Regression

Code

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About Linear Regression

1. In linear regression, we wish to find the relationship between predictor values and a target value in the form of a linear relationship. This linear relationship can be defined by parameters w and b, with w, the slope of the line, quantifying the amount that y changes with changes in x, and b serving as an intercept. Linear regression is a relatively simple and powerful model. However, this algorithm has a bias: it wants to see a line no matter what the data is (even if a line should not exist). Some other disadvantages could be interaction effects, confounding variables, and hidden variables.
2. This notebook explores song data from Kaggle (https://www.kaggle.com/datasets/yasserh/song-popularity-dataset)

Load the song_data.csv file.

Hide

```
df <- read.csv("song_data.csv")
str(df)
```

```
'data.frame':   18835 obs. of  15 variables:
 $ song_name       : chr  "Boulevard of Broken Dreams" "In The End" "Seven Nation Army" "By The
Way" ...
 $ song_popularity : int  73 66 76 74 56 80 81 76 80 81 ...
 $ song_duration_ms: int  262333 216933 231733 216933 223826 235893 199893 213800 222586 203346
...
 $ acousticness    : num  0.00552 0.0103 0.00817 0.0264 0.000954 0.00895 0.000504 0.00148 0.0010
8 0.00172 ...
 $ danceability    : num  0.496 0.542 0.737 0.451 0.447 0.316 0.581 0.613 0.33 0.542 ...
 $ energy          : num  0.682 0.853 0.463 0.97 0.766 0.945 0.887 0.953 0.936 0.905 ...
 $ instrumentalness: num  2.94e-05 0.00 4.47e-01 3.55e-03 0.00 1.85e-06 1.11e-03 5.82e-04 0.00
1.04e-02 ...
 $ key             : int  8 3 0 0 10 4 4 2 1 9 ...
 $ liveness        : num  0.0589 0.108 0.255 0.102 0.113 0.396 0.268 0.152 0.0926 0.136 ...
 $ loudness        : num  -4.09 -6.41 -7.83 -4.94 -5.07 ...
 $ audio_mode      : int  1 0 1 1 1 0 0 1 1 1 ...
 $ speechiness     : num  0.0294 0.0498 0.0792 0.107 0.0313 0.124 0.0624 0.0855 0.0917 0.054 ...
 $ tempo           : num  167 105 124 122 172 ...
 $ time_signature  : int  4 4 4 4 4 4 4 4 4 4 ...
 $ audio_valence   : num  0.474 0.37 0.324 0.198 0.574 0.32 0.724 0.537 0.234 0.374 ...
```

a. Divide df into 80/20 train/test

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```
set.seed(1234)
i <- sample(1:nrow(df), nrow(df)*0.8, replace = FALSE)
train <- df[i,]
test <- df[-i,]
```

b. Data Exploration

i. List the column names

song_popularity is the target variable and the rest are predictors.

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```
names(train)
```

```
 [1] "song_name"        "song_popularity"  "song_duration_ms" "acousticness"
 [5] "danceability"     "energy"           "instrumentalness" "key"
 [9] "liveness"         "loudness"         "audio_mode"       "speechiness"
[13] "tempo"            "time_signature"   "audio_valence"
```

ii. See the first 5 rows

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```
head(train, n=5)
```

	song_name <chr>	song_popularity <int>	song_duration_ms <int>	acc
7452	Never Recover (Lil Baby & Gunna, Drake)	89	194732	
8016	Come Through	58	265160	
7162	Superhero	82	179997	
8086	Macarena	62	249506	
9196	Passing Me By	13	301840	

5 rows | 1-5 of 15 columns

iii. Check the number of NAs in each column.

Hide

```
sapply(train, function(x) sum(is.na(x)))
```

```
      song_name  song_popularity song_duration_ms     acousticness     danceability 
              0                0                0                0                0 
         energy instrumentalness              key         liveness         loudness 
              0                0                0                0                0 
     audio_mode      speechiness            tempo   time_signature    audio_valence 
              0                0                0                0                0 
```

There are no NAs in this dataset. This means we do not have to delete/modify any rows.

iv. Converting columns into factors in train and test data.

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```
#str(df)
train$key = factor(train$key)
train$audio_mode = factor(train$audio_mode)
train$time_signature = factor(train$time_signature)
str(train)
```

```
'data.frame':   15068 obs. of  15 variables:
 $ song_name       : chr  "Never Recover (Lil Baby & Gunna, Drake)" "Come Through" "Superhero"
"Macarena" ...
 $ song_popularity : int  89 58 82 62 13 67 60 65 70 55 ...
 $ song_duration_ms: int  194732 265160 179997 249506 301840 257440 578040 295480 290706 205786
...
 $ acousticness    : num  0.0716 0.18 0.82 0.422 0.0762 0.42 0.125 0.17 0.167 0.684 ...
 $ danceability    : num  0.757 0.489 0.681 0.927 0.763 0.495 0.729 0.48 0.454 0.939 ...
 $ energy          : num  0.69 0.829 0.34 0.721 0.76 0.609 0.72 0.529 0.229 0.455 ...
 $ instrumentalness: num  0.00 0.00 0.00 4.36e-05 0.00 0.00 3.53e-01 4.27e-06 1.02e-01 6.63e-03
...
 $ key             : Factor w/ 12 levels "0","1","2","3",..: 2 10 8 9 5 8 4 7 3 12 ...
 $ liveness        : num  0.192 0.538 0.285 0.0422 0.26 0.187 0.178 0.257 0.202 0.0903 ...
 $ loudness        : num  -5.33 -8.07 -8.62 -12.56 -7.97 ...
 $ audio_mode      : Factor w/ 2 levels "0","1": 1 1 2 2 1 2 2 2 2 1 ...
 $ speechiness     : num  0.282 0.478 0.0339 0.0908 0.259 0.0339 0.0371 0.0275 0.0297 0.195 ...
 $ tempo           : num  132.1 139.6 130 103 87.1 ...
 $ time_signature  : Factor w/ 5 levels "0","1","3","4",..: 4 4 4 4 4 4 4 4 4 5 ...
 $ audio_valence   : num  0.914 0.694 0.417 0.965 0.599 0.33 0.0388 0.469 0.134 0.458 ...
```

Values for the key column range from 0-11 (inclusive) which can be factorized. Similarly, audio mode (2 possible values) and time signature (5 possible values) columns can also be turned into factors from integers.

v. Checking distribution of levels in key, time signature, and audio mode columns.

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```
summary(train$key)
```

```
   0    1    2    3    4    5    6    7    8    9   10   11 
1730 1715 1361  397 1047 1270 1091 1637 1102 1362 1087 1269 
```

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```
summary(train$time_signature)
```

```
   0    1    3    4    5
   3   65  589 14241  170
```

Hide

```
summary(train$audio_mode)
```

```
   0    1
5600 9468
```

The key levels are mostly balanced, with “3” being the least key value. The time signature levels are really skewed towards the “4” value. It is more common to have the audio mode of 1 than 0.

c. Creating informative graphs using training data.

i. Explore distribution of song_popularity and danceability.

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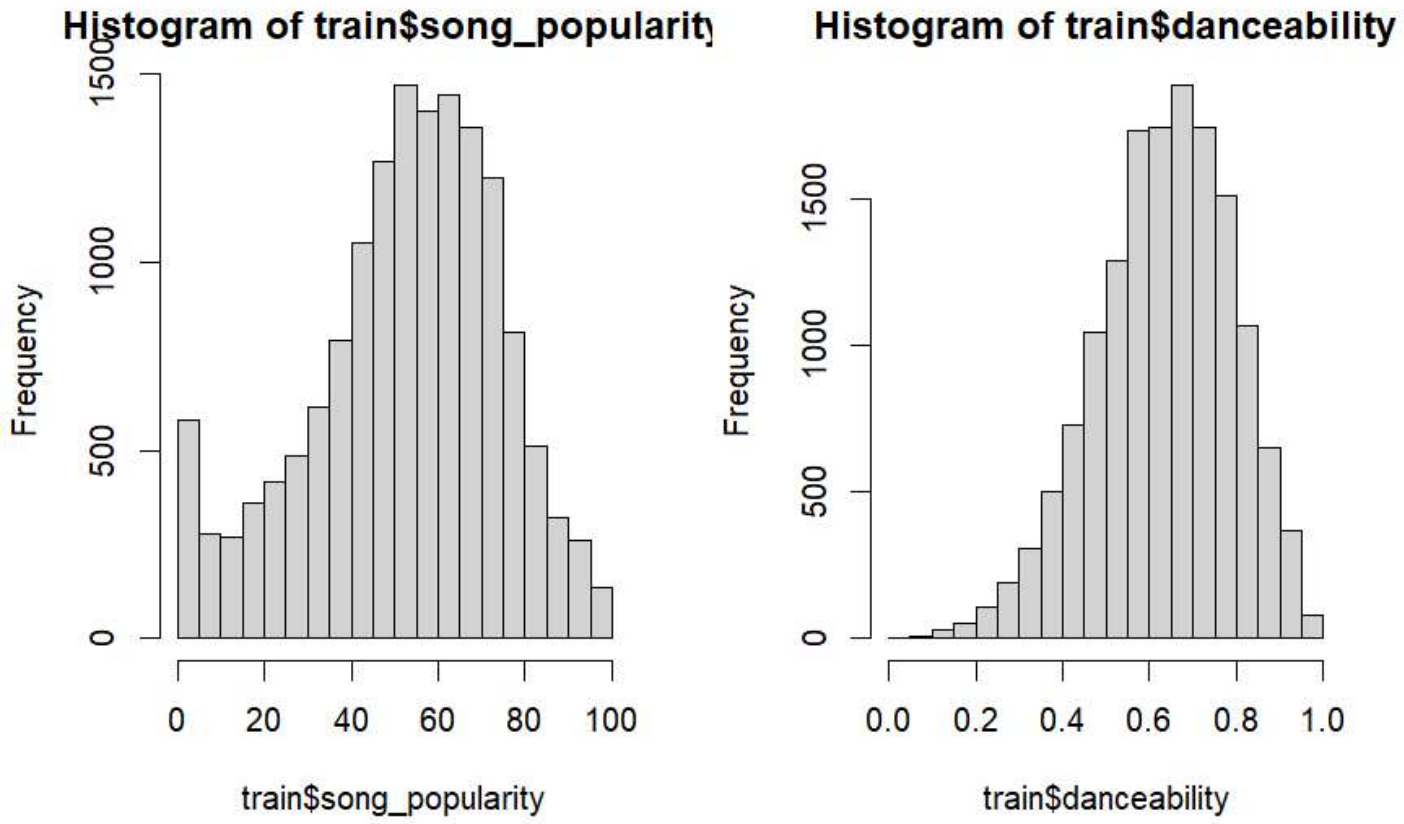
```
opar <- par()
par(mfrow=c(1,2))  # plots show up side by side
hist(train$song_popularity)
hist(train$danceability)
```

Hide

```
par(opar)
```



Song popularity and danceability are both slightly skewed to the right. This might mean that danceable songs are more popular.

ii. Comparing song popularity with time signature.

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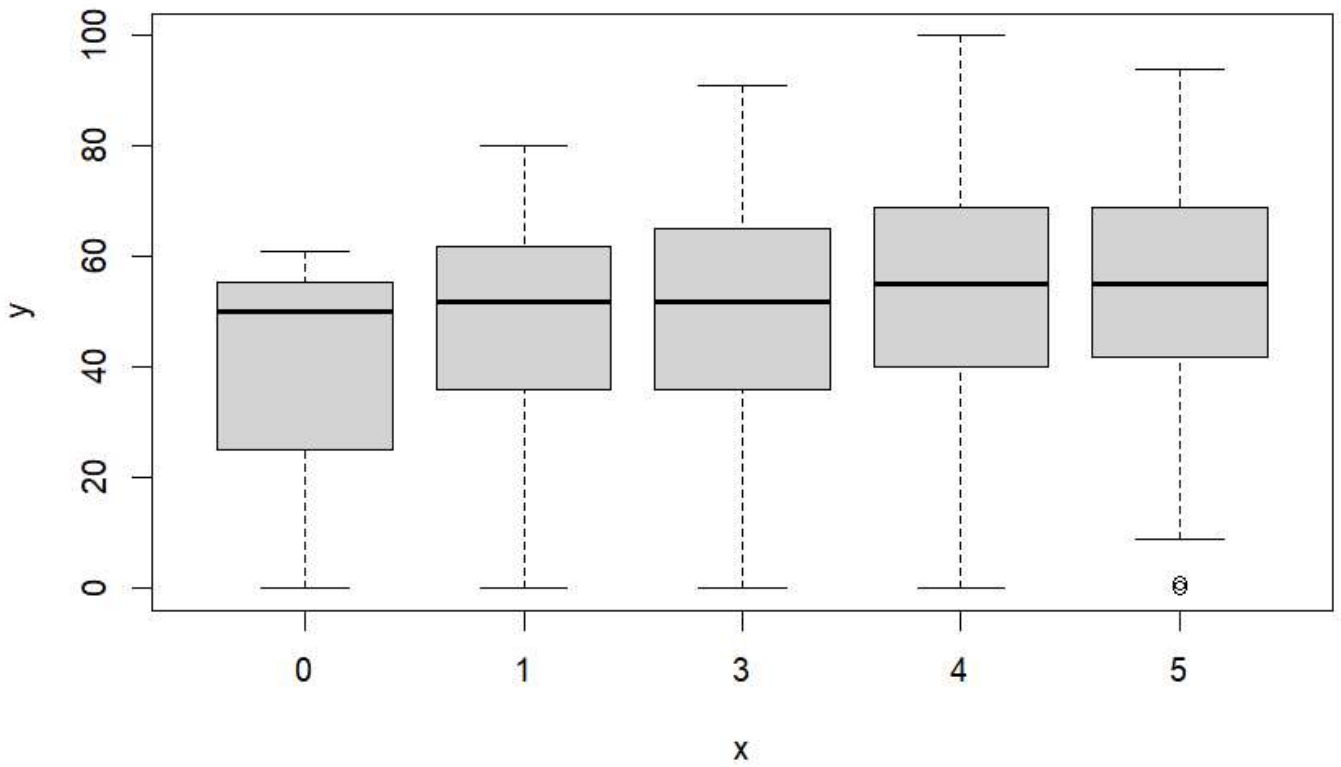
```
plot(train$time_signature,train$song_popularity)
```



The average popularity of songs with different time signatures is similar but the distribution varies. Songs with time signature of 1 have lower popularity, and songs with time signature of 5 have higher popularity.

d. Simple linear regression model

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```
lm1 <- lm(song_popularity~danceability, data=train)
summary(lm1)
```

```

Call:
lm(formula = song_popularity ~ danceability, data = train)

Residuals:
    Min      1Q  Median      3Q     Max 
-57.938 -12.535   2.693  15.817  46.313 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)   43.3678     0.7392   58.67   <2e-16 ***
danceability  15.0206     1.1324   13.26   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 21.77 on 15066 degrees of freedom
Multiple R-squared:  0.01154,   Adjusted R-squared:  0.01148 
F-statistic: 175.9 on 1 and 15066 DF,  p-value: < 2.2e-16
```

The residuals are not small, which is expected for a simple regression model. At most, there is a difference of about 58 from the predicted song popularity score and the actual score, which is large considering the range of scores (0-100). The p-value is low (which means there is high confidence) for danceability, which is good after comparing it to the significant codes section. [p-value is the probability of observing a larger t-statistic if the null hypothesis is true.] This means that it is a great predictor for the popularity score, and other predictors can be used to improve the model. From the coefficients, the linear equation derived from the model can be equated to be song popularity = 15.02 * danceability + 43.37. Residual standard error (RSE), which measures the lack of fit of the model, is 21.77 in this case. This is not a small value, which is further proved in the R-squared value of 0.01. [R-squared should be as close to 1 as possible.] At least the overall p-value is still low. The F-statistic provides evidence against the null hypothesis, and is not low in this model.

e. Plotting residuals

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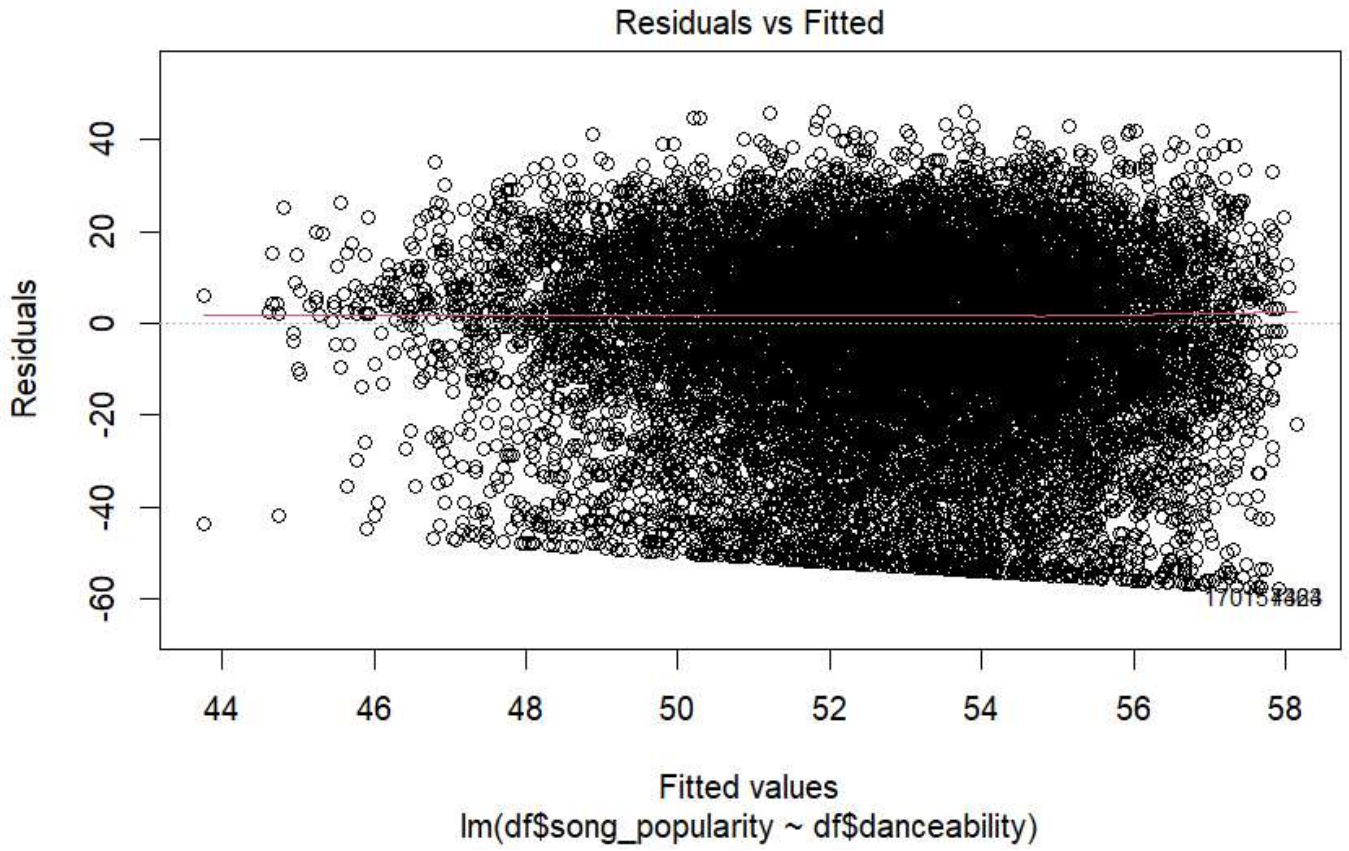
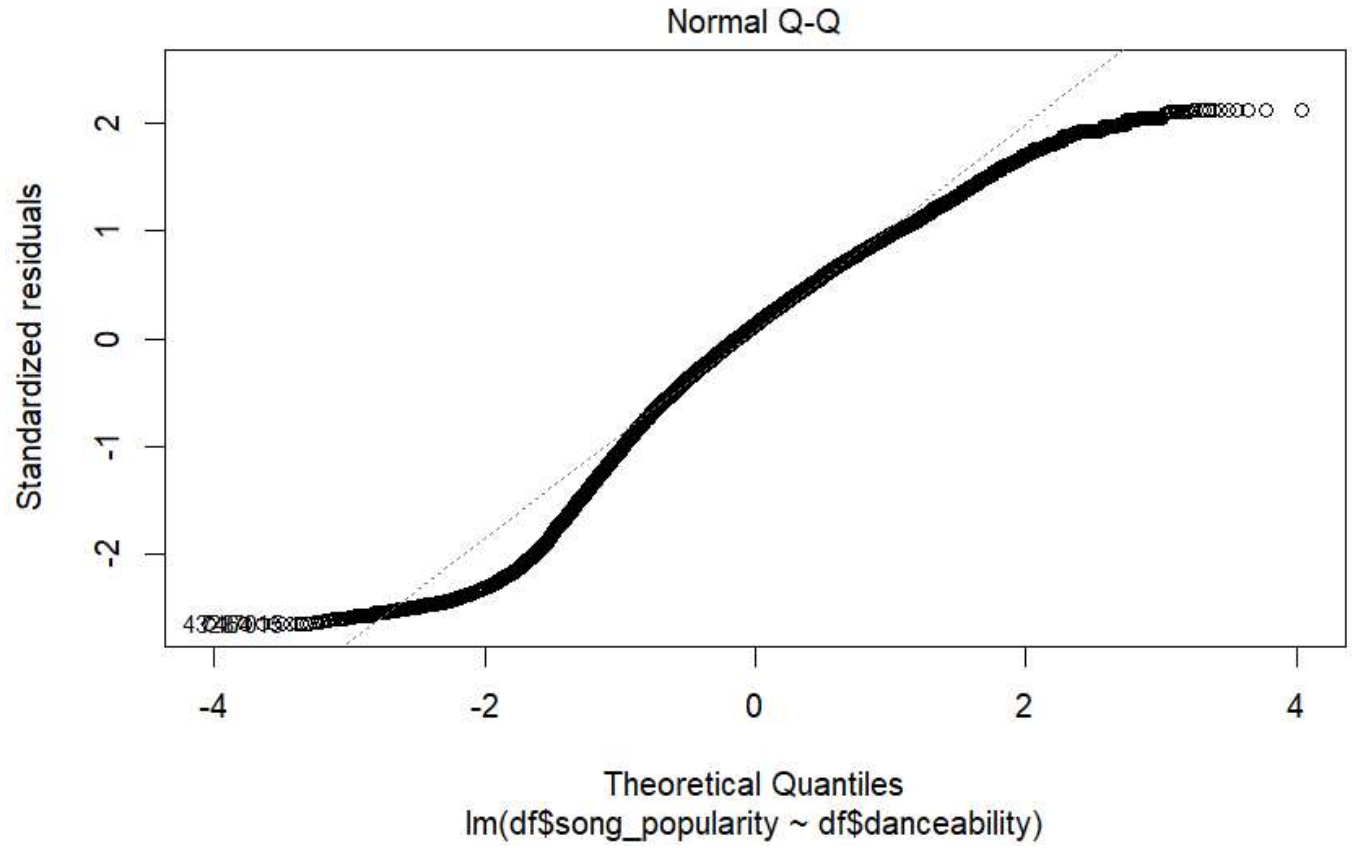
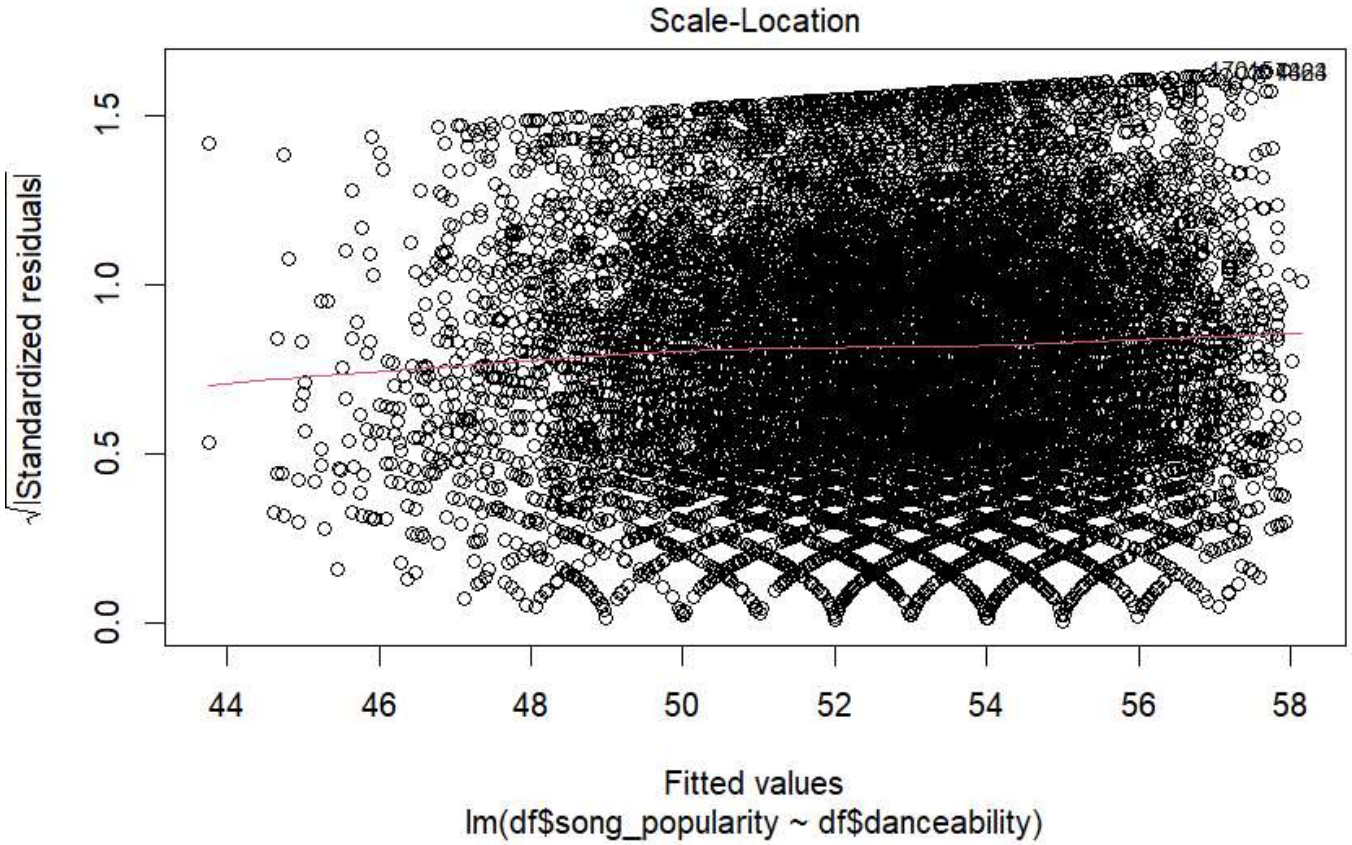
```
plot(lm1)
```







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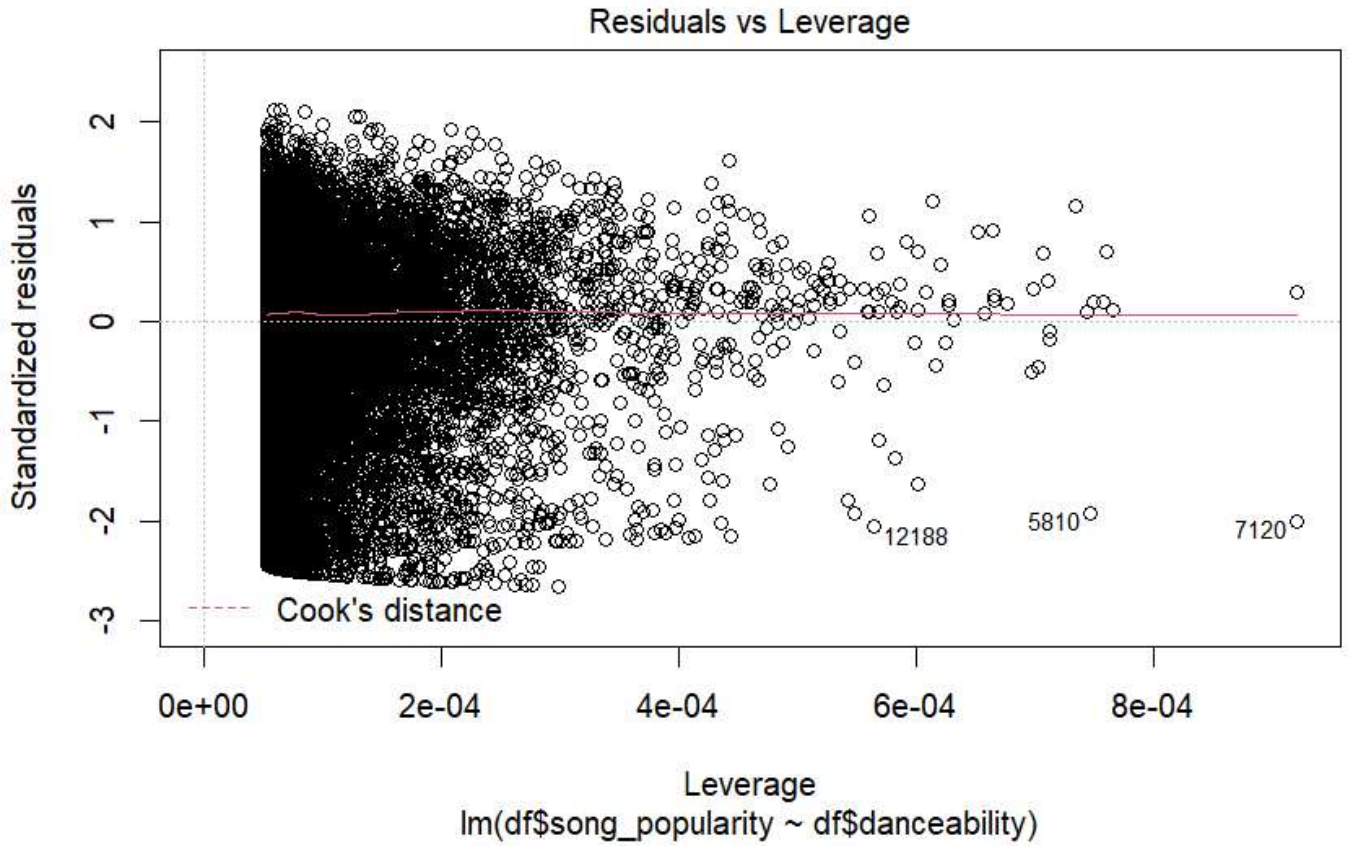
```
par(mfrow=c(1,1))
```



There are 4 different graphs as output:

i. Residuals vs fitted- shows if residuals have non-linear patterns. (There could be a non-linear relationship between predictor variables and an outcome variable and the pattern could show up in this plot if the model doesn't capture the non-linear relationship. If you find equally spread residuals around a horizontal line without distinct patterns, that is a good indication you don't have non-linear relationships.) There is no distinctive pattern which is good.

ii. Normal Q-Q- shows if residuals are normally distributed. It's good if residuals are lined well on the straight dashed line, which is the case here. Of course the residuals are not in a perfectly straight line.

iii. Scale-location- shows if residuals are spread equally along the ranges of predictors. (This is how you can check the assumption of equal variance (homoscedasticity). It's good if you see a horizontal line with equally (randomly) spread points.) The residuals appear to be scattered (mostly) everywhere which is good.

iv. Residuals vs Leverage- helps us to find influential cases (i.e., subjects) if any. (We watch out for outlying values at the upper right corner or at the lower right corner. Those spots are the places where cases can be influential against a regression line.) Cook's line is not visible in this case (because all cases are well inside Cook's line) which means there are no cases that can be influential against a regression line.

I used https://data.library.virginia.edu/diagnostic-plots/ (https://data.library.virginia.edu/diagnostic-plots/) for information about residual graphs to answer this question.

f. Multiple linear regression model (using all predictors except song_name)

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```
#str(df)
lm2 <- lm(song_popularity~danceability+song_duration_ms+acousticness+energy+instrumentalness+key
+liveness+audio_mode+speechiness+tempo+time_signature+audio_valence, data=train)
summary(lm2)
```

```

Call:
lm(formula = song_popularity ~ danceability + song_duration_ms +
    acousticness + energy + instrumentalness + key + liveness +
    audio_mode + speechiness + tempo + time_signature + audio_valence,
    data = train)

Residuals:
    Min      1Q  Median      3Q     Max
-65.625 -12.360   2.804  15.656  45.947

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       4.681e+01  1.243e+01   3.766 0.000167 ***
danceability      1.518e+01  1.316e+00  11.534  < 2e-16 ***
song_duration_ms -8.635e-06  3.083e-06  -2.801 0.005099 **
acousticness     -4.156e+00  8.518e-01  -4.878 1.08e-06 ***
energy           -2.743e+00  1.203e+00  -2.281 0.022588 *
instrumentalness -1.386e+01  8.119e-01 -17.075  < 2e-16 ***
key1              1.393e+00  7.365e-01   1.891 0.058641 .
key2             -1.535e+00  7.766e-01  -1.977 0.048111 *
key3             -1.089e+00  1.198e+00  -0.910 0.363004
key4             -1.298e+00  8.480e-01  -1.531 0.125823
key5             -5.417e-01  7.974e-01  -0.679 0.496904
key6              1.471e+00  8.375e-01   1.756 0.079078 .
key7             -2.571e+00  7.389e-01  -3.480 0.000503 ***
key8             -1.424e+00  8.283e-01  -1.719 0.085637 .
key9             -1.916e+00  7.803e-01  -2.456 0.014060 *
key10             1.349e-01  8.407e-01   0.160 0.872494
key11             4.238e-01  8.050e-01   0.526 0.598608
liveness         -4.708e+00  1.245e+00  -3.783 0.000156 ***
audio_mode1       5.584e-01  3.818e-01   1.463 0.143610
speechiness      -3.885e+00  1.790e+00  -2.170 0.030014 *
tempo            -1.037e-02  6.255e-03  -1.658 0.097309 .
time_signature1   7.874e+00  1.266e+01   0.622 0.534013
time_signature3   9.051e+00  1.242e+01   0.729 0.466141
time_signature4   1.016e+01  1.239e+01   0.820 0.412470
time_signature5   1.197e+01  1.249e+01   0.958 0.337912
audio_valence    -9.747e+00  8.268e-01 -11.790  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 21.4 on 15042 degrees of freedom
Multiple R-squared:  0.0462,    Adjusted R-squared:  0.04461
F-statistic: 29.14 on 25 and 15042 DF,  p-value: < 2.2e-16
```

Plotting residuals:

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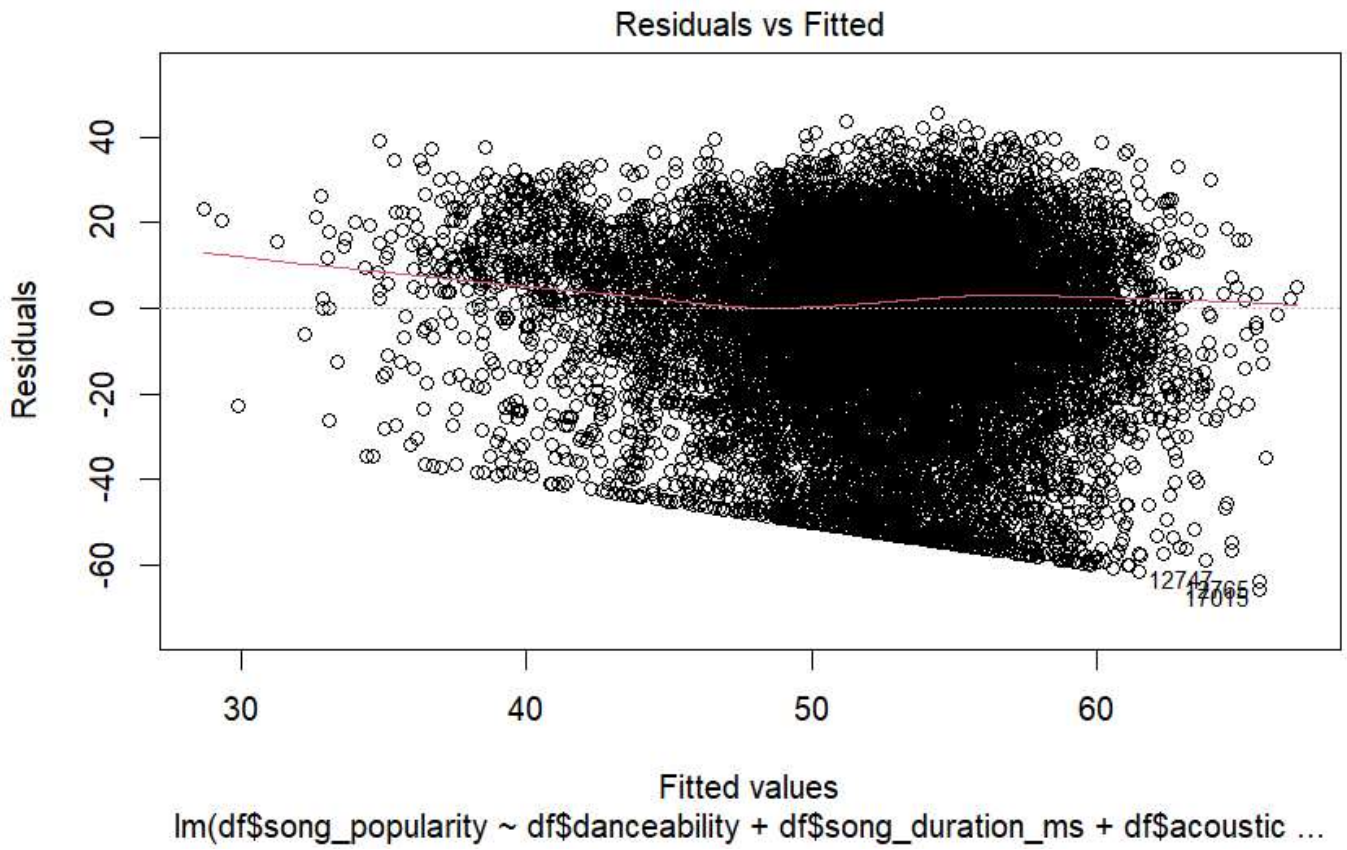
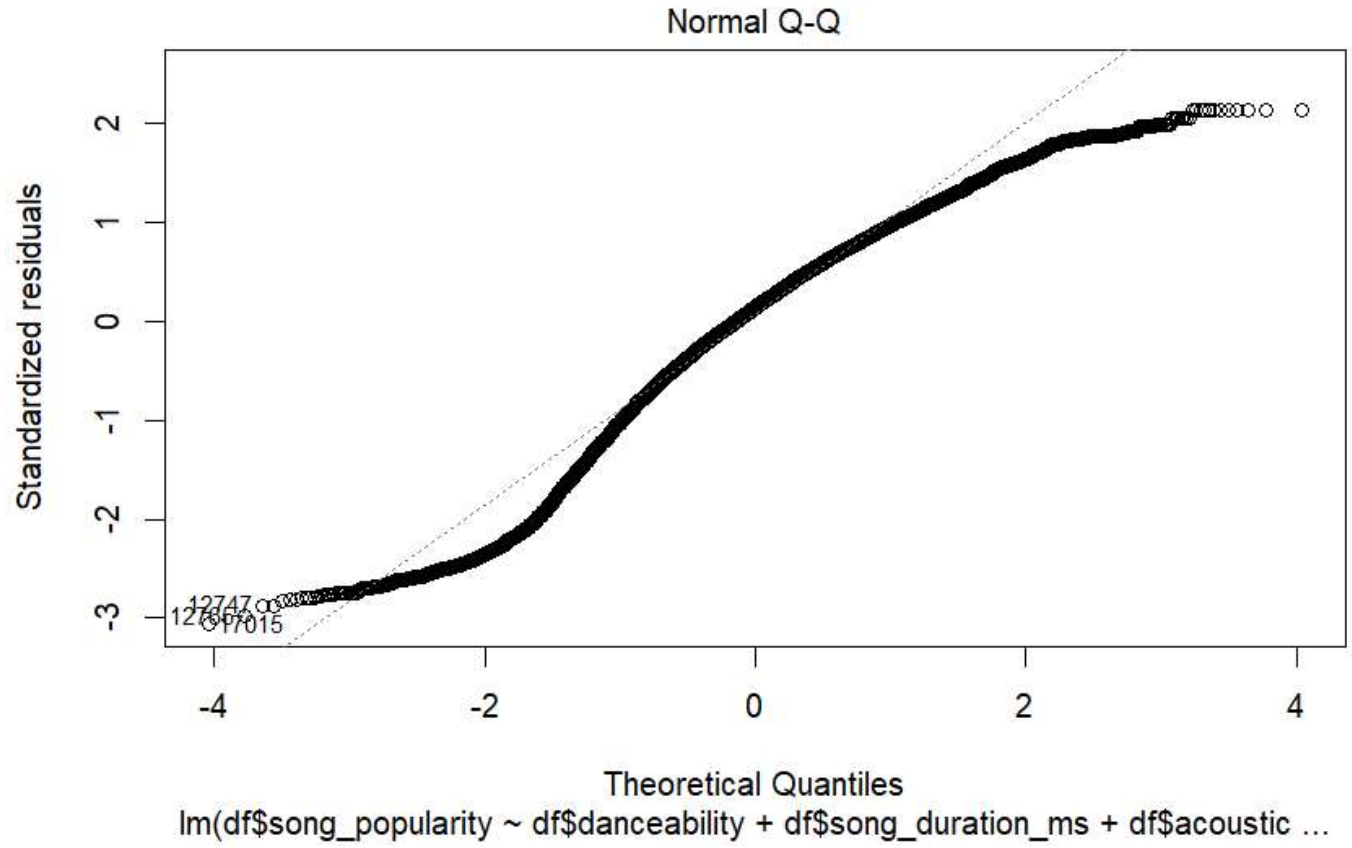
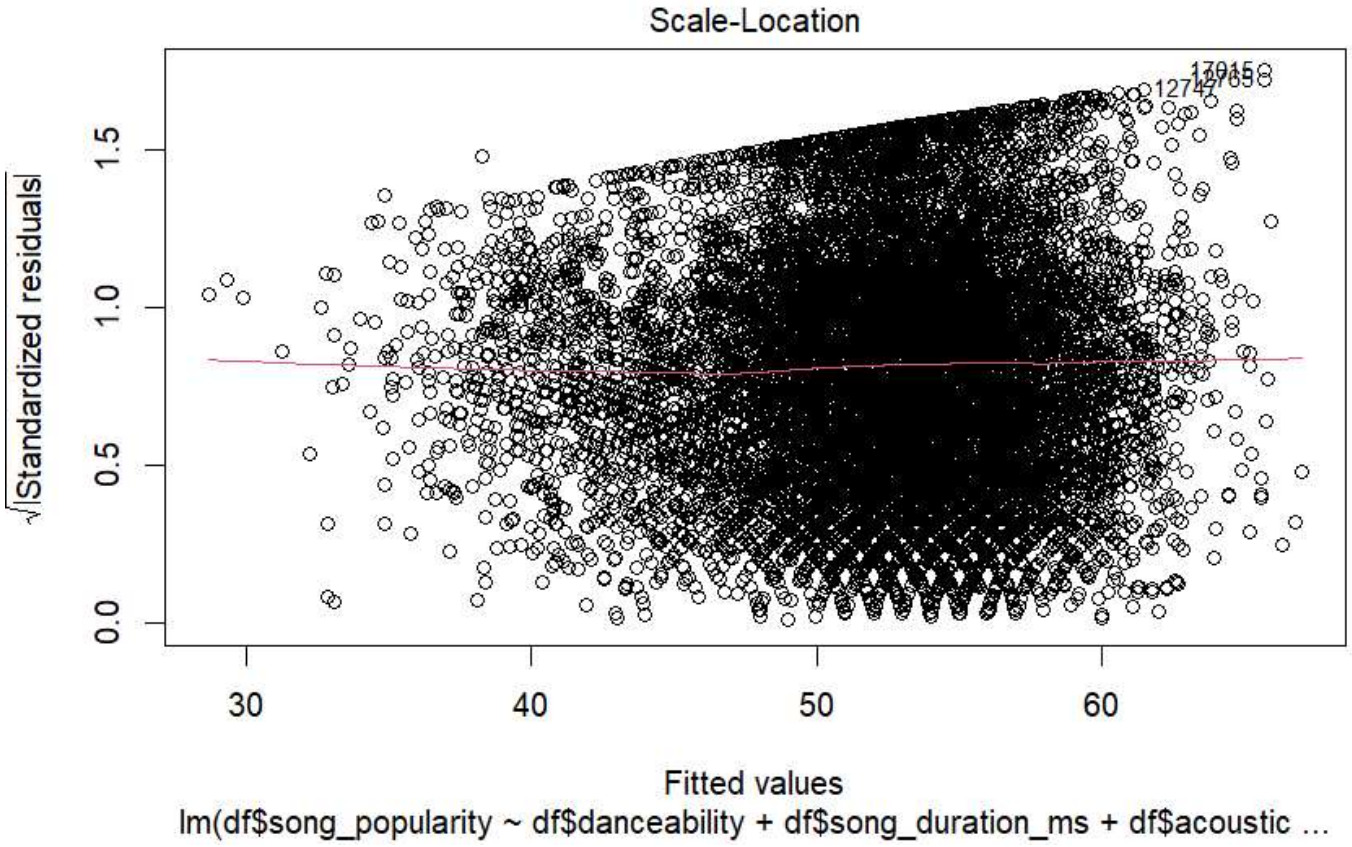
```
plot(lm2)
```







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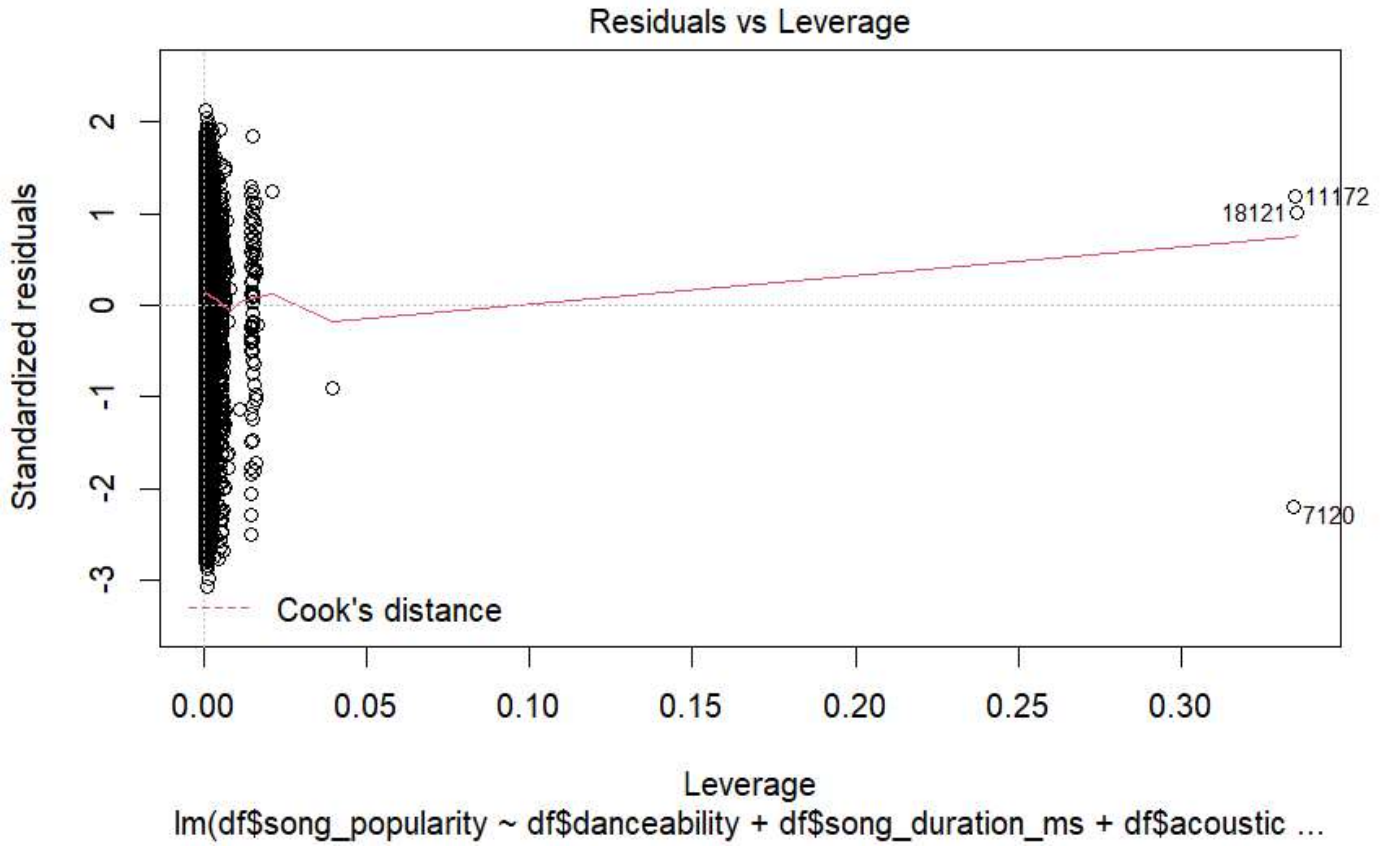
```
par(mfrow=c(1,1))
```



g. Third linear model to try to improve results

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```
str(df)
```

```
'data.frame':   18835 obs. of  15 variables:
 $ song_name       : chr  "Boulevard of Broken Dreams" "In The End" "Seven Nation Army" "By The
Way" ...
 $ song_popularity : int  73 66 76 74 56 80 81 76 80 81 ...
 $ song_duration_ms: int  262333 216933 231733 216933 223826 235893 199893 213800 222586 203346
...
 $ acousticness    : num  0.00552 0.0103 0.00817 0.0264 0.000954 0.00895 0.000504 0.00148 0.0010
8 0.00172 ...
 $ danceability    : num  0.496 0.542 0.737 0.451 0.447 0.316 0.581 0.613 0.33 0.542 ...
 $ energy          : num  0.682 0.853 0.463 0.97 0.766 0.945 0.887 0.953 0.936 0.905 ...
 $ instrumentalness: num  2.94e-05 0.00 4.47e-01 3.55e-03 0.00 1.85e-06 1.11e-03 5.82e-04 0.00
1.04e-02 ...
 $ key             : Factor w/ 12 levels "0","1","2","3",..: 9 4 1 1 11 5 5 3 2 10 ...
 $ liveness        : num  0.0589 0.108 0.255 0.102 0.113 0.396 0.268 0.152 0.0926 0.136 ...
 $ loudness        : num  -4.09 -6.41 -7.83 -4.94 -5.07 ...
 $ audio_mode      : Factor w/ 2 levels "0","1": 2 1 2 2 2 1 1 2 2 2 ...
 $ speechiness     : num  0.0294 0.0498 0.0792 0.107 0.0313 0.124 0.0624 0.0855 0.0917 0.054 ...
 $ tempo           : num  167 105 124 122 172 ...
 $ time_signature  : Factor w/ 5 levels "0","1","3","4",..: 4 4 4 4 4 4 4 4 4 4 ...
 $ audio_valence   : num  0.474 0.37 0.324 0.198 0.574 0.32 0.724 0.537 0.234 0.374 ...
```

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```
lm3 <- lm(song_popularity~danceability+song_duration_ms+acousticness+energy+instrumentalness+key
+liveness+speechiness+time_signature+audio_valence, data=train)
summary(lm3)
```

```
Call:
lm(formula = song_popularity ~ danceability + song_duration_ms +
    acousticness + energy + instrumentalness + key + liveness +
    speechiness + time_signature + audio_valence, data = train)

Residuals:
    Min      1Q  Median      3Q     Max
-65.475 -12.429   2.865  15.730  46.421

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       4.702e+01  1.242e+01   3.786 0.000154 ***
danceability      1.537e+01  1.295e+00  11.868  < 2e-16 ***
song_duration_ms -8.763e-06  3.080e-06  -2.845 0.004442 **
acousticness     -4.019e+00  8.492e-01  -4.733 2.24e-06 ***
energy           -2.912e+00  1.200e+00  -2.426 0.015263 *
instrumentalness -1.390e+01  8.111e-01 -17.133  < 2e-16 ***
key1              1.344e+00  7.359e-01   1.827 0.067792 .
key2             -1.511e+00  7.765e-01  -1.946 0.051699 .
key3             -1.194e+00  1.194e+00  -1.000 0.317485
key4             -1.477e+00  8.387e-01  -1.761 0.078340 .
key5             -6.768e-01  7.913e-01  -0.855 0.392388
key6              1.326e+00  8.293e-01   1.599 0.109773
key7             -2.597e+00  7.386e-01  -3.516 0.000439 ***
key8             -1.439e+00  8.282e-01  -1.738 0.082248 .
key9             -2.041e+00  7.763e-01  -2.629 0.008580 **
key10            -4.153e-02  8.313e-01  -0.050 0.960160
key11             2.386e-01  7.940e-01   0.300 0.763841
liveness         -4.658e+00  1.244e+00  -3.743 0.000182 ***
speechiness      -4.400e+00  1.775e+00  -2.479 0.013194 *
time_signature1   7.074e+00  1.265e+01   0.559 0.576173
time_signature3   8.015e+00  1.241e+01   0.646 0.518286
time_signature4   9.172e+00  1.238e+01   0.741 0.458827
time_signature5   1.103e+01  1.248e+01   0.884 0.376792
audio_valence    -9.783e+00  8.255e-01 -11.851  < 2e-16 ***
---
Signif. codes:
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 21.4 on 15044 degrees of freedom
Multiple R-squared:  0.0459,    Adjusted R-squared:  0.04444
F-statistic: 31.46 on 23 and 15044 DF,  p-value: < 2.2e-16
```

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```
#?predict
pred3 <- predict(lm3, newdata=test)
summary(pred3)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  30.32   50.61   53.36   52.93   55.95   66.81 
```

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```
#cor(pred1, test$song_popularity)
#sqrt(mean((pred1-test$song_popularity)^2))
#range(test$song_popularity)
```

Used all predictors except song name, loudness, audio mode, and tempo after observing their significance in linear regression models.

Plotting residuals:

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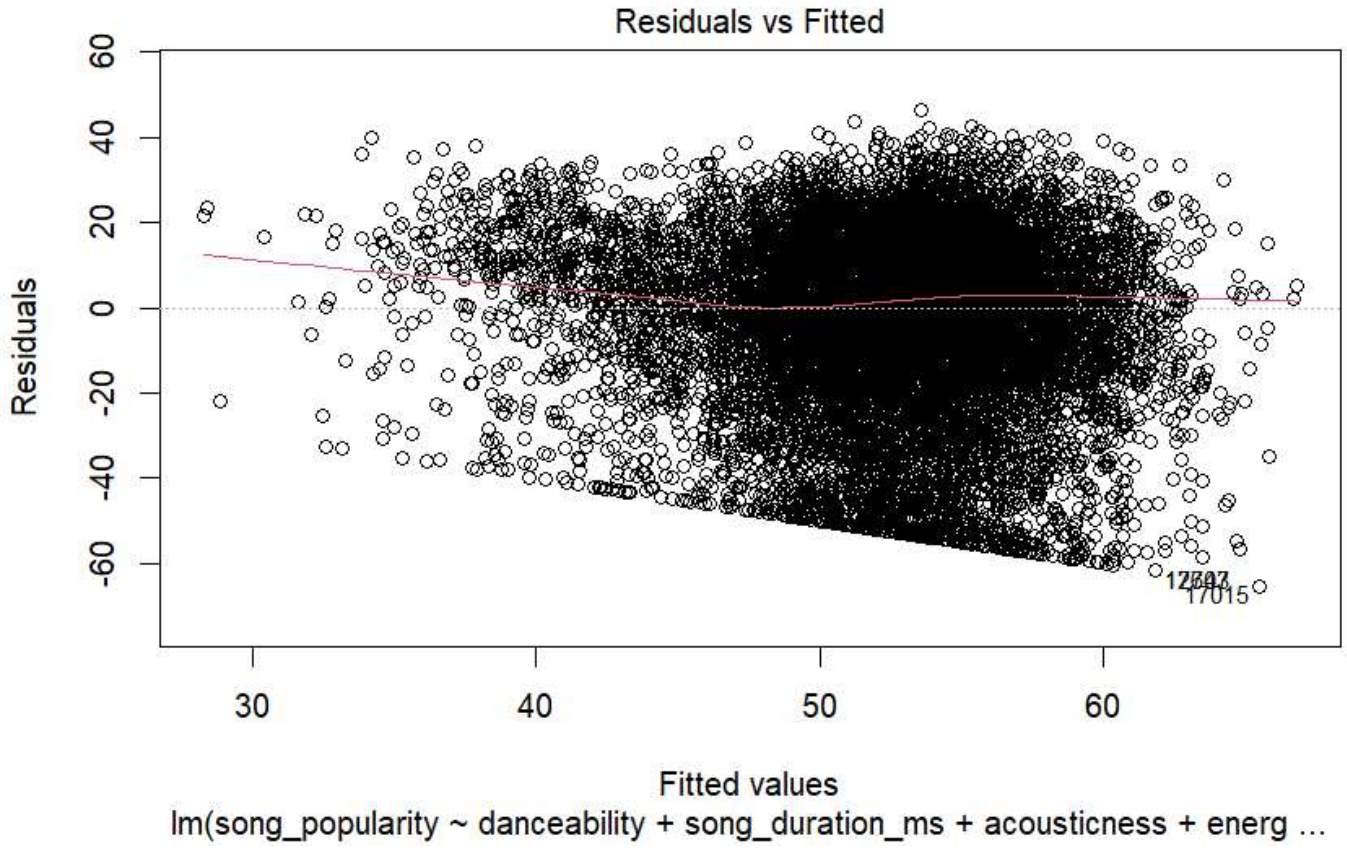
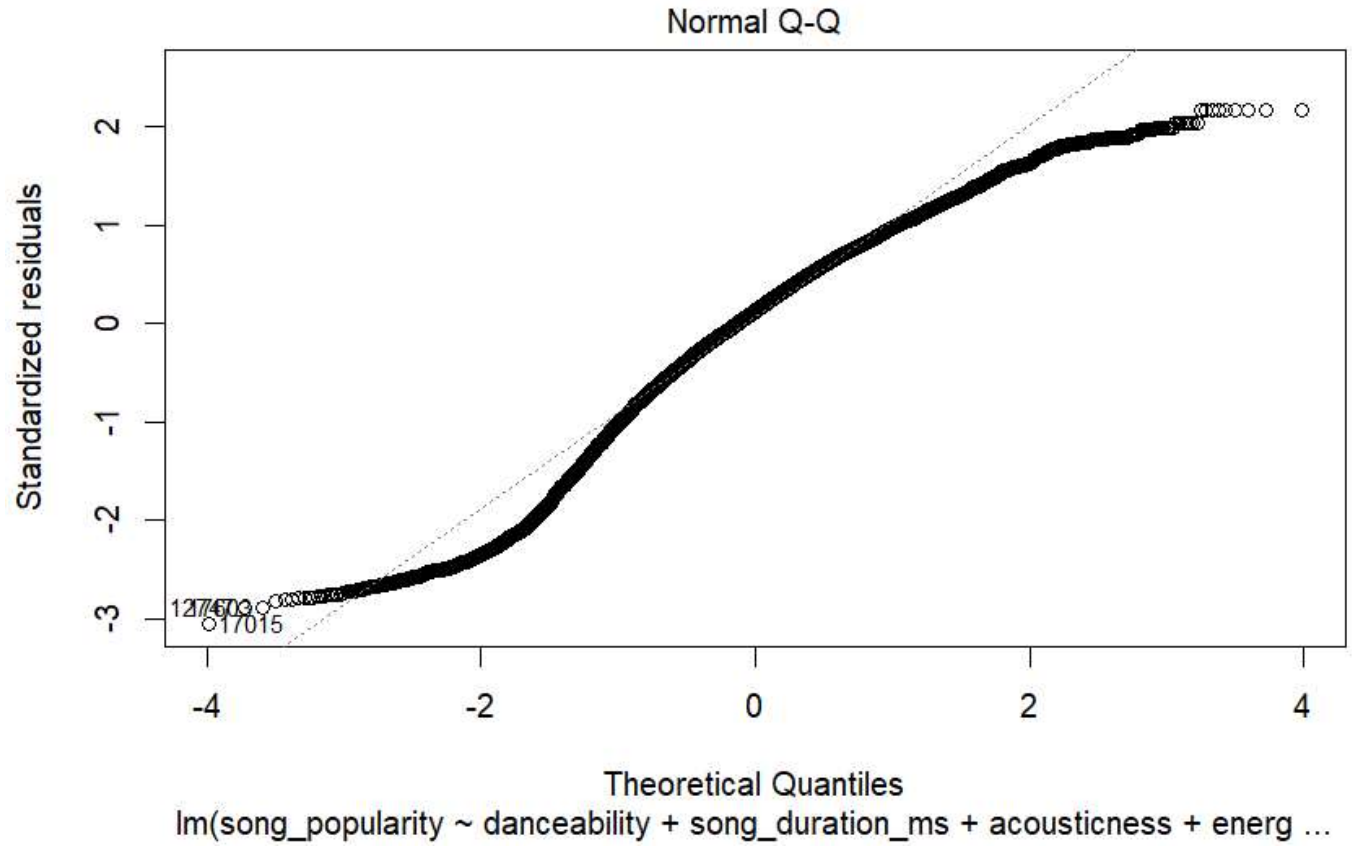
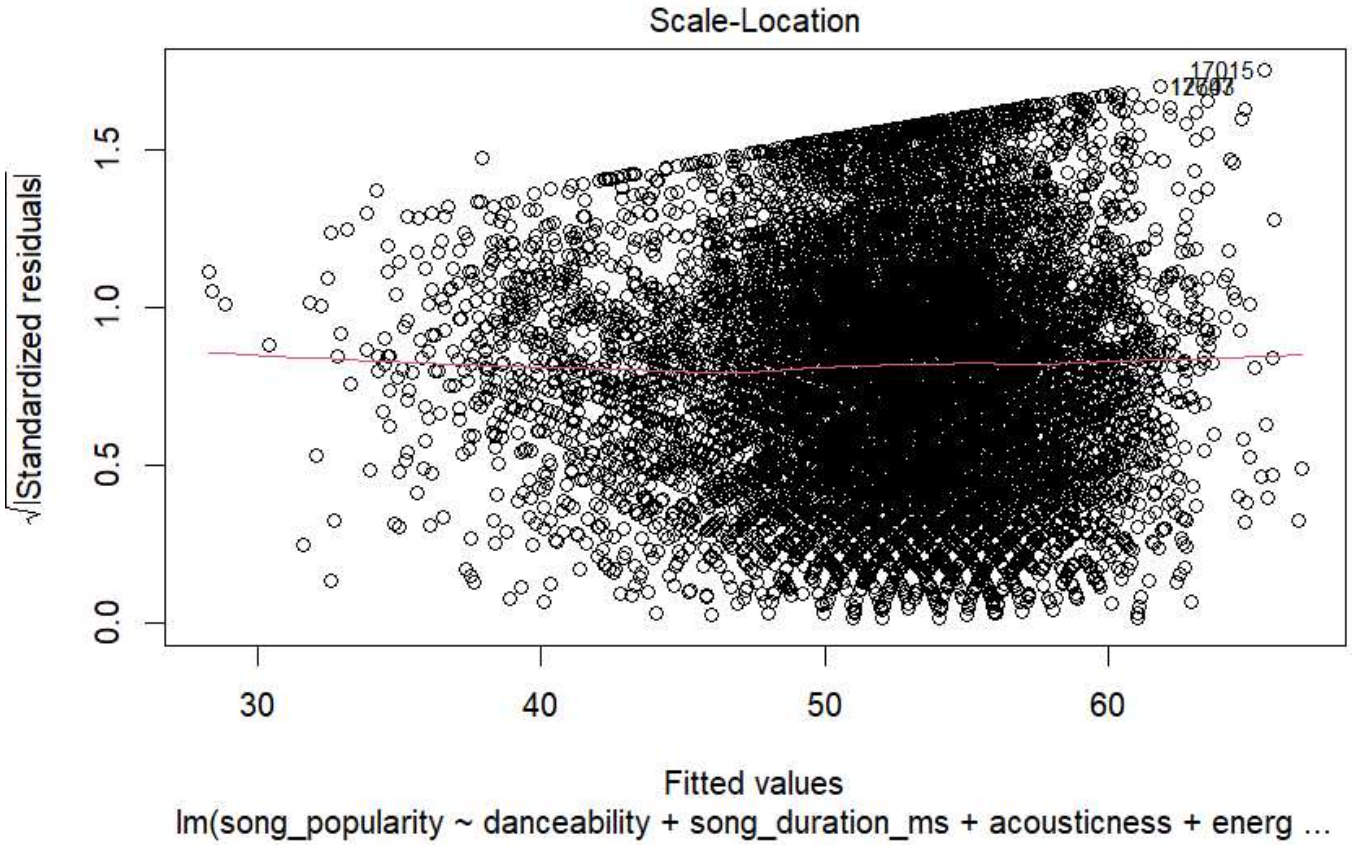
```
plot(lm3)
```

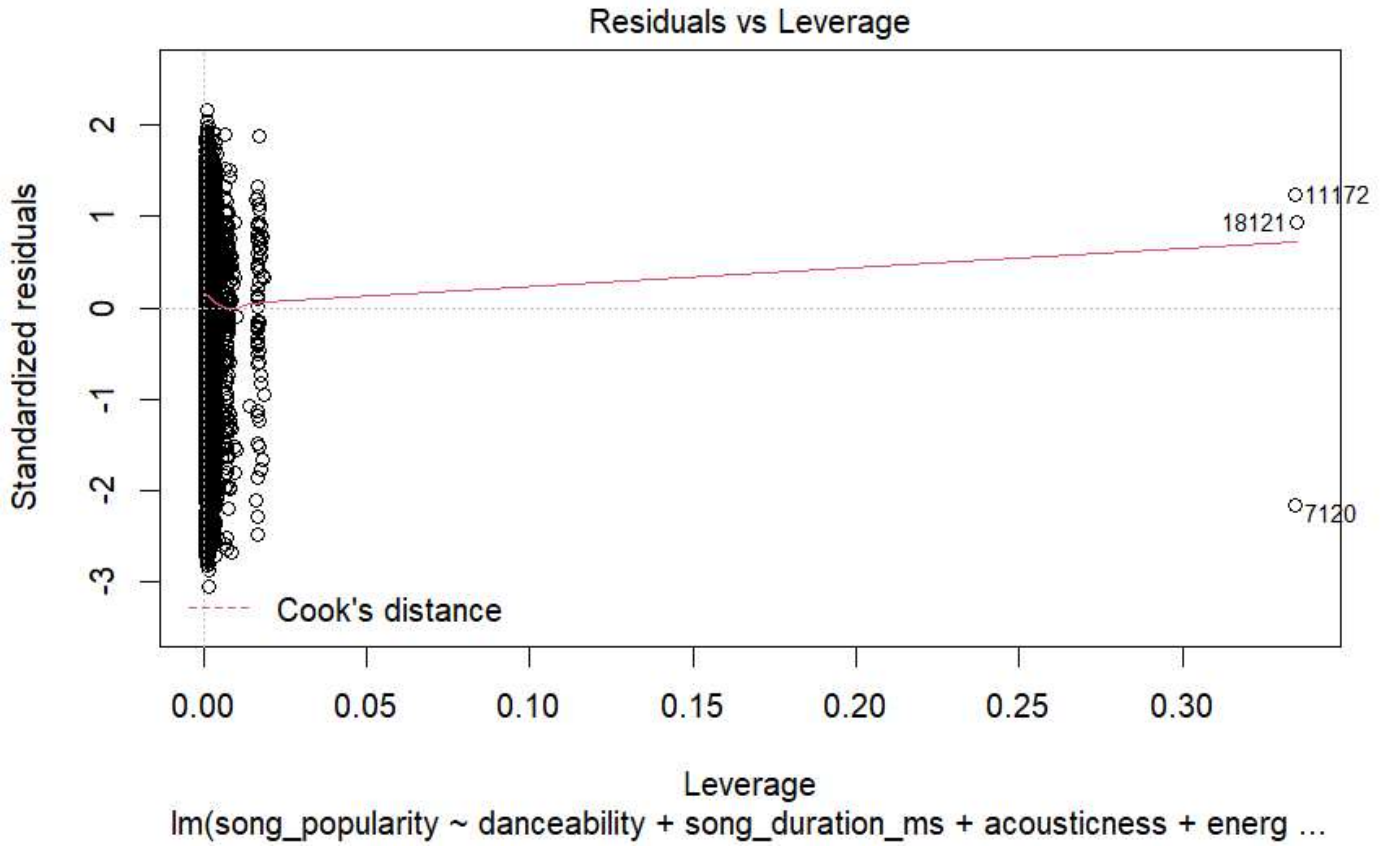






Hide

```
par(mfrow=c(1,1))
```



Comparing results

h. There is a minor difference between the residual plot of the first model and the others. On the other hand, there are differences in the logistic regression models. The minimum residual for the first model was -57.938, and was -65.625 and -65.475 for the second and third models. The maximum residuals are about the same, with a difference of about 1 unit (which in this case is popularity score). In all the three models, danceability was a significant predictor (with similar p-values) but its coefficient in the regression equation was different (~15 for the first model and ~1.5e+01 for the others). Obviously, there were other significant predictors in the second and third model, with the third model removing the predictors that the second model suggested were not helpful (loudness, audio mode, and tempo) since they didn't have a '.' or '*' after them. In the second and third models, the most significant predictors are danceability, instrumentalness, and audio valence. Acousticness and liveness are also important predictors. Other predictors like song duration, energy, key, and speechiness are not as important, but removing them from the model would decrease the accuracy. The R^2 values for the models are 0.01148, 0.04461, and 0.04444 respectively. There is a significant increase in the R^2 value from the first model, which is great. Unfortunately, I was unable to find a combination of predictors that improved the model to have a greater value of R^2 that is closer to 1. The residual standard error is similar in all models, but the F-statistic is different (it changes from 175.9 to 29.14). The overall p-value is small in all the models, which is ideal. I think the second model is better because it has all the predictors (as it seems that most predictors are greatly important in predicting the song popularity) and has the greatest R-squared value. The third model is not much different, but with less predictors, so it might predict the test values better.

i. Predict and evaluate on test data for all models

First model:

Hide

```
pred1 <- predict(lm1, newdata=test)
cor(pred1, test$song_popularity)
```

```
[1] 0.09199206
```

Hide

```
mean((pred1-test$song_popularity)^2)
```

```
[1] 477.7823
```

Hide

```
sqrt(mean((pred1-test$song_popularity)^2))
```

```
[1] 21.85823
```

Second model:

Hide

```
pred2 <- predict(lm2, newdata=test)
cor(pred2, test$song_popularity)
```

```
[1] 0.1871685
```

Hide

```
mean((pred2-test$song_popularity)^2)
```

```
[1] 465.2417
```

Hide

```
sqrt(mean((pred2-test$song_popularity)^2))
```

```
[1] 21.56946
```

Third model:

Hide

```
pred3 <- predict(lm3, newdata=test)
cor(pred3, test$song_popularity)
```

```
[1] 0.1875484
```

Hide

```
mean((pred3-test$song_popularity)^2)
```

```
[1] 465.1427
```

Hide

```
sqrt(mean((pred3-test$song_popularity)^2))
```

```
[1] 21.56717
```

The correlation is highest for the third model because the insignificant predictors have been removed. The second model has a similar correlation (since it had all of the same predictors plus a few more insignificant ones) but the first one is significantly less (due to only having one significant predictor). The mse is ~12 more in the first model compared to the second and third one, while the rmse amounts to about the same in each. It is interesting to note that the difference in predictions (mse and rmse) is about the same in all the models but the correlation varies. This might be because the second and third models have a greater difference in predicted and actual popularity for some test cases, while having higher accuracy overall. So, those models might have a greater standard deviation compared to the first model.