STAT 158 Group Project Final Report

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May 2021

1 Abstract

This study aims to examine the influence of song pitch, song tempo, and color of album to the perception, specifically, mood/emotion, of the listeners. We utilize a complete block design, CB[3], where the treatment factors (the conditions of interest) are pitch, tempo, and color of the album cover, and the response is a recorded through a systematic measure of mood known as the Brief Mood Introspection Scale (BMIS) (Mayer Cavallaro, 2019). Through experimentation on a group of STAT 158 Spring 2021 students and ANOVA analysis based on our model, we find out that none of the factors, song pitch, song tempo, and color of the album cover, have a significant impact on the emotion of the listener.

2 Introduction

In the creation of music, one core motive is enhancing the artistic quality of the song. In short, artistic quality is the ability of the listener to feel the emotion that the creator gives through the song. However, music can't express specific emotions. Its expression has to do with sensory receptors, such as the eyes and ears. Hearing can pick up signals which are interpreted as the direction in which sounds are moving, their frequency, the relationship between the ratios of the sounds, and the rate of changes in sounds. Coupled with the inner implication of visual effects, music is a strongly sensory experience. That's where our emotions drift. This particular experiment is of interest to us because of the extent music is incorporated in our modern lives, as music has much more influence than simply providing enjoyment and relaxation. A hot topic in the past few years is the influence of music on mood. Discoveries related to such influence could be applied to other fields, such as therapy for psychological disorders. By doing this experiment, we hope to expand the research into the influence of music combined with color. Music is considered a useful tool of therapy for psychological disorders on human mood. We hope that the results of our experiment could provide some insight on the effects of different combinations of music and color, and possibly contribute to future application of such combinations in the field of physical therapy.
Our results indicate that none of the three factors exhibit significant influence on

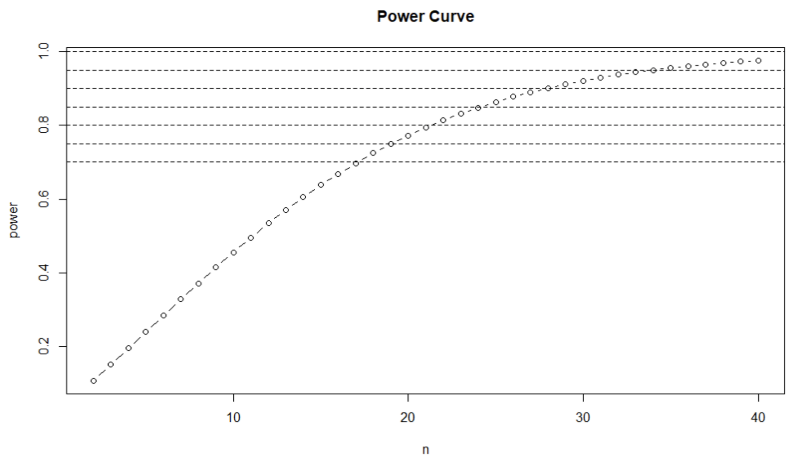
the mood of the listeners. Though the results suggest a null significance of the song pitch, song tempo, and album cover color and no interaction between the factors, we have reason to believe that more data and improved experimentation design would lead to a stronger conclusion.

3 Method

First, 12 songs are chosen. The details on this selection process are thoroughly explained below. The data was selected to minimize the variability in song qualities that were hypothesized to have impact on the mood of the listener, while retaining variability in the song parameters under study: pitch and tempo. The Spotify dataset (Ay, 2021), containing over 174,000 songs, has many parameters to classify each song, from danceability to acousticness. The first parameter used to narrow down the massive number of songs was popularity. On a scale of 0-100, popularity describes how popular the song is currently in the US. In order to minimize the chances of a subject recognizing a song, only songs with a popularity value of less than 50 were selected. Next, all songs with explicit lyrics were removed. Then, the data was filtered to select songs within 33rd quartile to 66th quartile in several key song parameters that we thought may influence the mood of the listener. This had the benefit of narrowing our search to songs that sounded relatively similar, so that our parameters of interest could be accurately compared against each other without additional bias from a broad distribution of song attributes. The parameters used to filter the values were danceability, energy, liveness, loudness, speechiness, and year. After finding songs that were toward the center of the distribution for all of these parameters, we were left with a much smaller list of songs: 150. Valence is probably the most important parameter to control for from the Spotify dataset. Valence is described as "the positiveness of the track" and varies from 0-1. Assuming this is directly linked to the mood of the listener, we chose a relatively narrow range toward the center of the distribution, 0.43 to 0.57. This narrow range, toward the center of the distribution, is meant to make sure that the positivity is relatively constant and medium-leveled. After narrowing our search to songs with medium valence, we were left with 80 songs. From this final list, the songs were sorted according to key and tempo and 12 were hand-picked to fit our full-factorial design of 3 factors (album cover color temperature, pitch, and tempo) with 3, 2, and 2 levels, respectively. From the dataset we have obtained, we had to manipulate the album cover colors and decide which songs were classified as low/high pitch and tempo. First, the album cover color temperature is a relatively easy constraint to work with. For each of the 12 songs selected, the album cover color temperature can be readily manipulated with photo manipulation software (ffmpeg-python). The goal is to see how the color temperature may affect the mood of the listener. Warmer colors are hypothesized to be associated with more positive moods, and the cooler with more negative moods. Neutral colors (mostly black, white, and grey) are meant to be a control, but it would be unsurprising if they were associated with more negative moods as well. The pitch factor is classified in the data with the key parameter, integers 1-11, with 1 being the lowest and 11 being the highest pitch. For the lower level of pitch, we choose values of key below 6, and for the higher level, we choose 6 and above. One source of error is that the key parameter seems to match the pitch of the instrumental and not the singer, and thus a vocal track of a different pitch can change the perceived pitch of the song. One way to avoid this issue would be to choose songs without a vocal track. This was considered in the hand-selection of our 12 songs, and ultimately songs with vocals were chosen. The higher pitch is hypothesized to be associated with more positive moods, and the lower pitch with more negative moods. For the tempo factor, the lower level is around 100 or lower, and the higher level is 125 or higher. This was roughly based upon the pitch classifications published on Symphony Nova Scotia's website (How do musicians know how fast to play a piece? And why are the terms in Italian?, n.d.) The higher tempo is hypothesized to be associated with more positive moods, and the lower tempo with more negative moods. We also had to randomize the run order for each song and the color of the album covers. We used the R sample command to randomly generate a set of 12 numbers for the order of the songs, and again to determine the color of the album cover, with numbers 1-4 corresponding to cool color, 5-8 corresponding to neutral, and 9-12 corresponding to warm color covers. With these two sets of 12, we have a completely random play order and album cover color combination for each subject.

For a single run, a subject, i.e., a single complete block, is randomly assigned to and provided with a Google Drive video that had each of the 12 songs in randomized run order and color temperature. The subject is asked to listen to the songs in the play order, and take the mood assessment via the Google Form following each 30 second song snippet. The assessment has a question about whether the subject knows the song. If a subject knows the song, that data point will be disqualified as it may mean that there is bias in their mood after listening to it. To prevent unbalanced data, we fill up as many batches as we can during the experimenting period and disqualify all data for subjects that knew any of the songs, and we use response from a replacement subject who was also randomly assigned to the specific order. The subject is presented with the 4-point, 16-level BMIS assessment and a brief questionnaire assessing subject song affinity, and then asked to rate the song on qualities such as enjoyability, recognizability, and relatability. The Google Form response is used to calculate the BMIS pleasant-unpleasant score using the subtractive method, yielding an integer with a range of 48 values. Of the 16 BMIS descriptors, 8 are associated with pleasant moods and 8 are associated with unpleasant moods. The subtractive scoring method sums the raw values (1-4) from the pleasant descriptors and subtracts the sum of the raw scores of the unpleasant descriptors. This yields a maximum value of 24, assuming each pleasant descriptor is 4, and each unpleasant descriptor is 1, (32-8=24) and a minimum score of -24 (8-32=-24). This means that the full breadth of the scale is very unlikely to be reached, meaning that most of the scores are centered around 0. This pleasant-unpleasant mood score is recorded as an integer, but analyzed as a numeric determined by the

BMIS, because non-integer values of mood are meaningful, i.e. a score of 5.25 is measurably more pleasant than 4.75. We should be able to analyze this as a continuous variable, as this scale has relatively good granularity of 0.25.
We have defined the sample size as the number of subjects. The final n is 24.28965, which is rounded up to 28. We divide the 28 by 4, which is the number of repetition for each of the levels in the factor color. Therefore, in total, we would need 7 subjects(the sample size), which yields the power of 0.8582366. In the following power curve, we see that with a total of 10 subjects (n = 40), the power would be above 95% as shown below. Thus, we ultimately decided to recruit 10 subjects to complete our 10 corresponding projects.



We assume that our above CB[3] design can be modelled by the following equation:
$y_{ijkl} = \mu + \alpha_i + \beta_j + \gamma_k + \rho_l + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik} + (\alpha\rho)_{il} + (\beta\rho)_{jl} + (\gamma\rho)_{kl} + (\alpha\beta\gamma)_{ijk} + \varepsilon_{ijkl}$
where,
μ is the benchmark,
α_i is the treatment effect for the ith pitch factor treatment,
β_j is the treatment effect for the tempo factor treatment,
γ_k is the treatment effect for the album color factor treatment,
ρ_l is the block effect for the lth subject,
$(\alpha\beta)_{ij}$ is the interaction effect between the ith pitch factor treatment and the jth tempo factor treatment,
$(\alpha\gamma)_{ik}$ is the interaction effect between the ith pitch factor treatment and the kth album color factor treatment,
$(\beta\gamma)_{jk}$ is the interaction effect between the jth tempo factor treatment and the kth album color factor treatment,
$(\alpha\rho)_{il}$ is the interaction effect between the ith pitch factor treatment and the lth subject,
$(\beta\rho)_{jl}$ is the interaction effect between the jth tempo factor treatment and the lth subject,
$(\gamma\rho)_{kl}$ is the interaction effect between the kth album color factor treatment

and the lth subject,
$(\alpha\beta\gamma)_{ijk}$ is the interaction effect between the ith pitch factor treatment and the jth tempo factor treatment and the kth album color factor treatment,
ε_{ijkl} is the error associated with the ith pitch treatment and jth tempo factor treatment and the kth album color factor treatment for the lth subject.

4 Results

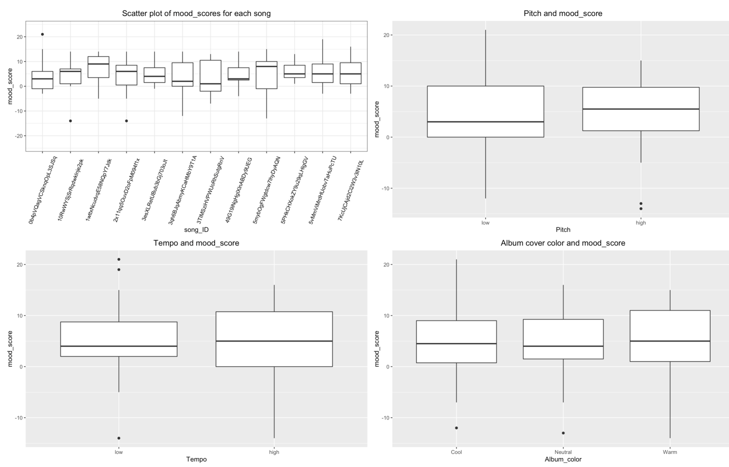
4.1 Informal Analysis

We conduct informal analysis to the data obtained first. To merge the data obtained from the ten projects into a large data frame, where the row represents each song, and the column represents the scores of the corresponding emotions of the song, as shown in Figure 1. It can be found that though the emotional score has a theoretical range of (-24, 24).

song_ID	Lively	Happy	Sad	Tired	Caring	Content	Gloomy	Jittery	Drowsy
3TIMSziHVPWUoRhSutgRnV	3	3	1	1	3	3	1	1	1
5vMmViMrdHUobvTaHuPcTU	2	2	2	2	1	1	1	1	2
5PHkCHXokZY9u29qLHIgGV	2	2	2	1	2	2	2	2	2
5mybOgFWgtdcw7IhyDyAQN	3	3	1	1	1	1	1	1	1
3qh6BJqAbmyKCaHMbY9T1A	2	1	2	2	2	2	2	2	2
49G19iNgHgIXInABDy9UEG	3	3	1	1	2	2	1	1	1
10RwWYSjSrRqdwkInje2pk	3	2	1	1	2	2	1	2	2
1wttxNcudvqE58NQpY7Jdk	2	2	1	1	3	2	1	1	2
0b4pVQagVCSknqOpL3SJSq	3	3	1	1	2	2	1	2	1
3esXLRetUBub3bGj703oJt	3	2	1	2	2	2	1	1	1
2x11qq5OuvD2oFpM094f1x	2	2	1	1	3	3	1	1	2
7KcUjCAjd2Cl2W3v3IN10L	4	3	1	1	3	3	1	1	1
3TIMSziHVPWUoRhSutgRnV	3	3	1	1	3	3	1	1	1
5vMmViMrdHUobvTaHuPcTU	2	2	2	2	1	1	1	1	2

Showing 1 to 15 of 132 entries

Figure 1

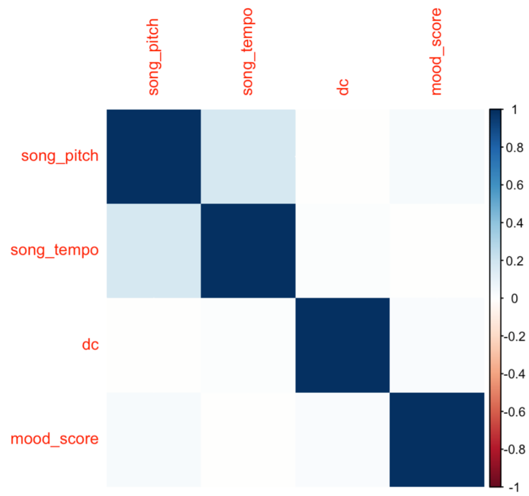


(Figure 2)

From the main effects plot (Figure 2), we see that the factor song pitch seems to have some correlation with the response score, exhibiting positive relation. However, the main effect plots for album cover and song tempo do not display much potential influence on response. To further confirm our initial guess, we then compute the Pearson Correlation between each of the factors and the response. After applying Pearson Correlation Analysis, we conclude that the pitch of the song has the strongest relationship with the mood, compared with other factors(tempo and cover). R=0.0306 shows there is positive correlation between them, which is consistent with the assumption. What's more, all correlations between all factors(pitch, tempo, cover) are weak, which range from -0.004 to 0.18. This also confirms the result that the combined factors in the analysis of variance have little effect on the emotional score of the song.

	song_pitch	song_tempo	dc	mood_score
song_pitch	1	0.178567504208368	-0.00331429737502148	0.0306499894088718
song_tempo	0.178567504208368	1	0.0143001879368755	-0.00190101393778385
dc	-0.00331429737502148	0.0143001879368755	1	0.0202338347549952
mood_score	0.0306499894088718	-0.00190101393778385	0.0202338347549952	1

Table 1



(Figure 3)

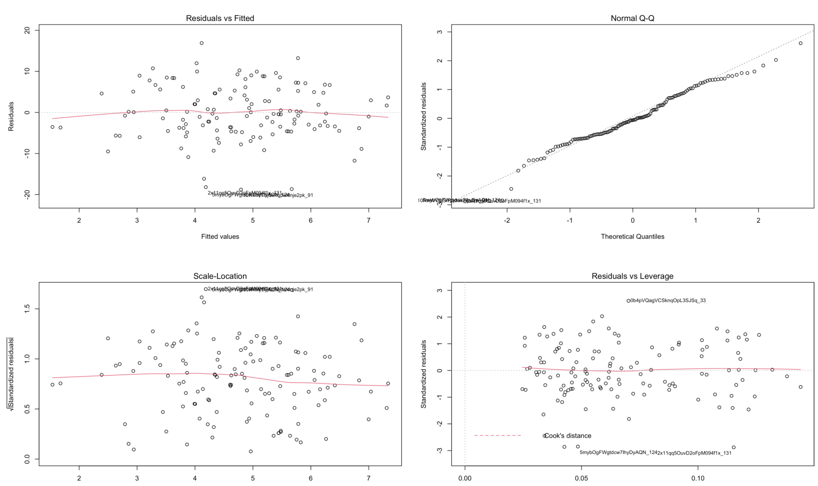
Identifying outliers:
The response score should theoretically have a range of -24 to +24. However, one of the subjects rated all of the songs as relatively positive, that is, all the ultimate scores are above 0. as the songs are randomly assigned into each group, the possibility of having all the relatively unpleasant songs in one project is minimal. In this case, we doubt that this subject may be identified as an outlier. More precise analysis is required using the ANOVA table.

4.2 ANOVA Analysis

Through our ANOVA analysis, we found that neither of our assigned treatment factors had a significant effect on our response. As indicated by the high (i.e. close to 1) p-values corresponding to our song pitch, album color, and song tempo factors shown in the ANOVA table (Table 2), there is very little evidence that the variability in our mood scores was a result of the assigned treatments. P-value compares the magnitude of residual mean square to the magnitude of treatment mean square; a small p-value like the ones we see in Table 2 indicates that under the null hypothesis, our observed, relatively small, effect sizes were very likely to occur as the treatment mean square was not sufficiently larger

	df	Sum sq	Mean sq	F value	Pr(>F)
pitch	1	5	4.73	0.106	0.745
tempo	1	8	8.25	0.185	0.668
color	2	3	1.46	0.033	0.968
project_ID	1	90	90.00	2.020	0.158
pitch:tempo	1	12	11.52	0.259	0.612
pitch:color	2	105	52.61	1.180	0.311
tempo:color	2	135	67.42	1.513	0.224
pitch:tempo:color	2	65	32.43	0.728	0.485
Residuals	119	5303	44.57		

than the residual mean square to suggest otherwise, i.e. we do not have sufficient statistical evidence to suggest that the between treatment variation is higher than the variation that already exists within each treatment group, and that the treatments themselves might not have much effect on our response. The most significant p-values is our blocking factor, the subject, which is approximately 0.16. As the subject is a blocking factor, we could not conclude that it has any causal effect on our response, but it does show that there is some relationship between subject and response, thus proving the correctness of our choice of subject as a blocking factor to separate its influence from the other factors.
The rest of the p-values are so large to describe them as sufficient, which render all of the corresponding terms in the model as lacking evidence to reject their nullity.



(Figure 4)
The residuals are basically independent of the fitted values, and conform to the basic assumptions of linear regression. The Q-Q plot aids in checking the normality assumption of our model. These points in the data fit a line with a gentle

slope, and the variance is basically determined, so it conforms to the assumption of equal variance. There are no extreme points in the display data, so our model can reflect the true impact of the above three factors on the emotional score of the song.

4.3 Further Discussion

The data of each song provided by Spotify is numeric, and we manually divided their pitch and tempo into two categories, which results in loss of precision and information. It is likely that the null results could be attributed to such lack of precision due to the categorical nature of our factors.To further improve our experiment, we could further divide our factors into more levels to compensate for the imprecision that might be caused by converting numerical information into categories.

5 Conclusion

In conclusion, our analysis indicates any one or a combination of the following is true: our testing methodology was completely flawed, our analysis was flawed, or color has no significant impact on the mood of the listener. There is the most evidence (albeit still non-statistically significant) that the run order of the songs in our particular experiment has the biggest impact on the mood of the listener. It's clear that more data or a more careful analysis of the data is required to make a decisive conclusion of the effects of the above three factors on the listeners' mood.

code_2.0.R

yanchengli

2021-05-13

```
library(ggplot2)
data1<-read.csv("~/desktop/data.csv")
project<-read.csv("~/desktop/project.csv")
p_tempo<-read.csv("~/desktop/pitch_tempo.csv")
project<-project[-13,]

no<-seq(3,242,20)
data1<-data1[,-no]



z<-data.frame()
for (j in 1:11) {
  x<-data.frame()
  pro_data<-data1[j,,drop=F]
  for (i in 0:11) {
    y<-as.vector(pro_data[,(3+(19*i)):(21+(19*i))])
    colnames(y)<-c("Lively","Happy","Sad","Tired","Caring","Content","Gloomy","Jittery","Drowsy","Grouc
                   "Active","Enjoyable","Recognizable","Relatable" )
    x<-rbind(x,y)
  }
  x<-data.frame(x,project=data1$X..project[j])
  z=rbind(z,x)
}





z[seq(1,132,12),]
```

```
##      Lively Happy Sad Tired Caring Content Gloomy Jittery Drowsy Grouchy Peppy
## 1         3     3   1     1      3       3      1       1      1       1     3
## 212       3     3   1     4      2       2      1       1      3       2     2
## 312       2     2   3     4      2       3      3       2      2       2     2
## 412       2     2   3     2      2       2      3       2      2       2     2
## 512       2     2   3     1      1       2      3       2      2       2     2
## 612       3     3   1     2      1       1      1       4      3       1     1
## 712       3     3   1     2      2       3      1       1      1       1     2
## 812       3     3   2     1      3       3      1       2      2       2     3
## 912       1     1   2     2      1       1      2       1      3       2     1
```

```
## 1012      3     3   1     2      2       3      1       1      1       1      1
## 1112      2     2   2     3      2       2      3       2      3       3      3
##       Nervous Calm Loving. Fed_up Active Enjoyable Recognizable Relatable
## 1           1    1       2      1      3         2            1         2
## 212         1    3       2      2      2         3            1         1
## 312         2    3       2      2      2         3            1         3
## 412         2    2       2      2      2         2            2         2
## 512         2    3       2      2      2         1            2         3
## 612         1    3       1      1      2         3            1         3
## 712         2    3       4      1      2         4            1         2
## 812         1    3       3      1      2         3            3         2
## 912         1    1       1      2      1         1            1         1
## 1012        1    3       2      1      2         3            2         2
## 1112        3    2       2      2      3         2            1         2
##       project
## 1           8
## 212         9
## 312         3
## 412         1
## 512         7
## 612        10
## 712         6
## 812         6
## 912         2
## 1012        5
## 1112        4
```

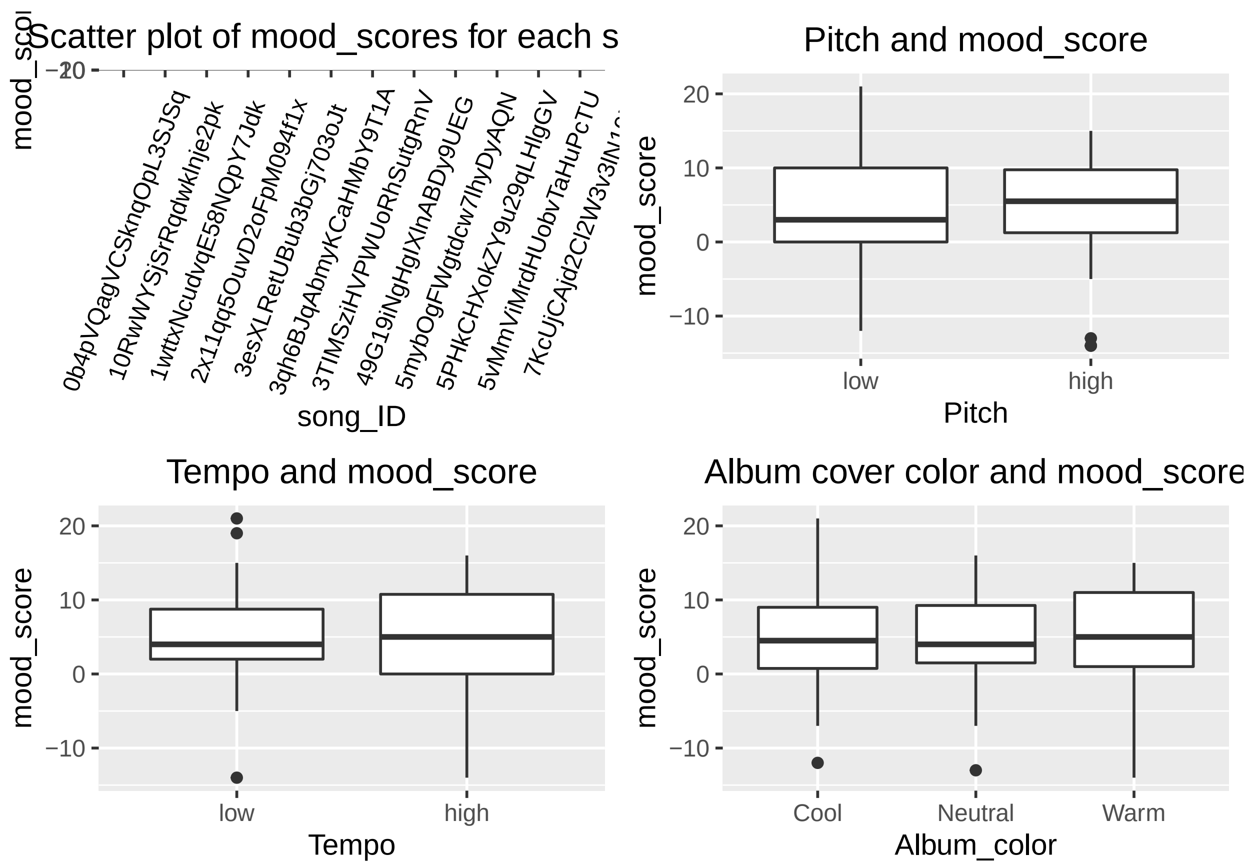
```r
song_rank<-project[,seq(1,30,3)]
consecutive_color_album<-project[,seq(2,30,3)]
discrete_color_album<-project[,seq(3,30,3)]

sr<-c()
cc<-c()
dc<-c()
a<-c(1:6,6:10)
for (i in a) {
  sr<-c(sr,song_rank[,i])
  cc<-c(cc,consecutive_color_album[,i])
  dc<-c(dc,discrete_color_album[,i])
  cat(i)
}
```

```
## 123456678910
```

```r
proj<-c(rep(1:10,12),rep(6,12))
d1<-data.frame(song_ID=p_tempo$Song.ID,song_pitch=p_tempo$Key..pitch.,song_tempo=p_tempo$Tempo,song_orde
d1$song_order<-as.numeric(d1$song_order)
d1<-d1[order(d1$song_order),]

a1111<-z[!duplicated(z$project),"project"]
y1<-data.frame()
for (i in a1111) {
  x1<-d1[which(d1$project==i),]
```

```r
  y1<-rbind(y1,x1)

}
dd<-cbind(z,y1)
pleasant<-c("Lively","Happy","Caring","Content","Peppy","Calm","Loving.","Active")
unpleasant<-c("Sad","Tired","Gloomy","Jittery","Drowsy","Grouchy","Nervous","Fed_up")
d_pleasant<-as.matrix(dd[,pleasant])
d_unpleasant<-as.matrix(dd[,unpleasant])

mood_score<-apply(d_pleasant, 1, sum)-apply(d_unpleasant, 1, sum)

result1<-data.frame(song_ID=p_tempo$Song.ID,song_pitch=p_tempo$Key..pitch.,song_tempo=p_tempo$Tempo,
                    song_RANK=dd[,"song_order"],mood_score=mood_score,cc,dc,project_ID=dd$project)



result2<-result1
write.csv(result2,"summary_data.csv",row.names = F)



###plot

result1$project_ID<-as.factor(result1$project_ID)

g0<-ggplot(result1,aes(x=song_ID, y=mood_score),group=song_ID)+
  geom_boxplot()+
  labs(title =  bquote("Scatter plot of mood_scores for each song"),
       x= "song_ID",
       y = 'mood_score')+
  theme_bw()+
  theme(plot.title = element_text(hjust = 0.5))+
  theme(axis.text.x = element_text(angle = 70, hjust = 0.5,
                                   vjust = 0.5,color = "black",size=9))+
  scale_y_continuous(limits=c(-24,24))

result1[result1$song_pitch>6,]$song_pitch<-"high"
result1[result1$song_pitch<=6,]$song_pitch<-"low"

h_tempo<-rownames(result1[result1$song_tempo>125,])
l_tempo<-rownames(result1[result1$song_tempo<=125,])
result1[h_tempo,]$song_tempo<-"high"
result1[l_tempo,]$song_tempo<-"low"

result1$song_pitch<-factor(result1$song_pitch,levels=c("low","high"))
result1$song_tempo<-factor(result1$song_tempo,levels=c("low","high"))
result1$dc<-factor(result1$dc,levels=c("Cool","Neutral","Warm"))


g1<-ggplot(result1, aes(x=song_pitch,y=mood_score,group=song_pitch))+
  geom_boxplot()+
  labs(title =  bquote("Pitch and mood_score"),
       x= "Pitch",
```

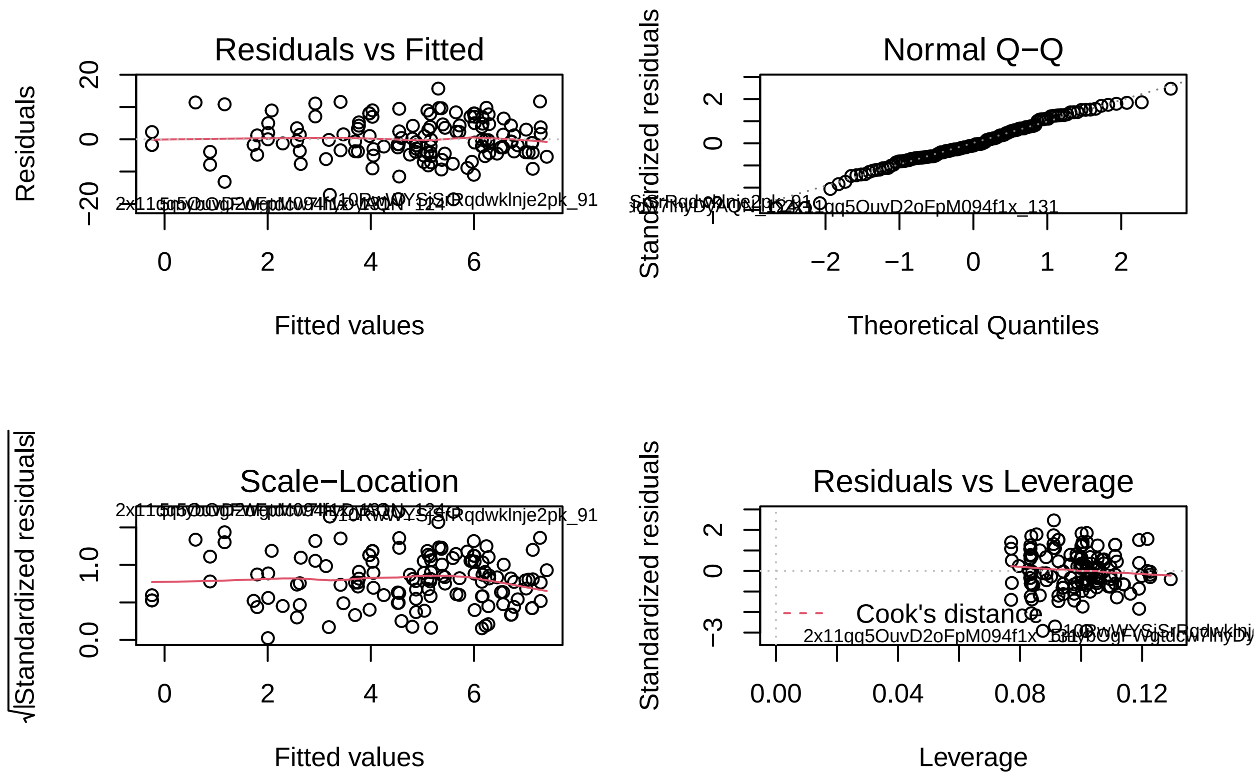
```
       y = 'mood_score')+
  theme(plot.title = element_text(hjust = 0.5))

g2<-ggplot(result1, aes(x=song_tempo,y=mood_score))+
  geom_boxplot()+
  labs(title =  bquote("Tempo and mood_score"),
       x= "Tempo",
       y = 'mood_score')+
  theme(plot.title = element_text(hjust = 0.5))

g3<-ggplot(result1, aes(x=dc,y=mood_score,group=dc))+
  geom_boxplot()+
  labs(title =  bquote("Album cover color and mood_score"),
       x= "Album_color",
       y = 'mood_score')+
  theme(plot.title = element_text(hjust = 0.5))
library(gridExtra)
grid.arrange(g0,g1,g2,g3,ncol=2,nrow=2)
```




```
###anova
result1<-read.csv("summary_data.csv")
row.names(result1)<-paste0(result1$song_ID,"_",1:length(result1[,1]))#


result1[which(result1[,"dc"]=="Warm"),"dc"]<-1.5
```

```r
result1[which(result1[,"dc"]=="Cool"),"dc"]<-c(-1)
result1[which(result1[,"dc"]=="Neutral"),"dc"]<-c(-0.5)

result1$dc<-as.numeric(result1$dc)

# assign new colmn for color as factor
result1$cc<-as.numeric(result1$cc)
for (i in (1:length(result1$cc))){
  if (result1$cc[i] > 8){
    result1$color[i]<- "Warm"
  }
  if (result1$cc[i] < 5){
    result1$color[i]<-"Cool"
  }
  if (result1$cc[i] > 4 & result1$cc[i] < 9){
    result1$color[i]<-"Neutral"
  }
  # print(result1$cc[i])
}
result1$color<-as.factor(result1$color)


# assign new column for pitch as factor
result1$song_pitch<-as.numeric(result1$song_pitch)
for (i in (1:length(result1$song_pitch))){
  if (result1$song_pitch[i] > 5){
    result1$pitch[i]<- "High"
  }
  if (result1$song_pitch[i] < 6){
    result1$pitch[i]<- "Low"
  }
  # print(result1$cc[i])
}
result1$pitch<-as.factor(result1$pitch)


# assign new column for pitch as factor
result1$song_tempo<-as.numeric(result1$song_tempo)
for (i in (1:length(result1$song_tempo))){
  if (result1$song_tempo[i] > 125){
    result1$tempo[i]<- "High"
  }
  if (result1$song_tempo[i] < 110){
    result1$tempo[i]<- "Low"
  }
  # print(result1$cc[i])
}
result1$tempo<-as.factor(result1$tempo)

# result1$cc<-as.factor()

fit3<-aov(mood_score~pitch*tempo*color+project_ID, data=result1)
fit<-summary(fit3)
```

```r
write.csv(fit[[1]],"anova.csv")
par(mfrow=c(2,2))
plot(fit3)
```




```r
###corr

library(Hmisc)
```

```
## Loading required package: lattice
```

```
## Loading required package: survival
```

```
## Loading required package: Formula
```

```
##
## Attaching package: 'Hmisc'
```

```
## The following objects are masked from 'package:base':
##
##     format.pval, units
```

```r
res2<-rcorr(as.matrix(result1[,c("song_pitch","song_tempo","dc","mood_score")]),type="pearson")

corr<-res2$r

write.csv(corr,"pearson.csv")#table2

library(corrplot)
```

```
## corrplot 0.84 loaded
```

```r
dev.new()
corrplot(corr, method = "shade")



########END#######
```

data

Timestamp	# project	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]
2021/04/26 9:34:39 AM MDT	8	No	3	3	1	1	3	3	1	1	1	1	3	1
2021/04/26 11:04:05 AM MDT	9	No	3	3	1	4	2	2	1	1	3	2	2	1
2021/04/26 11:11:43 AM MDT	3	No	2	2	3	4	2	3	3	2	2	2	2	2
2021/04/26 11:21:11 AM MDT	1	No	2	2	3	2	2	2	3	2	2	2	2	2
2021/04/26 11:36:27 AM MDT	7	No	2	2	3	1	1	2	3	2	2	2	2	2
2021/04/26 11:57:39 AM MDT	10	No	3	3	1	2	1	1	1	4	3	1	1	1
2021/04/26 1:08:07 PM MDT	6	No	3	3	1	2	2	3	1	1	1	1	2	2
2021/04/26 1:15:12 PM MDT	6	No	3	3	2	1	3	3	1	2	2	2	3	1
2021/04/26 8:08:56 PM MDT	2	No	1	1	2	2	1	1	2	1	3	2	1	1
2021/04/26 8:11:24 PM MDT	5	No	3	3	1	2	2	3	1	1	1	1	1	1
2021/04/26 8:13:16 PM MDT	4	No	2	2	2	3	2	2	3	2	3	3	3	3

Timestamp	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]
2021/04/26 9:34:39 AM MDT	1	2	1	3	2	1	2	No	2	2	2	2	1	1	1	1
2021/04/26 11:04:05 AM MDT	3	2	2	2	3	1	1	No	2	2	1	3	3	3	1	1
2021/04/26 11:11:43 AM MDT	3	2	2	2	3	1	3	No	4	3	2	2	2	4	2	3
2021/04/26 11:21:11 AM MDT	2	2	2	2	2	2	2	No	3	3	2	2	2	2	2	2
2021/04/26 11:36:27 AM MDT	3	2	2	2	1	2	3	No	3	1	2	1	1	2	2	1
2021/04/26 11:57:39 AM MDT	3	1	1	2	3	1	3	No	4	4	1	1	3	3	1	1
2021/04/26 1:08:07 PM MDT	3	4	1	2	4	1	2	No	3	3	1	1	2	1	1	1
2021/04/26 1:15:12 PM MDT	3	3	1	2	3	3	2	No	3	2	3	2	2	2	3	2
2021/04/26 8:08:56 PM MDT	1	1	2	1	1	1	1	No	3	1	1	1	2	2	1	1
2021/04/26 8:11:24 PM MDT	3	2	1	2	3	2	2	No	2	2	3	3	1	2	2	1
2021/04/26 8:13:16 PM MDT	2	2	2	3	2	1	2	No	4	4	1	1	2	2	1	1

[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?
2	1	2	1	3	3	1	2	2	1	1	No	2	2	2	1	2	2	2	2	2	1	2	1	3	2	1	2	1	1	1	No
2	1	2	1	3	3	2	2	3	1	1	No	2	2	1	3	3	2	1	1	3	1	2	1	3	3	2	2	2	1	1	No
2	2	3	2	3	2	2	2	3	2	3	No	3	2	2	2	2	3	2	3	2	2	2	2	3	2	2	2	2	2	2	No
2	2	2	2	2	2	2	2	3	1	1	No	3	3	2	2	2	2	2	2	2	2	3	2	2	2	2	3	3	1	1	No
2	2	2	2	2	2	2	2	1	2	3	No	2	3	1	1	3	3	1	2	2	2	2	1	3	2	2	2	2	3	4	No
1	1	1	1	4	4	1	4	4	2	2	No	3	2	3	3	4	1	2	1	1	1	1	2	2	3	1	1	2	1	1	No
1	1	1	1	3	3	1	2	4	1	2	No	3	4	1	1	1	1	1	1	1	1	1	1	3	3	1	3	4	2	3	No
3	1	3	2	2	2	2	2	2	2	1	No	4	4	1	1	3	3	1	2	2	1	3	1	3	2	2	2	4	3	3	No
1	1	1	1	2	1	1	1	3	2	2	No	2	2	2	2	2	2	3	1	2	1	1	1	2	2	1	1	3	2	1	No
3	1	1	1	2	1	1	1	1	1	1	No	3	3	1	1	1	3	1	1	1	1	1	1	2	1	1	3	3	2	1	No
1	1	1	1	3	3	1	4	4	3	3	No	3	2	3	2	3	3	4	2	2	1	2	2	4	4	2	2	3	2	2	No

[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]
3	3	1	1	1	1	1	1	1	1	3	1	1	2	2	3	2	2	2	No	2	1	2	2	2	2	2	2	2	1	1	1	2	2	2	2
2	3	1	2	3	3	1	1	2	1	2	1	3	3	2	2	3	1	1	No	2	2	1	3	3	3	1	1	3	1	2	1	3	3	2	2
4	4	1	1	3	4	2	3	2	2	3	2	4	4	2	4	4	3	3	No	1	3	3	1	1	1	1	1	1	1	1	1	1	1	1	1
2	2	3	3	2	2	3	2	2	2	2	2	2	2	2	2	2	1	1	No	2	2	2	2	2	2	2	2	2	2	3	2	3	2	2	2
2	2	2	1	2	2	1	2	2	2	2	2	3	1	2	2	2	3	3	No	3	1	1	1	1	1	1	1	1	1	1	3	1	1	1	3
4	3	1	1	2	2	1	1	2	1	1	1	3	1	1	2	2	1	1	No	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	3	1	1	1	1	1	1	1	1	1	1	3	3	1	3	4	1	3	No	4	4	1	1	3	1	1	1	1	1	1	1	3	3	1	3
3	2	2	4	2	2	3	1	3	2	1	3	2	2	3	2	1	1	1	No	2	1	3	3	2	1	3	3	3	3	1	3	1	2	3	2
2	2	2	2	2	3	2	2	2	2	2	2	2	2	1	1	2	2	1	No	3	3	1	1	3	3	1	1	1	1	2	1	3	3	1	2
3	3	1	1	1	3	1	1	1	1	2	1	2	1	1	3	3	2	3	No	1	1	2	2	1	1	3	2	2	1	1	2	1	1	1	1
1	1	4	4	1	3	3	3	3	3	2	3	2	2	4	2	2	1	1	No	4	3	2	2	3	3	2	4	1	1	4	2	3	3	1	4

[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]
1	2	1	No	3	3	1	1	2	2	1	1	1	1	3	1	1	2	1	3	3	2	2	No	3	2	1	1	2	2	1	2
3	1	1	No	2	2	1	3	2	2	1	1	3	1	2	1	3	2	2	1	2	1	1	No	1	2	1	3	3	2	1	1
2	1	3	No	4	3	2	2	2	3	3	1	1	1	1	1	1	1	3	1	4	3	2	No	4	4	1	1	1	4	1	4
3	1	1	No	3	2	2	2	2	2	2	2	2	2	2	2	3	2	2	3	3	1	1	No	3	3	3	3	2	2	2	2
1	1	1	No	2	2	2	1	1	3	1	2	2	2	2	2	3	1	1	2	3	2	2	No	3	2	1	1	1	2	1	2
2	1	1	No	3	2	3	2	2	1	1	1	1	1	1	1	2	1	1	2	3	1	1	No	3	3	1	1	1	2	1	1
4	1	3	No	4	4	1	1	2	1	1	1	1	1	1	1	3	3	1	3	4	1	2	No	4	4	1	1	3	1	1	1
1	2	1	No	3	2	2	2	2	2	1	2	2	2	3	2	2	2	2	3	3	2	3	No	1	1	3	3	2	1	3	3
3	3	2	No	2	2	2	2	2	2	2	2	3	1	1	1	3	1	1	1	2	2	2	No	3	2	2	2	3	3	3	1
1	1	1	No	3	3	1	1	3	3	1	1	1	1	1	1	4	3	1	2	4	3	3	No	3	3	2	2	2	3	2	1
3	3	3	No	3	2	3	3	2	2	3	2	3	2	2	2	2	2	3	2	1	1	1	No	3	2	3	2	2	2	3	2

[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?
2	1	2	1	2	2	2	2	1	1	1	No	2	2	1	1	3	2	1	1	2	1	2	1	3	3	2	2	3	2	3	No
3	2	1	1	3	2	2	1	2	1	1	No	2	2	1	4	3	2	1	1	4	3	1	1	3	2	2	1	2	1	1	No
3	1	4	1	1	1	1	3	4	3	1	No	4	4	1	1	1	4	1	1	1	1	3	1	1	1	1	3	4	3	4	No
2	2	2	2	2	2	2	2	3	1	1	No	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	3	3	1	1	No
2	2	2	1	3	1	1	2	3	1	2	No	2	3	1	2	2	3	1	2	2	2	1	1	2	3	2	3	2	3	2	No
1	1	1	1	1	2	1	1	4	1	1	No	4	4	1	1	1	1	1	1	1	1	1	1	3	3	1	2	4	1	1	No
1	1	1	1	3	3	1	3	4	1	2	No	4	4	1	1	2	1	1	1	1	1	1	1	3	3	1	3	4	3	2	No
4	3	1	3	2	1	3	2	1	2	1	No	3	3	2	2	2	2	1	3	1	2	3	3	2	2	1	2	3	3	3	No
1	1	1	1	3	2	1	1	2	3	1	No	3	3	1	1	3	2	1	1	1	1	1	1	3	3	1	1	4	3	1	No
1	1	1	1	3	3	1	1	3	3	3	No	4	4	1	1	1	4	1	1	1	1	2	1	1	2	1	4	4	4	4	No
2	2	2	2	4	2	2	2	3	1	1	No	1	2	3	3	3	3	3	2	3	3	2	2	2	3	3	1	1	1	1	No

[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]
3	3	1	1	2	2	1	2	1	1	2	2	1	2	2	2	1	1	1	No	3	2	1	2	2	2	1	1	1	1	2	1	1	1	2	2
2	2	1	3	3	2	1	1	3	1	1	1	2	2	1	1	2	1	1	No	2	2	1	3	2	2	1	1	2	1	1	1	3	2	1	1
4	4	1	1	4	4	1	4	1	1	4	1	4	4	1	4	4	4	3	No	4	1	1	1	1	1	1	4	1	1	4	1	1	1	1	1
3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	3	1	1	No	2	2	2	3	2	2	2	2	2	2	2	2	2	2	2	2
1	2	1	3	1	1	1	2	2	2	2	2	3	2	2	3	1	2	3	No	3	3	1	2	1	2	2	2	2	2	3	2	3	2	2	2
3	3	1	2	1	1	1	1	1	1	1	1	1	1	2	2	2	1	1	No	3	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1
4	4	1	1	3	1	1	1	1	1	1	1	3	3	1	4	4	3	3	No	4	4	1	1	3	1	1	1	1	1	1	1	3	3	1	3
3	3	1	2	2	3	1	3	2	1	3	3	2	2	2	3	3	3	3	No	3	3	2	3	2	2	2	2	3	2	2	2	4	2	2	1
2	2	2	2	2	2	3	2	2	2	1	1	2	1	1	1	2	1	1	No	3	3	1	1	2	3	1	1	1	1	2	1	3	3	1	1
2	2	2	1	1	2	3	2	3	2	2	2	2	1	1	1	1	1	1	No	1	2	1	4	1	2	1	2	3	1	1	1	4	2	1	1
3	2	3	2	2	1	2	3	2	2	3	2	1	1	1	2	2	2	2	No	4	3	3	1	3	4	2	2	2	2	2	2	3	4	2	3

[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]	[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]	Did you recognize this song?	[Lively]	[Happy]	[Sad]	[Tired]	[Caring]	[Content]	[Gloomy]	[Jittery]
2	1	2	No	2	2	1	1	3	3	1	1	2	1	1	1	3	3	2	1	2	1	1	No	4	3	1	1	3	3	1	1
2	1	1	No	2	2	1	3	2	2	1	1	2	2	1	1	2	2	1	1	2	1	1	No	2	2	1	3	2	2	1	1
4	2	1	No	4	1	2	1	1	4	3	4	1	1	4	1	4	1	1	4	4	3	2	No	4	1	1	1	1	4	4	4
2	1	1	No	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	3	3	1	1	No	2	2	3	3	2	2	2	2
2	3	3	No	1	3	1	1	1	2	1	2	2	2	2	3	1	2	2	1	1	1	1	No	3	3	1	1	3	3	1	2
1	1	1	No	3	3	1	1	1	3	1	1	1	1	1	1	1	1	1	1	3	1	1	No	2	1	2	3	1	1	1	1
4	3	3	No	4	4	1	1	3	1	1	1	1	1	1	1	3	3	1	3	4	2	3	No	4	4	1	2	1	1	1	1
3	3	2	No	2	1	2	4	3	3	4	2	4	2	1	1	3	2	2	1	3	3	2	No	2	3	2	3	4	3	2	2
4	3	1	No	3	3	1	1	2	3	1	1	1	1	2	1	3	3	1	1	3	3	1	No	3	1	1	2	1	2	1	1
2	2	2	No	3	2	1	2	1	2	1	1	2	1	3	1	2	2	1	2	3	3	3	No	1	1	2	3	1	1	1	1
3	3	3	No	1	1	4	4	2	3	4	2	4	4	1	3	2	3	3	1	1	2	2	No	3	3	2	2	2	1	1	3

[Drowsy]	[Grouchy]	[Peppy]	[Nervous]	[Calm]	[Loving]	[Fed up]	[Active]	[Enjoyable]	[Recognizable]	[Relatable]
1	1	3	1	1	3	1	4	4	3	4
2	1	1	1	3	2	1	1	3	1	1
1	1	1	1	4	3	1	1	4	4	4
2	2	2	2	2	2	2	2	2	1	1
2	2	3	1	3	4	3	2	3	3	2
1	1	1	1	1	1	1	1	2	1	1
1	1	1	1	4	4	1	3	4	3	3
3	1	2	2	3	3	2	2	3	2	2
1	1	3	1	1	2	1	3	2	1	1
2	1	1	1	2	1	1	1	1	1	1
1	1	3	1	2	2	1	4	4	3	3