## Modeling Spotify User Behaviour

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```
library(tidyverse)
library(data.table)
library(glue)
library(lubridate)
# PCA
library("FactoMineR")
library("factoextra")
#library(psych)
# For visualization
library(cowplot)
library(ggplot2)
library(quantreg)
library(tidyquant) ## rolling average for geom_smooth
library(grid)
# Themes
library(ggthemes)
library(egg)
library(RColorBrewer)
```

### Data Exploration

```
# User 1
usr1_lib <- read.csv('Enhanced_Data/User1/usr1_lib.csv')
usr1_streams <- read.csv('Enhanced_Data/User1/usr1_streams.csv')

# User 2
usr2_lib <- read.csv('Enhanced_Data/User2/usr2_lib.csv')
usr2_streams <- read.csv('Enhanced_Data/User2/usr2_streams.csv')

data <- list(usr1_lib, usr1_streams, usr2_lib, usr2_streams)</pre>
```

- Most undefined rows that the API couldn't retrieve information for have been removed in the original data acquisition file.
- It seems just a few rows still contain na values but will be removed.
- Our cleanup function also scales the data for later processing.

```
cleanup <- function(df) {
    # Keep only rows without NA values
    df <- df[!rowSums(is.na(df)) >= 1, ]
```

```
df
}
# Rows including NA
unlist(lapply(data, nrow))
## [1] 29980 55278 6806 52283
# Rows excluding NA
clean_data <- lapply(data, cleanup)</pre>
unlist(lapply(clean_data, nrow))
## [1] 29979 55278 6790 52267
top_100_songs <- function(streaming_frame) {</pre>
  summary_streams <- streaming_frame %>%
    group_by(trackName, artistName, # main vars
             danceability, energy, key, loudness, mode, speechiness, acousticness, instrumentalness, li
    summarise(plays = n(), hoursPlayed = sum(msPlayed)/(1000*60*60))
  top_tracks <- head(summary_streams[order(summary_streams$hoursPlayed, decreasing = TRUE), ], 100)
  top_tracks
}
top_100_genres <- function(lib_frame) {</pre>
  summary_lib <- lib_frame %>%
    group_by(genres) %>%
    summarise(instances = n())
  # need n_songs to get genre occurence across the library
  songs <- lib_frame %>%
    group_by(id) %>%
    summarise()
  summary_lib$`%occurence` <- round(100*summary_lib$instances / nrow(songs), 2)</pre>
  top_genres <- head(summary_lib[order(summary_lib$instances, decreasing = TRUE), ], 100)
  top_genres
}
top_100_songs(clean_data[[2]])
## `summarise()` has grouped output by 'trackName', 'artistName', 'danceability', 'energy', 'key', 'lou
## # A tibble: 100 x 16
## # Groups:
               trackName, artistName, danceability, energy, key, loudness, mode,
## #
       speechiness, acousticness, instrumentalness, liveness, valence, tempo [100]
##
      trackName
                   artistName danceability energy
                                                      key loudness mode speechiness
##
      <chr>
                   <chr>
                                       <dbl>
                                             <dbl> <int>
                                                             <dbl> <int>
                                                                                <dbl>
                                                             -8.81
## 1 Marigold
                   Periphery
                                       0.788 0.533
                                                                               0.0573
                                       0.856 0.841
                                                             -7.74
                                                                              0.335
## 2 Doomsday
                   Architects
                                                        6
                                                                       0
## 3 Reptile
                   Periphery
                                       0.277 0.91
                                                        7
                                                             -5.72
                                                                               0.117
                                                                       1
## 4 Hereafter
                                      0.513 0.973
                                                        6
                                                             -4.12
                                                                       0
                                                                              0.0849
                   Architects
## 5 Blood Eagle Periphery
                                       0.492 0.982
                                                        1
                                                             -5.25
                                                                       1
                                                                              0.147
                                      0.295 0.679
                                                             -6.18
                                                                              0.15
## 6 Ludens
                   BringMeThe~
                                                                       1
                                                        1
## 7 Satellites
                   Periphery
                                      0.669 0.9
                                                       10
                                                             -3.53
                                                                       0
                                                                              0.178
## 8 Stranded
                                      0.513 0.88
                                                        7
                                                             -4.69
                                                                       Λ
                                                                              0.0309
                   Gojira
```

```
## 9 Take Me Out FranzFerdi~
                                      0.277 0.663
                                                             -8.82
                                                                              0.0377
## 10 The Hand Th~ NineInchNa~
                                      0.587 0.99
                                                        0
                                                             -4.50
                                                                       1
                                                                              0.0783
## # ... with 90 more rows, and 8 more variables: acousticness <dbl>,
       instrumentalness <dbl>, liveness <dbl>, valence <dbl>, tempo <dbl>,
       time_signature <int>, plays <int>, hoursPlayed <dbl>
top_100_songs(clean_data[[4]])
## `summarise()` has grouped output by 'trackName', 'artistName', 'danceability', 'energy', 'key', 'lou
## # A tibble: 100 x 16
               trackName, artistName, danceability, energy, key, loudness, mode,
## # Groups:
## #
       speechiness, acousticness, instrumentalness, liveness, valence, tempo [100]
##
                    artistName danceability energy
                                                      key loudness mode speechiness
##
                                       <dbl> <dbl> <int>
                                                             <dbl> <int>
      <chr>
                    <chr>
                                                                               <dbl>
##
  1 Summer 99
                    Tchami
                                      0.81
                                             0.968
                                                        2
                                                             -3.98
                                                                              0.103
##
  2 Red Light Gr~ DukeDumont
                                      0.811 0.825
                                                        2
                                                             -5.48
                                                                              0.0654
                                                                       1
## 3 Deceiver
                    ChrisLake
                                      0.881 0.883
                                                             -5.49
                                                                              0.0633
                                                       11
                                                                       1
## 4 Brothers In ~ DireStrai~
                                                             -9.46
                                      0.22
                                             0.44
                                                        8
                                                                       0
                                                                              0.0352
                                                             -8.09
## 5 Conjure Drea~ MaceoPlex
                                      0.687 0.744
                                                        2
                                                                              0.0545
                                                                       1
  6 Lies, Decept~ ChrisLake
                                      0.809 0.935
                                                        1
                                                             -4.81
                                                                              0.06
## 7 IM GONE
                    JOYRYDE
                                      0.253 0.676
                                                             -6.13
                                                                              0.0455
                                                       10
                                                                       1
## 8 Walk
                                      0.871 0.701
                    Pantera
                                                        5
                                                             -5.59
                                                                       0
                                                                              0.0458
## 9 San Frandisc~ DomDolla
                                      0.762 0.826
                                                             -4.87
                                                                              0.0406
                                                        1
                                                                       1
## 10 Never Let Yo~ SNBRN
                                      0.728 0.94
                                                        4
                                                             -5.03
                                                                              0.0368
## # ... with 90 more rows, and 8 more variables: acousticness <dbl>,
       instrumentalness <dbl>, liveness <dbl>, valence <dbl>, tempo <dbl>,
## #
       time_signature <int>, plays <int>, hoursPlayed <dbl>
top_100_genres(clean_data[[1]])
## # A tibble: 100 x 3
##
      genres
                        instances `%occurence`
##
      <chr>
                            <int>
                                          <dbl>
## 1 alternative metal
                                          30.4
                             1859
## 2 rock
                             1712
                                          28
## 3 nu metal
                             1616
                                          26.4
## 4 modern rock
                             1443
                                          23.6
## 5 pop punk
                             1120
                                          18.3
                                          15.7
##
   6 metalcore
                              958
                                          12.3
##
   7 post-grunge
                              751
## 8 screamo
                              727
                                          11.9
## 9 melodic metalcore
                                          11.0
                              672
## 10 alternative rock
                              658
                                          10.8
## # ... with 90 more rows
top_100_genres(clean_data[[3]])
## # A tibble: 100 x 3
                     instances `%occurence`
##
      genres
##
      <chr>
                         <int>
                                       <dbl>
## 1 edm
                           337
                                      19.9
## 2 electro house
                                      18.5
                           313
                                      12.9
## 3 pop dance
                           218
                           166
                                       9.82
## 4 rap
## 5 hip hop
                                       8.93
                           151
```

8.4

142

## 6 Unknown

```
## 7 pop 140 8.28
## 8 tropical house 139 8.22
## 9 house 121 7.16
## 10 pop rap 108 6.39
## # ... with 90 more rows
```

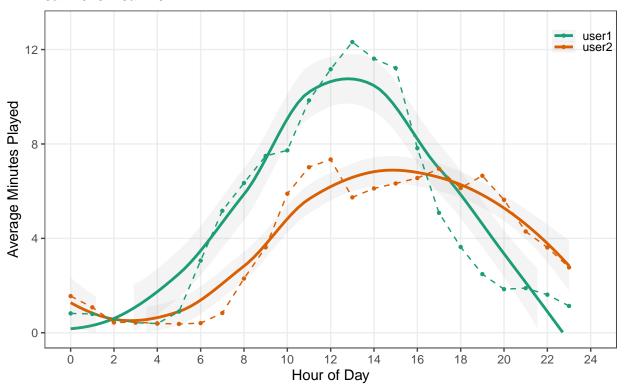
### Visualizing Average Daily Play Time

```
# Function for binding user streaming data
stream_together <- function(frames) {</pre>
 n <- length(frames)</pre>
 for (i in 1:n) {
   frames[[i]] <- frames[[i]] %>%
    group_by(endTime, trackName, artistName, msPlayed, # main vars
            danceability, energy, key, loudness, mode,
            speechiness, acousticness, instrumentalness,
            liveness, valence, tempo, time_signature) %>%
    summarise()
   frames[[i]]$minPlayed <- frames[[i]]$msPlayed/(1000*60)</pre>
   frames[[i]] <- frames[[i]][-4]</pre>
   frames[[i]]$user <- as.factor(glue('user{i}'))</pre>
 frames <- rbindlist(frames)</pre>
 frames
}
all_streams_UTC <- stream_together(clean_data[c(2,4)]) # Universal Standard Time
# Manual adjustment for user timezones
# This can only be done if one knows where the user has been when
all_streams <- rbind(</pre>
 # User 2 Ontario
 all_streams_UTC %>% filter(user == "user2" & month(endTime) < 9) %>%
   # User 2 British Columbia
 all_streams_UTC %>% filter(user == "user2" & month(endTime) >= 9) %>%
   # User 1 Ontario
 all streams UTC %>% filter(user == "user1" & month(endTime) < 5) %>%
   # User 1 British Columbia
 all_streams_UTC %>% filter(user == "user1" & month(endTime) >= 5) %>%
   )
# Plotting
tot_days <- as.numeric(max(all_streams$endDate) - min(all_streams$endDate))</pre>
all_streams %>%
 group by(endHour, endDate, user) %>%
 summarise(hourdayPlayTime = sum(minPlayed)) %>% # total minutes played by hour by day
 group_by(endHour, user) %>%
```

```
summarise(avg = sum(hourdayPlayTime)/tot_days) %>% # avg minutes played by hour over all days
          \#n = n() # days played at given hour
          \#q1 = quantile(c(hourdayPlayTime, rep(0, tot_days-n())), 0.5), \# quantiles including days
          #q3 = quantile(c(hourdayPlayTime, rep(0, tot_days-n())), 0.8)) %>%
ggplot(aes(y = avg, x = endHour, color = user)) +
geom smooth(level = 0.95, method = loess, alpha = 0.1) +
geom_line(alpha = 1, size = 0.5, linetype = 'dashed') +
geom_point(alpha = 1.2, shape = 16, size=1.2) +
scale_x_continuous(name = 'Hour of Day', breaks=seq(0,24,2), limits = c(0,24)) +
scale_y_continuous(name = 'Average Minutes Played', breaks=seq(0, 20, 4), limits = c(0,13)) +
ggtitle('Average Music Playtime by Hour of the Day', subtitle = 'Jan 2020 - Jan 2021') +
scale_color_brewer(palette = 'Dark2') +
theme_article() +
theme(legend.title = element_blank(),
     legend.position = c(0.94,0.92),
     panel.grid.major = element_line(color = '#ededed'))
```

# Average Music Playtime by Hour of the Day

Jan 2020 - Jan 2021

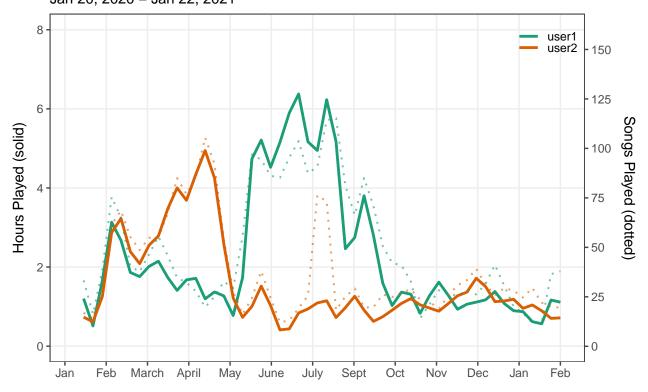


### Visualizing Play Time through the Year

```
tot_weeks <- length(unique(all_streams$week_of_year))</pre>
all_streams %>%
  group_by(week_of_year, endDate, user) %>%
  summarise(dailyPlayTime = sum(minPlayed)/60,
            dailyPlays = n() %>%
  group_by(week_of_year, user) %>%
  summarise(avg weeklyPlayTime = mean(dailyPlayTime),
            avg_weeklyPlays = mean(dailyPlays)) %>%
  ggplot(aes(x = week_of_year, color = user)) +
  #geom_line(aes(y=avg_weeklyPlayTime), linetype = 1, size = 1) +
  #geom_line(aes(y=avg_weeklyPlays/16), linetype = 3, size = 0.7) +
  geom_ma(aes(y=avg_weeklyPlayTime), n = 2, linetype = 1, size = 1, alpha = 1.0) +
  geom_ma(aes(y=avg_weeklyPlays/20), n = 2, linetype = 3, size = 0.7, alpha = 0.6) +
  scale_x_continuous(name = element_blank(), labels = months, breaks = seq(0, 57, 4.4167)) +
  scale_y_continuous(name = 'Hours Played (solid)', limits = c(0,8), breaks = seq(0,10,2),
                     sec.axis = sec_axis(name = 'Songs Played (dotted)', ~.*20, breaks = seq(0,200,25),
  ggtitle('2-Week Average Play Time and Play Counts for Eric and Luka',
          subtitle = 'Jan 20, 2020 - Jan 22, 2021') +
  scale color brewer(palette = 'Dark2') +
  theme_article() +
  theme(legend.title = element_blank(),
        legend.position = c(0.93,0.93),
        axis.title.y.left = element_text(vjust = 3),
        axis.title.y.right = element_text(vjust = 3, angle = -90),
        panel.grid.major = element_line(color = '#ededed'))
```

## `summarise()` has grouped output by 'week\_of\_year', 'endDate'. You can override using the `.groups`
## `summarise()` has grouped output by 'week\_of\_year'. You can override using the `.groups` argument.

# 2–Week Average Play Time and Play Counts for Eric and Luka Jan 20, 2020 – Jan 22, 2021



### Unsupervised Exploration to find Emotional Groupings in Libraries

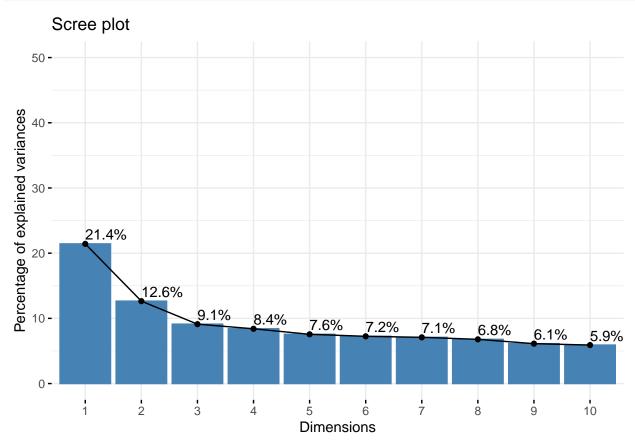
- Genres do not form clear clusters
- PC1 is related to energy/positivity/loudness in one direction and calmness in the other.
- PC2 is related to duration/energy in one direction and mode in the other.
- Ultimately, we won't be able to cluster music tastes into specific subgroups for either user.
- Perhaps clusters may appear when comparing user data but it's not clear if they exist within user data.
- Therefore, further clustering methods won't be performed.

```
# Function to scale and remove non-numeric rows
convenient_scale <- function(df) {
    # Save genre classes
    genres <- as.factor(df$genres)
    # Scale numeric columns
    df <- df %>% mutate_if(is.numeric, scale) %>% select_if(is.numeric)
    # Readd genre classes
    df$genres <- cbind(genres, df)
}

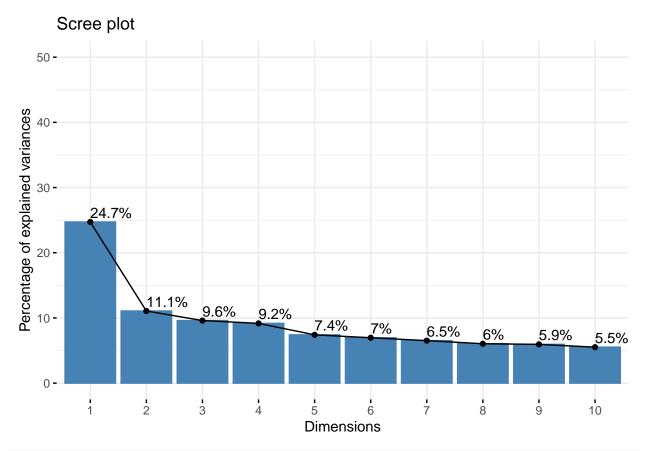
# Scale data
usr1_lib_scaled <- convenient_scale(clean_data[[1]])
usr2_lib_scaled <- convenient_scale(clean_data[[3]])

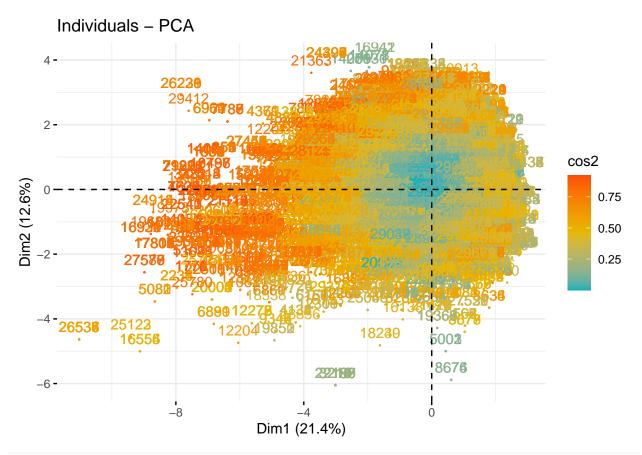
# PCA
usr1_pca <- PCA(usr1_lib_scaled[,-1], graph = FALSE)
usr2_pca <- PCA(usr2_lib_scaled[,-1], graph = FALSE)</pre>
```

```
# Skree plot
fviz_eig(usr1_pca, addlabels = TRUE, ylim = c(0, 50))
```

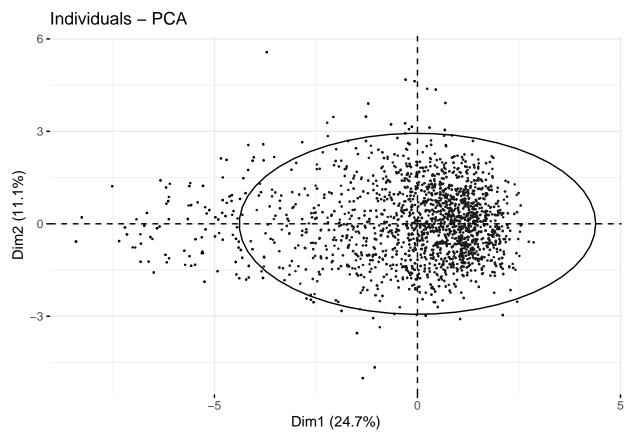


fviz\_eig(usr2\_pca, addlabels = TRUE, ylim = c(0, 50))



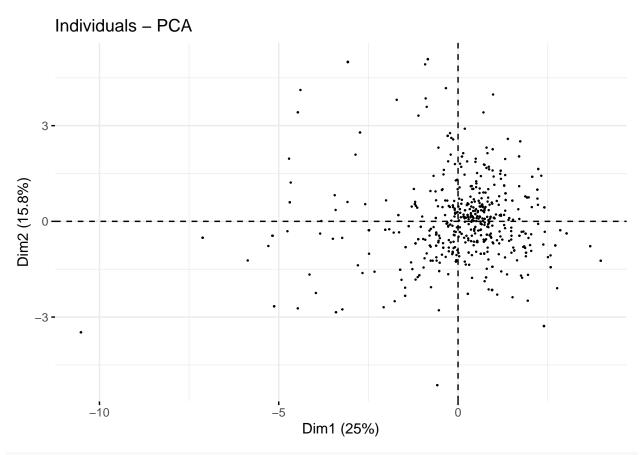


fviz\_pca\_ind(usr2\_pca, geom.ind = "point", pointsize = 0.2, addEllipses = TRUE,)



```
# Check if average genre features alone cluster based on audio features
# (summarize average audio features by genre)
gens <- usr1_lib_scaled %>%
    group_by(genres) %>%
    summarise_all(mean)

# PCA on average genre feature
gens_pca <- PCA(gens[,-1], ncp = 10, graph = FALSE)
fviz_pca_ind(gens_pca, geom.ind = "point", pointsize = 0.2)</pre>
```



### library(teigen)

```
## Warning: package 'teigen' was built under R version 4.0.3 
#obj1 \leftarrow teigen(gens\_pca\$ind\$cos2[,1:2], Gs = 1:5, model = 'UCCU', scale = FALSE, verbose = FALSE)
```

```
#obj1 <- tergen(gens_pca$ind$cos2[,1:2], Gs = 1:5, model = 'UCCU', scale = FALSE, verbose = FALSE) #obj2 <- tergen(usr1_pca$ind$cos2[,1:2], Gs = 1:5, model = 'UCCU', scale = FALSE, verbose = FALSE) #obj3 <- tergen(usr2_pca$ind$cos2[,1:2], Gs = 1:5, model = 'UCCU', scale = FALSE, verbose = FALSE) #plot(obj1, xmarg=1, ymarg=7, what="contour") #plot(obj2, xmarg=1, ymarg=7, what="contour") #plot(obj3, xmarg=1, ymarg=7, what="contour")
```

## Supervised Learning

Predicting genres on audio features

### Modeling daily, weekly, and monthly listening habits

Modeling play time, and specific audio feature play time