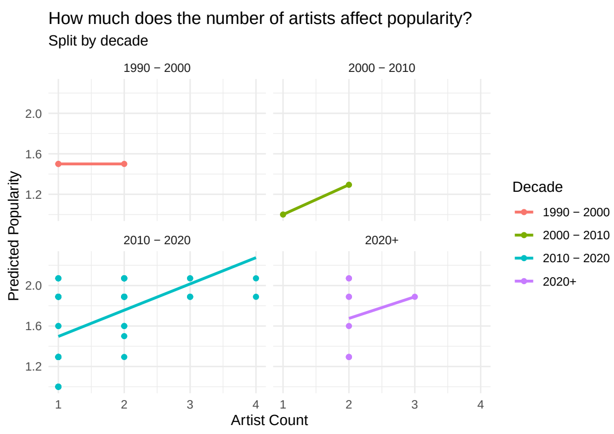
The bar graph above showcases how the musical key of our data changes throughout the decades, this could suggest changes in the differences of the musical taste. This data may suggest that but the main difficulty with this interpretation is the affect of the small sample size therefore any conclusions must be taken with a grain of salt.

The future possibility of this study could further dive into the impacts of society of music with certain keys potentially being more popular in certain decades.

Exploratory Linear Model 1 - Linear Model

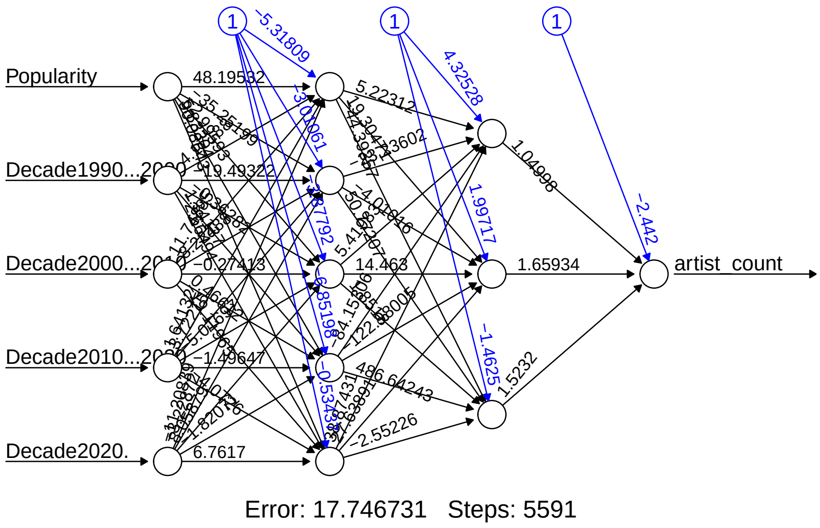
```r
set.seed(1234)
valid_set <- vfold_cv(training(complete_set_split), v = 5)

model <- linear_reg() |>
  set_engine("lm")

fit_artist_pop <- model |>
  fit(artist_count ~ pop_scale, data = training(complete_set_split))

model_coef <- tidy(fit_artist_pop)
model_aug <- augment(fit_artist_pop, new_data = training(complete_set_split))

recipe_artist_pop <- recipe(artist_count ~ Popularity + Decade, data = training(complete_set_split)) |>
  step_dummy(all_nominal_predictors())

artists_vs_popularity <- model_aug |>
  ggplot(aes(x = artist_count, y = .pred)) +
  geom_point(aes(colour = Decade)) +
  facet_wrap(~Decade) +
  geom_smooth(aes(colour = Decade), method = "lm", se = FALSE) +
  #geom_smooth(color = "black", method = "loess", se = FALSE) +
  theme_minimal() +
  labs(
    x = "Artist Count",
    y = "Predicted Popularity",
    title = "How much does the number of artists affect popularity?",
    subtitle = "Split by decade"
  )
```

```
artists_vs_popularity
```



Exploratory Linear Model 2 - Neural Net/MLP

```
model_data <- model.matrix(~ Popularity + Decade - 1, data = training(complete_set_split))
model_data <- cbind(model_data, artist_count = training(complete_set_split)$artist_count)

scaled_data <- as.data.frame(scale(model_data))
colnames(scaled_data) <- make.names(colnames(scaled_data))

formula <- artist_count ~ Popularity + Decade1990...2000 + Decade2000...2010 + Decade2010...2020 + Deca
mlp_model <- neuralnet(formula,
                       data = scaled_data,
                       hidden = c(5, 3),
                       linear.output = TRUE)

mlp_predictions <- predict(mlp_model, newdata = scaled_data)

plot(mlp_model, rep = "best")
```



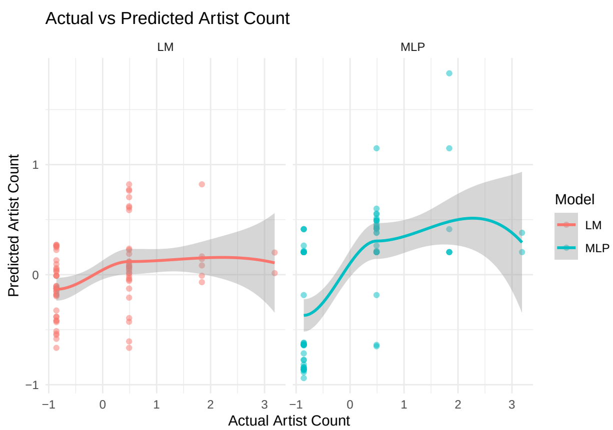

```
rmse <- sqrt(mean((mlp_predictions - scaled_data$artist_count)^2))
print(paste("RMSE:", rmse))
```

```
## [1] "RMSE: 0.678935963440089"
```

Final Model Comparison

```
set.seed(1234)

# Prepare data
model_data <- model.matrix(~ Popularity + Decade - 1, data = training(complete_set_split))
model_data <- cbind(model_data, artist_count = training(complete_set_split)$artist_count)
scaled_data <- as.data.frame(scale(model_data))
colnames(scaled_data) <- make.names(colnames(scaled_data))

# Define formula based on actual column names
formula <- artist_count ~ Popularity + Decade1990...2000 + Decade2000...2010 + Decade2010...2020 + Deca

# MLP model
mlp_model <- neuralnet(formula,
                       data = scaled_data,
                       hidden = c(5, 3),
                       linear.output = TRUE)
mlp_predictions <- predict(mlp_model, newdata = scaled_data)
mlp_rmse <- sqrt(mean((mlp_predictions - scaled_data$artist_count)^2))

# Define and fit the linear model using the same formula
lm_model <- lm(formula, data = scaled_data)

# Make predictions with the linear model
lm_predictions <- predict(lm_model, newdata = scaled_data)
lm_rmse <- sqrt(mean((lm_predictions - scaled_data$artist_count)^2)) # Note: No need for $.pred here
```

```r
# Compare RMSE
rmse_comparison <- data.frame(
    Model = c("MLP", "LM"), # Removed RF as it was not defined here
    RMSE = c(mlp_rmse, lm_rmse)
)

# Visualize predictions
predictions_df <- data.frame(
    Actual = scaled_data$artist_count,
    MLP = as.vector(mlp_predictions),
    LM = lm_predictions # Removed RF as it was not defined here
)

predictions_long <- pivot_longer(predictions_df, cols = c(MLP, LM), names_to = "Model", values_to = "Pre

ggplot(predictions_long, aes(x = Actual, y = Predicted, color = Model)) +
    geom_point(alpha = 0.5) +
    geom_smooth() +
    facet_wrap(~ Model) +
    labs(title = "Actual vs Predicted Artist Count",
         x = "Actual Artist Count",
         y = "Predicted Artist Count") +
    theme_minimal()
```



Conclusion

In this project, we aimed to predict the popularity of tracks on Spotify using various models and features. We explored two modelling techniques, including Linear Regression and a Machine Learning Model called Multilayer Perceptron (MLP), to try and develop a proper prediction model. One notable approach was creating a custom metric, similar to the one used by Spotify, to better capture the factors influencing track popularity.

Our results showed that the MLP model followed the data points significantly more accurately than the linear regression model. The linear model provided much less accuracy, as it struggled to capture the complexities and non-linear relationships in the data. In contrast, the MLP model was able to capture more detailed patterns, resulting in better predictive performance. This was clearly evident in the scatter plot, where the MLP model demonstrated a tighter clustering of predictions around the true values, while the linear model showed more spread, indicating less accurate predictions.

We also performed feature engineering to enhance the quality of our input variables, but chose not to use certain features like loudness and energy, as they did not contribute meaningfully to our model. Instead, we focused on variables that had a stronger correlation with track popularity, such as dancibility, acousticness, and valence. This targeted approach helped in refining the model and improving the accuracy of our predictions.

In conclusion, this project highlighted the importance of choosing appropriate features and models for predictive analysis. While the linear regression model served as a baseline, the superior performance of the MLP model underscored the value of leveraging advanced machine learning techniques for complex datasets. Our work illustrates how thoughtful feature selection and robust modeling approaches can yield significant insights into predicting track popularity on Spotify.

Limitations

Throughout this project, we faced a very large number of technical challenges, which severely limited our analysis. All of these limitations came from the Spotify API. Using the Spotify API was not necessarily hard. We used a library (spotipy) to allow for the use of the python programming language, and made calls to the api for various data. However, the actual data itself proved to a large challenge. The first issue we faced was that during the development of the "dancibility" script which pulled this metric from each artists top 100 songs, Spotify actually removed the endpoint from their API. This meant that we could no longer pull this data. Simultaneously, all other "audio feature" endpoints were pulled. This was a huge blow to our progress in the analysis, but luckily we found a creative workaround: the Spotify IOS api had not yet been updated to reflect the change in functionality. So by manually adding songs into a playlist on our Spotify accounts, we were able to use the IOS api to pull all of the audio features. The result of this was about 2,000 songs and their data being pulled, which is being used in this analysis now.

The second major issues that we faced was the "popularity" metric. This metric is based on current relevance, which meant songs from older artists such as The Beatles would be predestined to do worse in the metric based on their older release date. It seems obvious that instead of using the popularity metric the "total streams" metric should be used, except that Spotify does not allow that data to be pulled. The lack of a total song streams metric dealt a serious blow to this analysis, and while there are creative workarounds (such as scraping the online web player for each artist) they are both too time consuming and beyond the current scope of our ability for this project.

It is also important to recognize that due to our workaround, songs were being handpicked. While we tried to be as diverse as possible with our picks, there is obviously a degree of bias to our representative sample of Spotify data. Also, handpicking data meant that we could only collect so much, and the lack of data explains the instability/inaccuracy of the models.