

Spotify Data Bayesian Analysis

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```
Logs <- data.frame(read_csv("data/log_sample_reduced.csv"))
```

```
##
## -- Column specification -----
## cols(
##   track_id_clean = col_character(),
##   not_skipped = col_logical()
## )
```

```
Tracks <- data.frame(read_csv("data/tf_sample_1.csv"))
```

```
##
## -- Column specification -----
## cols(
##   track_id = col_character(),
##   duration = col_double(),
##   release_year = col_double(),
##   us_popularity_estimate = col_double(),
##   acousticness = col_double(),
##   beat_strength = col_double()
## )
```

```
Append <- data.frame(read_csv("data/tf_sample_2.csv"))
```

```
##
## -- Column specification -----
## cols(
##   bounciness = col_double(),
##   danceability = col_double(),
##   energy = col_double(),
##   instrumentalness = col_double(),
##   mode = col_character(),
##   speechiness = col_double(),
##   tempo = col_double(),
##   valence = col_double()
## )
```

```
Tracks$bounciness <- Append$bounciness
Tracks$danceability <- Append$danceability
Tracks$energy <- Append$energy
Tracks$instrumentalness <- Append$instrumentalness
Tracks$mode <- Append$mode
```

```

Tracks$speechiness <- Append$speechiness
Tracks$tempo <- Append$tempo
Tracks$valence <- Append$valence

```

```

Tracks.bool <- Tracks
Tracks.bool$skipped <- rep(1, length(Tracks$track_id))
c <- rep(1,length(Tracks$track_id))
for (i in 1:length(Tracks$track_id)) {
  c[i] <- i
}
vect <- rep(1,17468)
for (i in 33236:50704) {
  vect[i-33235] <- i
}
Leftover <- Tracks.bool[-vect,]
Tracks.final <- rbind(Tracks.bool, Leftover)

```

```

for (i in 1:length(Logs$track_id_clean)) {
  x <- Logs$track_id_clean[[i]]
  y <- which(Tracks$track_id == x)
  bool <- 1
  if (Logs$not_skipped[[i]] == TRUE) {
    bool <- 0
  }
  z <- cbind(Tracks[y,], skipped = bool)
  Tracks.final[i,] <- z
}

```

```

Tracks.final$skipped <- as.factor(Tracks.final$skipped)
Track_features <- Tracks.final[Tracks.final$release_year >= 2010,]
Track_features <- Track_features[Track_features$speechiness <= 0.4,]
Track_features <- Track_features[Track_features$instrumentalness <= 0.6,]
Track_features <- Track_features[Track_features$duration <= 360,]

```

```

p1= ggplot(data = Track_features, aes(x = duration)) +
  geom_histogram()
p2= ggplot(data = Track_features, aes(x = us_popularity_estimate)) +
  geom_histogram()
p3= ggplot(data = Track_features, aes(x = acousticness)) +
  geom_histogram()
p4= ggplot(data = Track_features, aes(x = beat_strength)) +
  geom_histogram()
p5= ggplot(data = Track_features, aes(x = bounciness)) +
  geom_histogram()
p6=ggplot(data = Track_features, aes(x = danceability)) +
  geom_histogram()
p7= ggplot(data = Track_features, aes(x = energy)) +
  geom_histogram()
p8=ggplot(data = Track_features, aes(x = instrumentalness)) +
  geom_histogram()
p9=ggplot(data = Track_features, aes(x = mode)) +
  geom_bar()

```

```

p10=ggplot(data = Track_features, aes(x = speechiness)) +
  geom_histogram()
p11= ggplot(data = Track_features, aes(x = tempo)) +
  geom_histogram()
p12=ggplot(data = Track_features, aes(x = valence)) +
  geom_histogram()
p13=ggplot(data = Track_features, aes(x = skipped)) +
  geom_bar()

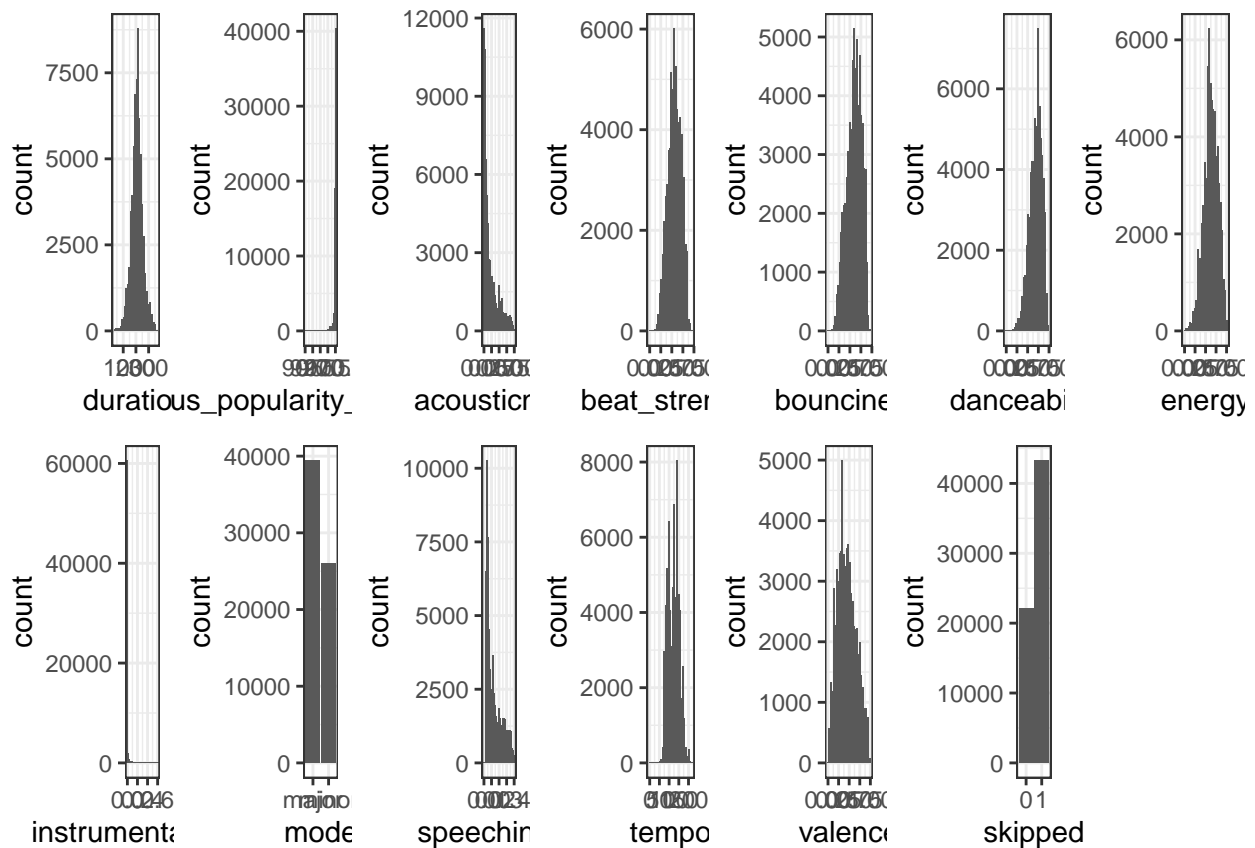
grid.arrange(p1, p2, p3, p4, p5, p6, p7, p8, p9, p10,p11, p12, p13, nrow=2)

```

```

## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
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## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
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## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.

```

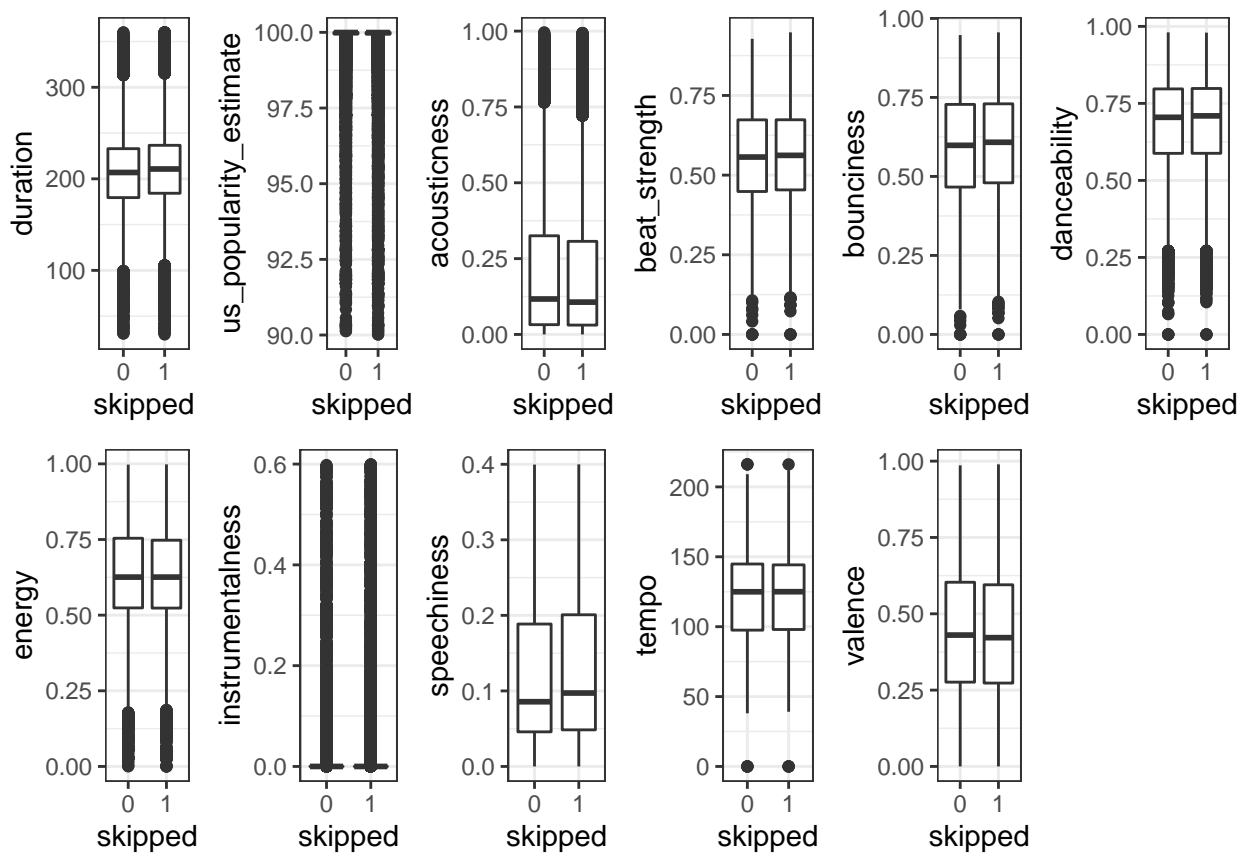


```

g1= ggplot(Track_features, aes(skipped, duration)) + geom_boxplot()
g2=ggplot(Track_features, aes(skipped, us_popularity_estimate)) + geom_boxplot()
g3=ggplot(Track_features, aes(skipped, acousticness)) + geom_boxplot()
g4=ggplot(Track_features, aes(skipped, beat_strength)) + geom_boxplot()
g5=ggplot(Track_features, aes(skipped, bounciness)) + geom_boxplot()
g6=ggplot(Track_features, aes(skipped, danceability)) + geom_boxplot()
g7=ggplot(Track_features, aes(skipped, energy)) + geom_boxplot()
g8=ggplot(Track_features, aes(skipped, instrumentalness)) + geom_boxplot()
g9=ggplot(Track_features, aes(skipped, speechiness)) + geom_boxplot()
g10=ggplot(Track_features, aes(skipped, tempo)) + geom_boxplot()
g11=ggplot(Track_features, aes(skipped, valence)) + geom_boxplot()

grid.arrange(g1, g2, g3, g4, g5, g6, g7, g8, g9, g10,g11, nrow=2)

```



```

set.seed(4)
a <- sample.int(length(Track_features$track_id), 1000)
Track_features_a <- Track_features[a,]
Track_features_a <- Track_features_a[2:15]
Track_features_a <- Track_features_a[-c(2)]

seed <- 1
posterior1 <- stan_glm(skipped ~ ., data = Track_features_a,
  family = binomial(link = "logit"),
  prior = normal(0,1), prior_intercept = normal(0,1),

```

```
seed = seed,
refresh = 0)

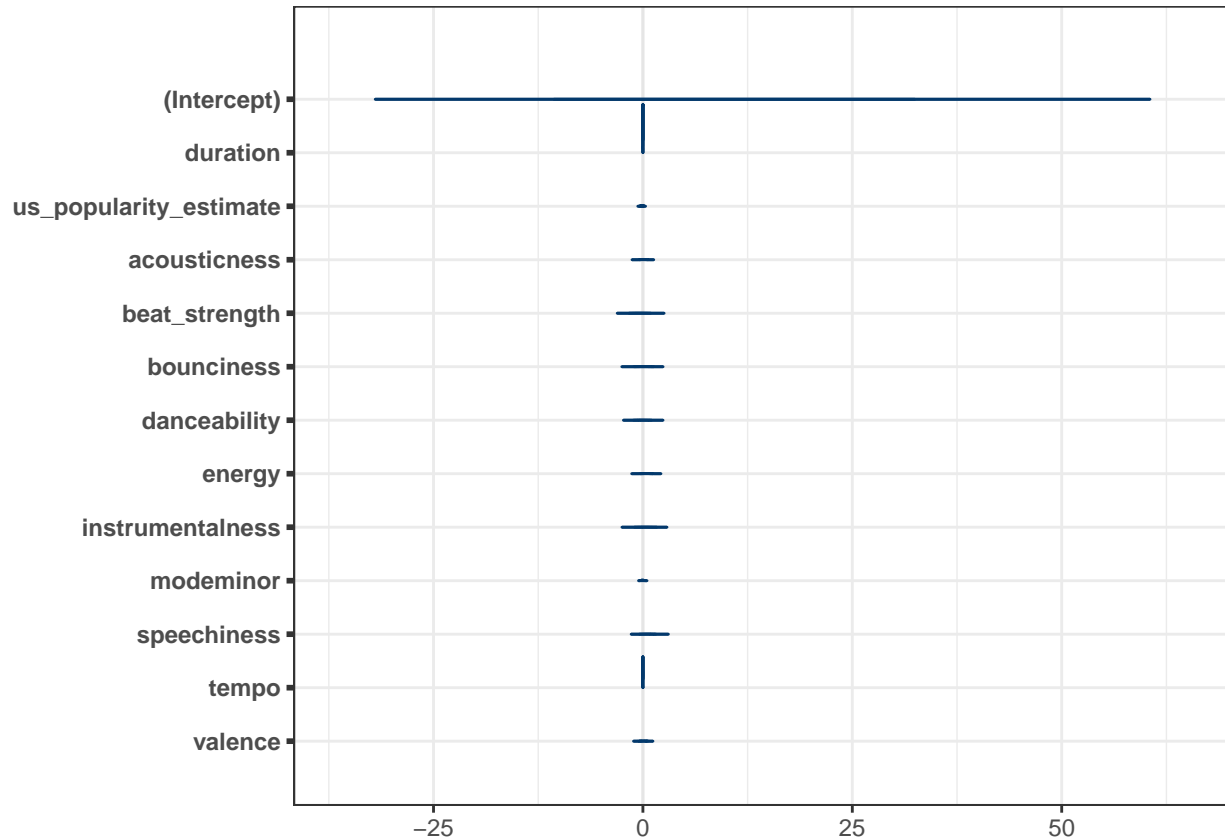
summary(posterior1)
```

```
##
## Model Info:
## function:      stan_glm
## family:        binomial [logit]
## formula:       skipped ~ .
## algorithm:     sampling
## sample:        4000 (posterior sample size)
## priors:        see help('prior_summary')
## observations:  1000
## predictors:    13
##
## Estimates:
##              mean    sd   10%   50%   90%
## (Intercept)    10.2   13.1  -6.2    9.7   27.3
## duration        0.0    0.0   0.0    0.0    0.0
## us_popularity_estimate -0.1    0.1  -0.3   -0.1    0.1
## acousticness    0.1    0.3  -0.3    0.1    0.5
## beat_strength   -0.4    0.8  -1.4   -0.4    0.6
## bounciness      0.1    0.7  -0.8    0.1    1.0
## danceability    0.0    0.6  -0.9   -0.1    0.8
## energy          0.4    0.5  -0.2    0.4    1.0
## instrumentalness 0.3    0.8  -0.7    0.3    1.4
## modeminor      -0.1    0.1  -0.2   -0.1    0.1
## speechiness     0.6    0.6  -0.2    0.6    1.3
## tempo          0.0    0.0   0.0    0.0    0.0
## valence         0.1    0.3  -0.3    0.1    0.5
##
## Fit Diagnostics:
##              mean    sd   10%   50%   90%
## mean_PPD 0.6      0.0  0.6   0.6   0.7
##
## The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for de
##
## MCMC diagnostics
##              mcse Rhat n_eff
## (Intercept)    0.2   1.0  5826
## duration        0.0   1.0  3901
## us_popularity_estimate 0.0   1.0  5820
## acousticness    0.0   1.0  4125
## beat_strength    0.0   1.0  3430
## bounciness      0.0   1.0  3314
## danceability    0.0   1.0  4175
## energy          0.0   1.0  3524
## instrumentalness 0.0   1.0  6275
## modeminor       0.0   1.0  5472
## speechiness     0.0   1.0  5218
## tempo          0.0   1.0  6757
## valence         0.0   1.0  4111
```

```
## mean_PPD          0.0  1.0  4438
## log-posterior     0.1  1.0  1739
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample
```

```
launch_shinystan(posterior1)
```

```
mcmc_areas(as.matrix(posterior1), prob = 0.90, prob_outer = 1)
```



```
round(coef(posterior1), 3)
```

```
##      (Intercept)      duration us_popularity_estimate
##      9.721      0.003      -0.101
##      acousticness      beat_strength      bounciness
##      0.082      -0.372      0.097
##      danceability      energy      instrumentalness
##      -0.062      0.421      0.295
##      modeminor      speechiness      tempo
##      -0.062      0.561      0.001
##      valence
##      0.070
```

```
round(posterior_interval(posterior1, prob = 0.90), 3)
```

```
##              5%    95%
## (Intercept)  -10.625 32.464
## duration      0.001  0.006
## us_popularity_estimate -0.330 0.103
## acousticness  -0.434 0.631
## beat_strength  -1.649 0.906
## bounciness     -1.096 1.300
## danceability  -1.114 1.021
## energy         -0.330 1.171
## instrumentalness -1.008 1.651
## modeminor     -0.282 0.164
## speechiness    -0.422 1.550
## tempo         -0.003 0.005
## valence        -0.440 0.595
```

```
(loo1 <- loo(posterior1, save_psis = TRUE))
```

```
##
## Computed from 4000 by 1000 log-likelihood matrix
##
##      Estimate   SE
## elpd_loo  -652.5 10.0
## p_loo      10.2  0.6
## looic      1304.9 19.9
## -----
## Monte Carlo SE of elpd_loo is 0.0.
##
## All Pareto k estimates are good (k < 0.5).
## See help('pareto-k-diagnostic') for details.
```

```
post0 <- stan_glm(skipped ~ 1, data = Track_features_a,
  family = binomial(link = "logit"),
  prior = normal(0,1), prior_intercept = normal(0,1),
  seed = seed,
  refresh = 0)
(loo0 <- loo(post0, save_psis = T))
```

```
##
## Computed from 4000 by 1000 log-likelihood matrix
##
##      Estimate   SE
## elpd_loo  -648.5  9.3
## p_loo       1.0  0.0
## looic      1297.0 18.7
## -----
## Monte Carlo SE of elpd_loo is 0.0.
##
## All Pareto k estimates are good (k < 0.5).
## See help('pareto-k-diagnostic') for details.
```

```
rstanarm::loo_compare(loo0, loo1)
```

```
##           elpd_diff se_diff
## post0      0.0      0.0
## posterior1 -4.0      3.3
```

```
###New Data
```

```
spotify <- data.frame(read_csv("data/spotify.csv"))
```

```
## Warning: Missing column names filled in: 'X1' [1]
```

```
##
## -- Column specification -----
## cols(
##   X1 = col_double(),
##   acousticness = col_double(),
##   danceability = col_double(),
##   duration_ms = col_double(),
##   energy = col_double(),
##   instrumentalness = col_double(),
##   key = col_double(),
##   liveness = col_double(),
##   loudness = col_double(),
##   mode = col_double(),
##   speechiness = col_double(),
##   tempo = col_double(),
##   time_signature = col_double(),
##   valence = col_double(),
##   target = col_double(),
##   song_title = col_character(),
##   artist = col_character()
## )
```

```
#View(spotify)
```

```
#Drop un-needed variables
spotify1 <- spotify[-c(1,16,17)]
#View(spotify1)
spotify1$target <- factor(spotify1$target)
spotify1$mode <- factor(spotify1$mode)
spotify1$key <- factor(spotify1$key)
spotify1 <- spotify1 %>%
  mutate(duration_ms = duration_ms / 1000)
```

```
#EDA
a1= ggplot(data = spotify1, aes(x = duration_ms)) +
  geom_histogram()
a2= ggplot(data = spotify1, aes(x = instrumentalness)) +
  geom_histogram()
a3= ggplot(data = spotify1, aes(x = liveness)) +
```



```

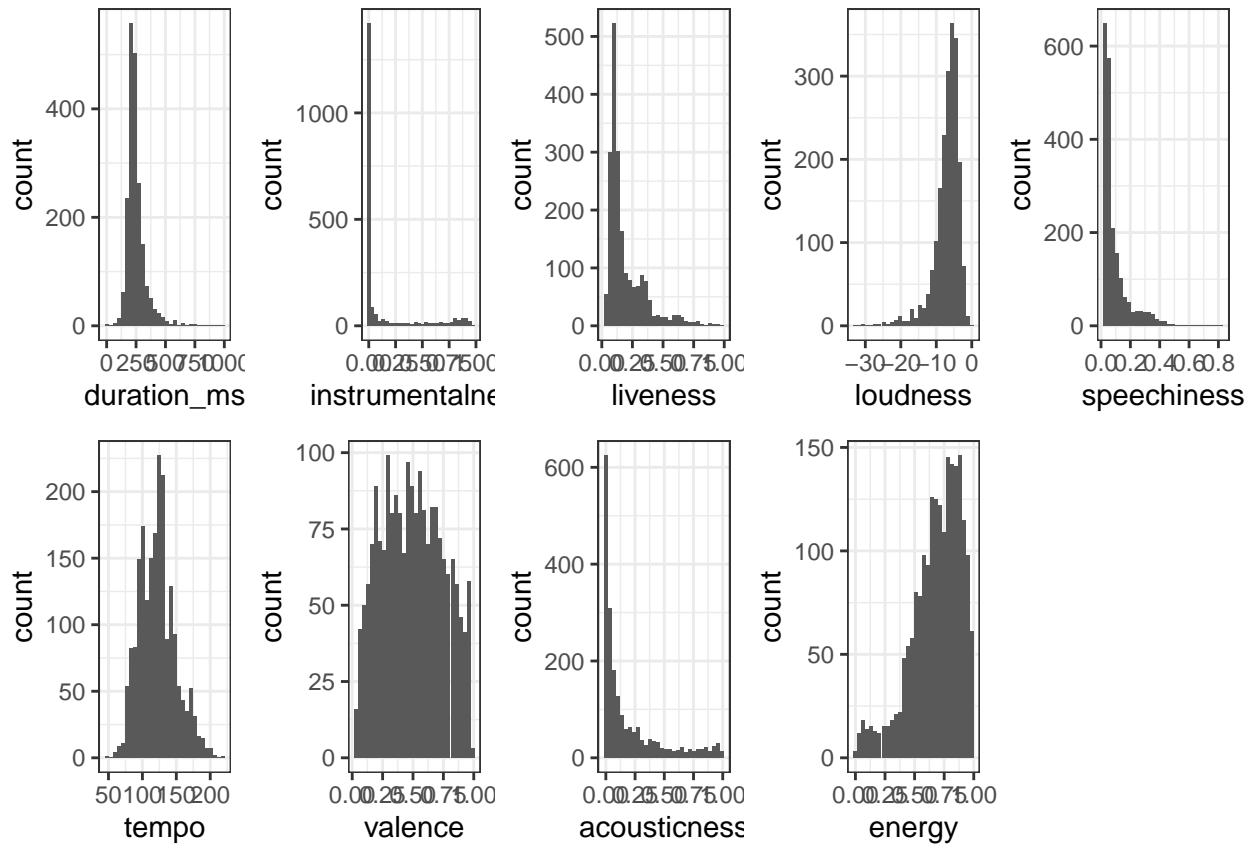
    geom_histogram()
a4= ggplot(data = spotify1, aes(x = loudness)) +
    geom_histogram()
a5= ggplot(data = spotify1, aes(x = speechiness)) +
    geom_histogram()
a6=ggplot(data = spotify1, aes(x = tempo)) +
    geom_histogram()
a7= ggplot(data = spotify1, aes(x = valence)) +
    geom_histogram()
a8=ggplot(data = spotify1, aes(x = acousticness)) +
    geom_histogram()
a9=ggplot(data = spotify1, aes(x = danceability)) +
    geom_histogram()
a9=ggplot(data = spotify1, aes(x = energy)) +
    geom_histogram()
grid.arrange(a1, a2, a3, a4, a5, a6, a7, a8, a9, nrow=2)

```

```

## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.

```



```
seed=1
post2 <- stan_glm(target ~ ., data = spotify1,
  family = binomial(link = "logit"),
  prior = normal(0,1), prior_intercept = normal(0,1),
  seed = seed,
  refresh = 0)

summary(post2)
```

```
##
## Model Info:
## function:      stan_glm
## family:        binomial [logit]
## formula:       target ~ .
## algorithm:     sampling
## sample:        4000 (posterior sample size)
## priors:        see help('prior_summary')
## observations:  2017
## predictors:    24
##
## Estimates:
##              mean    sd  10%  50%  90%
## (Intercept)  -3.9    1.0 -5.1  -3.9  -2.7
## acousticness -1.5    0.3 -1.8  -1.5  -1.1
## danceability  1.9    0.3  1.4   1.9   2.3
```

```

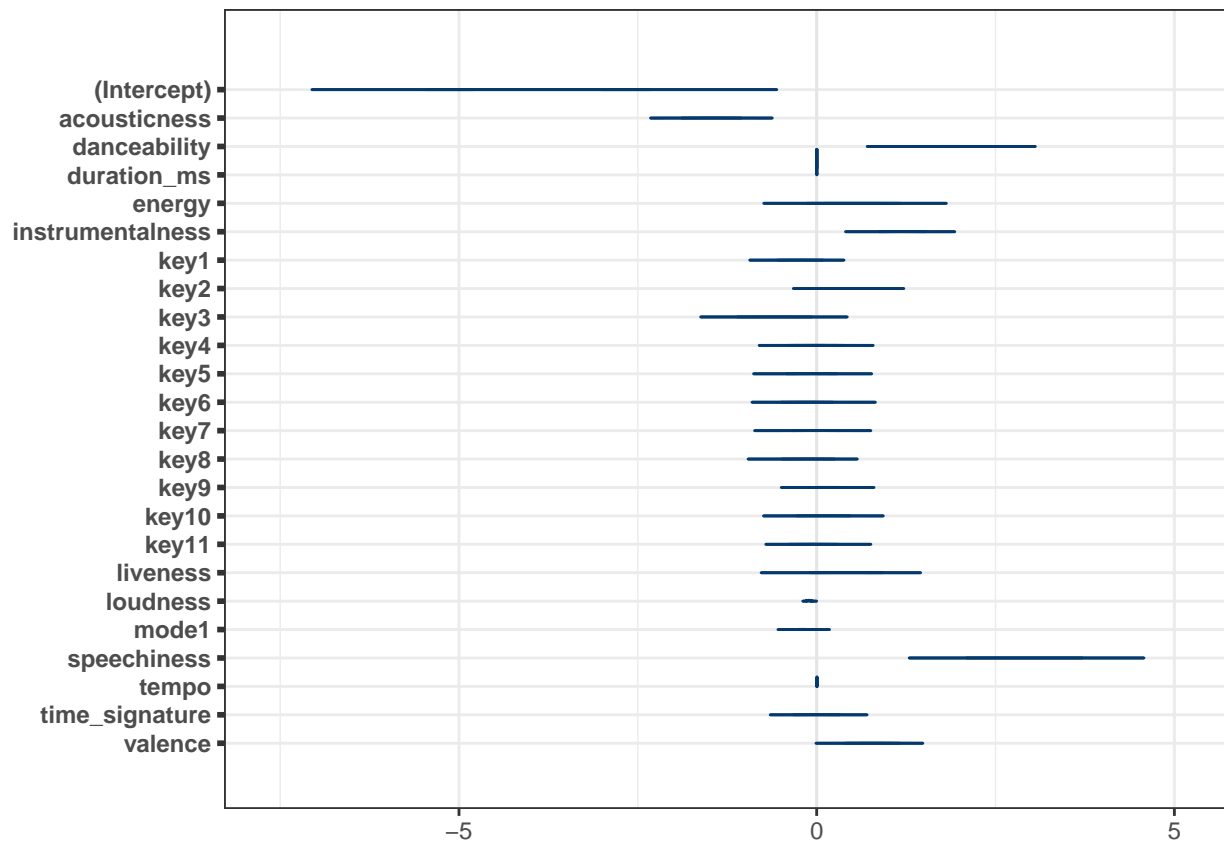
## duration_ms      0.0    0.0  0.0   0.0   0.0
## energy           0.5    0.4  0.0   0.5   1.0
## instrumentalness 1.2    0.2  0.9   1.2   1.5
## key1            -0.2    0.2 -0.5  -0.2   0.0
## key2            0.5    0.2  0.2   0.5   0.8
## key3           -0.6    0.3 -1.0  -0.6  -0.2
## key4            0.0    0.2 -0.3   0.0   0.3
## key5           -0.1    0.2 -0.3  -0.1   0.2
## key6           -0.1    0.2 -0.4  -0.1   0.1
## key7            0.0    0.2 -0.3   0.0   0.2
## key8           -0.1    0.2 -0.4  -0.1   0.2
## key9            0.2    0.2 -0.1   0.2   0.4
## key10           0.1    0.2 -0.2   0.1   0.4
## key11           0.0    0.2 -0.3   0.0   0.2
## liveness        0.4    0.3  0.0   0.4   0.8
## loudness       -0.1    0.0 -0.1  -0.1  -0.1
## model1         -0.2    0.1 -0.3  -0.2  -0.1
## speechiness     2.9    0.5  2.3   2.9   3.5
## tempo           0.0    0.0  0.0   0.0   0.0
## time_signature  0.0    0.2 -0.3   0.0   0.3
## valence         0.8    0.2  0.5   0.8   1.1
##
## Fit Diagnostics:
##           mean    sd   10%   50%   90%
## mean_PPD 0.5     0.0  0.5   0.5   0.5
##
## The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for de
##
## MCMC diagnostics
##           mcse Rhat n_eff
## (Intercept) 0.0  1.0  4989
## acousticness 0.0  1.0  4846
## danceability 0.0  1.0  4350
## duration_ms  0.0  1.0  3965
## energy        0.0  1.0  3140
## instrumentalness 0.0  1.0  5027
## key1          0.0  1.0  1889
## key2          0.0  1.0  2246
## key3          0.0  1.0  3447
## key4          0.0  1.0  2721
## key5          0.0  1.0  2315
## key6          0.0  1.0  2215
## key7          0.0  1.0  2402
## key8          0.0  1.0  2519
## key9          0.0  1.0  2207
## key10         0.0  1.0  2399
## key11         0.0  1.0  2371
## liveness      0.0  1.0  5539
## loudness      0.0  1.0  3396
## model1        0.0  1.0  5168
## speechiness   0.0  1.0  4780
## tempo         0.0  1.0  4846
## time_signature 0.0  1.0  5077
## valence       0.0  1.0  4466

```

```
## mean_PPD      0.0  1.0  4960
## log-posterior 0.1  1.0  1758
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample
```

```
launch_shinystan(post2)
```

```
mcmc_areas(as.matrix(post2), prob = 0.90, prob_outer = 1)
```



```
round(coef(post2), 3)
```

```
##      (Intercept)      acousticness      danceability      duration_ms
##      -3.903      -1.478      1.853      0.003
##      energy instrumentalness      key1      key2
##      0.502      1.197      -0.227      0.497
##      key3      key4      key5      key6
##      -0.588      -0.016      -0.061      -0.134
##      key7      key8      key9      key10
##      0.002      -0.121      0.159      0.096
##      key11      liveness      loudness      mode1
##      -0.046      0.409      -0.109      -0.201
##      speechiness      tempo      time_signature      valence
##      2.893      0.004      0.001      0.764
```

```
round(posterior_interval(post2, prob = 0.90), 3)
```

```
##              5%    95%
## (Intercept)  -5.458 -2.318
## acousticness -1.886 -1.056
## danceability  1.277  2.442
## duration_ms   0.002  0.004
## energy        -0.133  1.170
## instrumentalness 0.862  1.532
## key1          -0.544  0.087
## key2           0.149  0.836
## key3          -1.109 -0.071
## key4          -0.397  0.373
## key5          -0.420  0.278
## key6          -0.498  0.225
## key7          -0.333  0.323
## key8          -0.486  0.250
## key9          -0.179  0.481
## key10         -0.274  0.466
## key11         -0.388  0.298
## liveness      -0.094  0.921
## loudness      -0.145 -0.073
## model         -0.376 -0.030
## speechiness   2.093  3.715
## tempo         0.001  0.007
## time_signature -0.323  0.321
## valence       0.395  1.156
```

```
(loo1 <- loo(post2, save_psis = TRUE))
```

```
##
## Computed from 4000 by 2017 log-likelihood matrix
##
##           Estimate   SE
## elpd_loo  -1268.3 15.7
## p_loo       23.5  0.6
## looic       2536.6 31.5
## -----
## Monte Carlo SE of elpd_loo is 0.1.
##
## All Pareto k estimates are good (k < 0.5).
## See help('pareto-k-diagnostic') for details.
```

```
post4 <- stan_glm(target ~ 1, data = spotify1,
  family = binomial(link = "logit"),
  prior = normal(0,1), prior_intercept = normal(0,1),
  seed = seed,
  refresh = 0)
(loo0 <- loo(post4, save_psis = T))
```

```
##
```

```
## Computed from 4000 by 2017 log-likelihood matrix
##
##           Estimate  SE
## elpd_loo  -1398.9 0.5
## p_loo      1.0 0.0
## looic      2797.9 1.0
## -----
## Monte Carlo SE of elpd_loo is 0.0.
##
## All Pareto k estimates are good (k < 0.5).
## See help('pareto-k-diagnostic') for details.
```

```
rstanarm::loo_compare(loo0, loo1)
```

```
##           elpd_diff se_diff
## post2      0.0      0.0
## post4 -130.6     15.7
```