STAT - 427/627 Final Project

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Reading in the Data and Libraries

```
library(tidyverse)
library(e1071)
```

```
## Warning: package 'e1071' was built under R version 3.6.3
```

```
library(MASS)
library(readr)
library(leaps)
library(car)
library(ISLR)
library(pls)
```

```
## Warning: package 'pls' was built under R version 3.6.3
```

```
library(glmnet)
```

```
## Warning: package 'glmnet' was built under R version 3.6.3
```

```
top50 = read_csv("../data/top50cleaned.csv",
                 col_types = cols(Genre = col_factor()))
attach(top50)
```

Introduction to the Data

The data we decided to use is called "Top 50 Spotify Songs - 2019" and cand be found **here**

The variables that are used from the dataset are described below:

- Popularity: Numerical rank of song

- Genre: Categorical variable of three categories (Hip Hop, Pop and Latin)
- Beats Per Minute: The tempo of the song

- Energy: Higher values indicate higher levels of energy from the song
- Dancibilty: Higher values indicate higher dancibility of song
- Loudness: Loudness of song measured in decibles
- Liveness: Likelihood song is a live recording
- Valence: The higher the value, the more positive the mood of the song
- Length: Duration of song
- Acousticness: The higher the value, the more acoustic the song is
- Speechiness: Higher values indicate more lyrics

Predicting Genre with SVM

Model Selection

First, let's determine which kernel and costs to use.

```
set.seed(1)
S1tuned = tune(svm,Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = top50,kernel='linear',ranges
```

```
set.seed(1)
S2tuned = tune(svm,Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = top50,kernel='polynomial',ran
```

```
set.seed(1)
S3tuned = tune(svm,Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = top50,kernel='radial',ranges
```

```
set.seed(1)
S4tuned = tune(svm,Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = top50,kernel='sigmoid',range
```

```
summary(S1tuned)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost
##   0.1
##
## - best performance: 0.28
##
## - Detailed performance results:
##    cost error dispersion
## 1 1e-03  0.50  0.1943651
```

```
## 2 1e-02  0.50  0.1943651
## 3 1e-01  0.28  0.1932184
## 4 1e+00  0.30  0.1414214
## 5 1e+01  0.32  0.1686548
## 6 1e+02  0.30  0.1699673
## 7 1e+03  0.30  0.1699673
```

```r
summary(S2tuned)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost
##    10
##
## - best performance: 0.34
##
## - Detailed performance results:
##    cost error dispersion
## 1 1e-03  0.50  0.1943651
## 2 1e-02  0.50  0.1943651
## 3 1e-01  0.50  0.1943651
## 4 1e+00  0.42  0.1135292
## 5 1e+01  0.34  0.1646545
## 6 1e+02  0.40  0.1333333
## 7 1e+03  0.40  0.1333333
```

```r
summary(S3tuned)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost
##     1
##
## - best performance: 0.28
##
## - Detailed performance results:
##    cost error dispersion
## 1 1e-03  0.50  0.1943651
## 2 1e-02  0.50  0.1943651
## 3 1e-01  0.50  0.1943651
## 4 1e+00  0.28  0.1032796
## 5 1e+01  0.34  0.1349897
## 6 1e+02  0.34  0.1349897
## 7 1e+03  0.34  0.1349897
```

```r
summary(S4tuned)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost
##     1
##
## - best performance: 0.3
##
## - Detailed performance results:
##    cost error dispersion
## 1 1e-03  0.50  0.1943651
## 2 1e-02  0.50  0.1943651
## 3 1e-01  0.50  0.1943651
## 4 1e+00  0.30  0.1699673
## 5 1e+01  0.38  0.1751190
## 6 1e+02  0.42  0.1751190
## 7 1e+03  0.44  0.1837873
```

The two most promising models appear to be the Linear kernel with cost = .1 and the Radial kernel with cost = 1. Now, let's evaluate the predictive accuracy of these two models.

Evaluating Predictive Accuracy

This is a small dataset, so rather than splitting the data into training/testing, let's use LOOCV to determine predictive accuracy.

```r
n = nrow(top50)
preds = c()
for (i in 1:n) {
  d.train = top50[-i,]
  d.test = top50[i,]
  s.temp = svm(Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = d.train,kernel='linear',cost=.1)
  yhat = predict(s.temp,d.test['Genre'])[i]
  preds = append(preds,yhat)
}
preds = recode_factor(preds,`1` ='Pop', `2`='Latin',`3`='Hip Hop')
table(Predicted= preds,Actual= Genre)
```

```
##          Actual
## Predicted Pop Latin Hip Hop
##   Pop      21     5       6
##   Latin     3     8       0
##   Hip Hop   1     0       6
```

```
svm.linear.MSPE = mean(preds == Genre)
svm.linear.MSPE
```

```
## [1] 0.7
```

```
n = nrow(top50)
preds = c()
for (i in 1:n) {
  d.train = top50[-i,]
  d.test = top50[i,]
  s.temp = svm(Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = d.train,kernel='radial',cost=1)
  yhat = predict(s.temp,d.test['Genre'])[i]
  preds = append(preds,yhat)
}
preds = recode_factor(preds,`1` ='Pop', `2`='Latin',`3`='Hip Hop')
table(Predicted= preds,Actual= Genre)
```

```
##          Actual
## Predicted Pop Latin Hip Hop
##   Pop      24     9       4
##   Latin     1     4       0
##   Hip Hop   0     0       8
```

```
mean(preds == Genre)
```

```
## [1] 0.72
```

```
svm.radial.MSPE = mean(preds == Genre)
svm.radial.MSPE
```

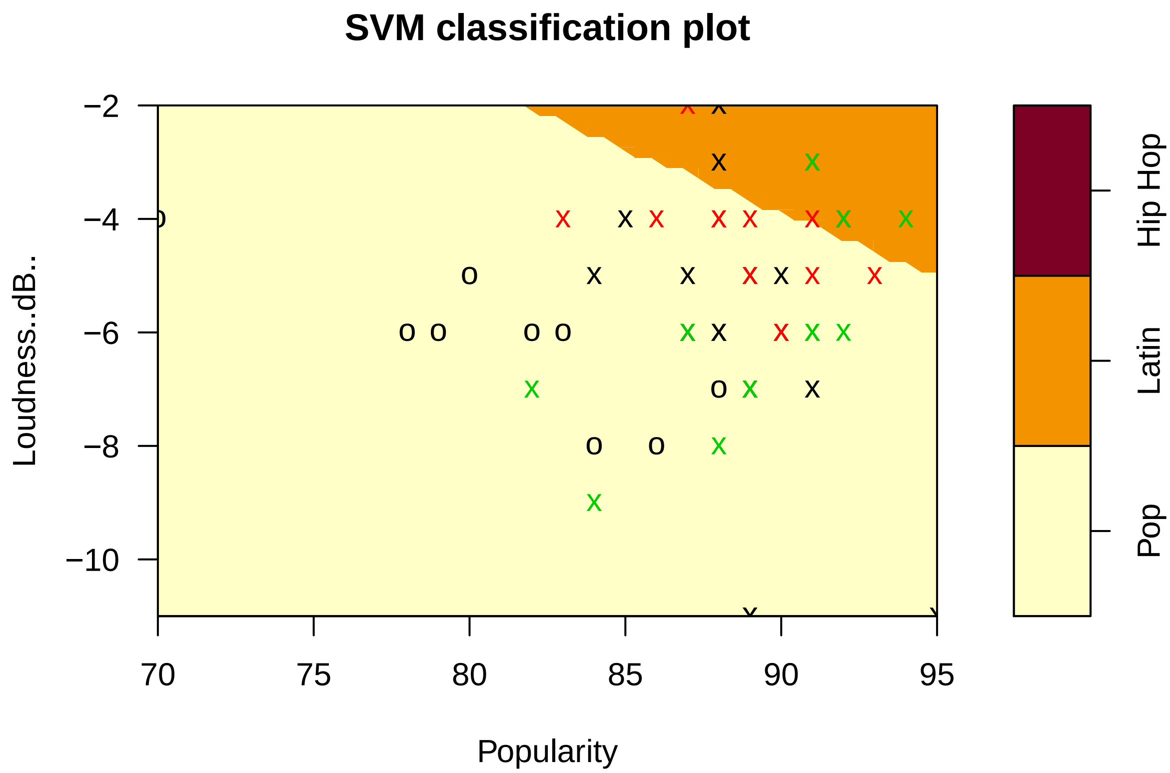
```
## [1] 0.72
```

The Linear kernal model has a classification rate of .7, while the Radial kernal model has a classification rate of .72. The first model is better at classifying Latin, but can predict Hip Hop with only 50% accuracy. Meanwhile, second model is better at classifying Pop and Hip Hop, but misclassifies Latin as Pop over 2/3 of the time.

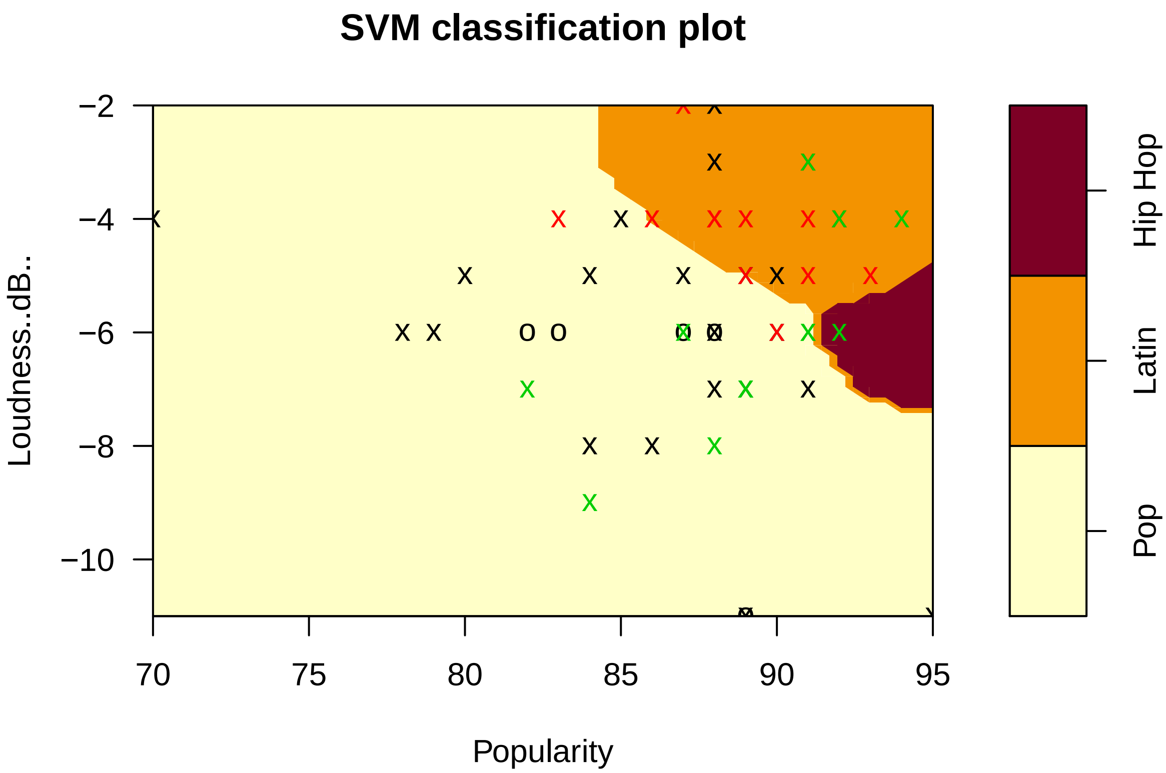
Visualizing the Models

SVM is not a very interpretable model, and it is tough to visualize with more than two dimensions. However, let's refit SVM models using just Loudness and Popularity, and then visualize them.

```
plot(svm(Genre ~ Loudness..dB.. + Popularity,data = top50,kernel='linear',cost=.1),top50,Loudness..dB..
```




```
plot(svm(Genre ~ Loudness..dB.. + Popularity,data = top50,kernel='radial',cost=1),top50,Loudness..dB..
```



In both models, most songs are classified as Pop, except louder and more popular songs are classified as Latin.

LDA/QDA

Evaluating Predictive Accuracy

We will evaluate the MSPE of the models using LOOCV, which is conveniently built into the `lda()` and `qda()` functions as an option.

```
lda.cv = lda(Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = top50,CV = TRUE)
table(Predicted= lda.cv$class,Actual= Genre)
```

```
##           Actual
## Predicted Pop Latin Hip Hop
##   Pop      20     2       3
##   Latin     2    10       0
##   Hip Hop   3     1       9
```

```
lda.MSPE = mean(Genre == lda.cv$class)
lda.MSPE
```

```
## [1] 0.78
```

```r
qda.cv = qda(Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = top50,CV = TRUE)
table(Predicted= qda.cv$class,Actual= Genre)
```

```
##           Actual
## Predicted Pop Latin Hip Hop
##   Pop      22    10      10
##   Latin     2     3       1
##   Hip Hop   1     0       1
```

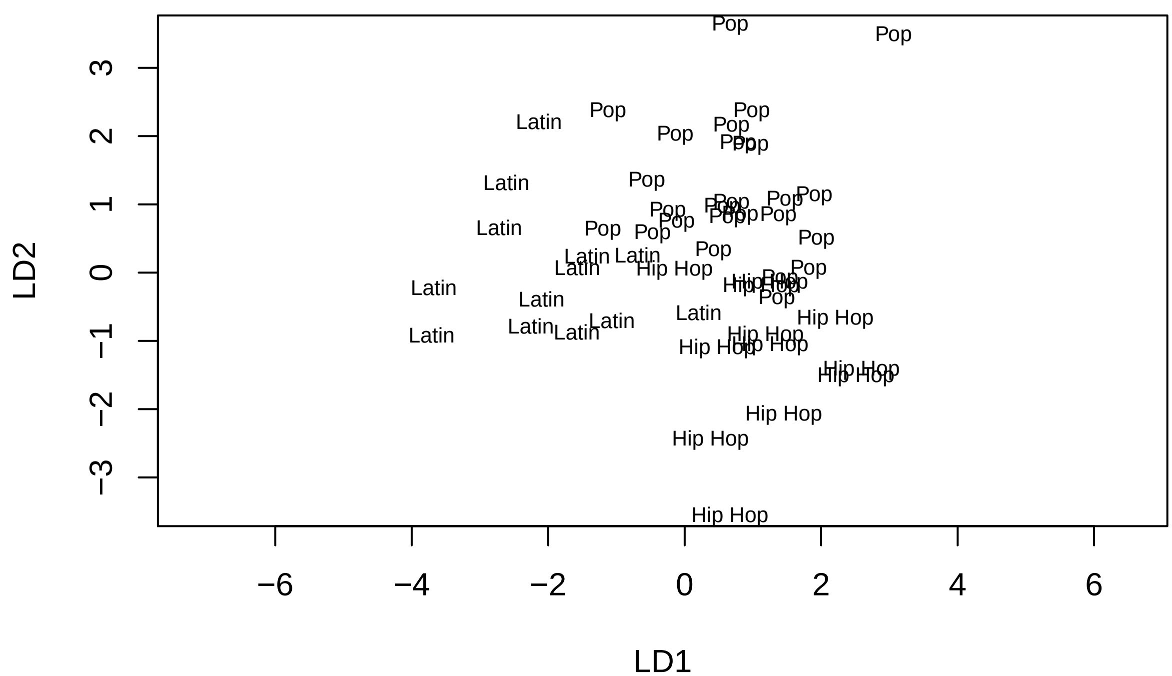
```r
qda.MSPE = mean(Genre == qda.cv$class)
qda.MSPE
```

```
## [1] 0.52
```

The LDA performs which better than the QDA, which indicates that a linear decision boundary, thus equal variances between prior probabilities. The LDA has a classification rate of .78. The QDA, on the other hand, has a dismal classification rate of .52, which is only barely better than guessing.

Plotting LDA

```r
lda.fit = lda(Genre ~ . -Genre - X1 - Track.Name - Artist.Name,data = top50)
plot(lda.fit)
```



We can see that LDA does a nice job separating the three genres, but that there is some overlap in the middle.

Comparison

Let us compare the MSPE for each of our four models that predict Genre:

```
c(SVM.Lin= svm.linear.MSPE, SVM.Rad= svm.radial.MSPE, LDA= lda.MSPE, QDA= qda.MSPE)
```

```
## SVM.Lin SVM.Rad     LDA     QDA
##    0.70    0.72    0.78    0.52
```

LDA has the best MSPE, while the two SVM models are not too far behind. QDA, meanwhile has a poor MSPE. It is also worth noting a finding which is not captured by MSPE: LDA is much better at correctly classifying Latin and Hip Hop, whereas SVM takes advantage of the class imbalance by overclassifying to Pop.

Linear Regression with Variable Selection

This test focuses on variable selection for the response "Popularity." In other words, finding the most optimal linear regression function for the prediction of a song's popularity. First we are going to find the VIF's of each predictor in the full model to see if there is any multicolinearity between our predictors.

```
reg.full <- lm(Popularity ~ . -X1 -Track.Name -Artist.Name -Popularity,
           data = top50)

vif(reg.full)
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## Genre            4.542409  2        1.459895
## Beats.Per.Minute 1.769805  1        1.330340
## Energy           3.148049  1        1.774274
## Danceability     1.430850  1        1.196181
## Loudness..dB..   2.908789  1        1.705517
## Liveness         1.182530  1        1.087442
## Valence.         1.609168  1        1.268530
## Length.          1.555532  1        1.247210
## Acousticness..   1.304786  1        1.142272
## Speechiness.     2.095509  1        1.447587
```

The categorical varaible Genre has the largest VIF, with a value of 4.54. This means there exists some correlation between Genre and the other predictors. This intuitively makes sense since musical genres are categories that songs fall into based on similar characteristics, such as lyric frequency, beats per minute, length, mood conveyed by the song, etc.

Below is an exhaustive varaible selection testing models of different size in order to determine which set of predictors is the strongest model.

```r
reg.fit <- regsubsets(Popularity ~ . -X1 -Track.Name -Artist.Name -Popularity,
          data = top50, nvmax = 11, method = "exhaustive")

summary(reg.fit)
```

```
## Subset selection object
## Call: regsubsets.formula(Popularity ~ . - X1 - Track.Name - Artist.Name -
##     Popularity, data = top50, nvmax = 11, method = "exhaustive")
## 11 Variables  (and intercept)
##                  Forced in Forced out
## GenreLatin           FALSE      FALSE
## GenreHip Hop         FALSE      FALSE
## Beats.Per.Minute     FALSE      FALSE
## Energy               FALSE      FALSE
## Danceability         FALSE      FALSE
## Loudness..dB..       FALSE      FALSE
## Liveness             FALSE      FALSE
## Valence.             FALSE      FALSE
## Length.              FALSE      FALSE
## Acousticness..       FALSE      FALSE
## Speechiness.         FALSE      FALSE
## 1 subsets of each size up to 11
## Selection Algorithm: exhaustive
##           GenreLatin GenreHip Hop Beats.Per.Minute Energy Danceability
## 1  ( 1 )  " "        " "          " "              " "    " "
## 2  ( 1 )  "*"        " "          " "              " "    " "
## 3  ( 1 )  "*"        " "          " "              " "    " "
## 4  ( 1 )  "*"        " "          " "              " "    " "
## 5  ( 1 )  "*"        " "          " "              " "    " "
## 6  ( 1 )  "*"        "*"          " "              " "    " "
## 7  ( 1 )  "*"        "*"          " "              " "    "*"
## 8  ( 1 )  "*"        "*"          " "              " "    "*"
## 9  ( 1 )  "*"        "*"          "*"              " "    "*"
## 10  ( 1 ) "*"        "*"          " "              "*"    "*"
## 11  ( 1 ) "*"        "*"          "*"              "*"    "*"
##           Loudness..dB.. Liveness Valence. Length. Acousticness.. Speechiness.
## 1  ( 1 )  " "            " "      "*"      " "     " "            " "
## 2  ( 1 )  " "            " "      "*"      " "     " "            " "
## 3  ( 1 )  " "            " "      "*"      "*"     " "            " "
## 4  ( 1 )  " "            "*"      "*"      "*"     " "            " "
## 5  ( 1 )  " "            "*"      "*"      "*"     " "            "*"
## 6  ( 1 )  " "            "*"      "*"      "*"     " "            "*"
## 7  ( 1 )  "*"            "*"      "*"      "*"     " "            " "
## 8  ( 1 )  "*"            "*"      "*"      "*"     "*"            " "
## 9  ( 1 )  "*"            "*"      "*"      "*"     "*"            " "
## 10  ( 1 ) "*"            "*"      "*"      "*"     "*"            "*"
## 11  ( 1 ) "*"            "*"      "*"      "*"     "*"            "*"
```

Using the Adjusted R^2 criterion, the model with the highest adjusted R^2 is the model with 7 predictors. It has an adjusted R^2 value of 0.2319. The 7 chosen predictors are: - GenreLatin*
- GenrePop*
- Danceability
- Loudness

- Liveness
- Valence
- Length

*Note: GenreLatin and GenrePop are dummy variables for the categorical variable Genre, which can either be Hip Hop, Pop or Latin.

```
summary(reg.fit)$adjr2
```

```
##  [1] 0.0822367 0.1529003 0.2178352 0.2221503 0.2258999 0.2261826 0.2319301
##  [8] 0.2241151 0.2093685 0.1929890 0.1727235
```

```
which.max(summary(reg.fit)$adjr2)
```

```
## [1] 7
```

```
summary(reg.fit)$adjr2[7]
```

```
## [1] 0.2319301
```

The Mallow's Cp criterion finds that the closest Cp to p is the model with two predictors: GenrePop and Valence.

```
summary(reg.fit)$cp
```

```
##  [1]  7.250199  4.126215  1.491604  2.311411  3.171731  4.221314  4.994139
##  [8]  6.453024  8.228163 10.044631 12.000000
```

BIC chooses the thrid model, with the three predictos: GenreLatin, Valence, Length.

```
summary(reg.fit)$bic
```

```
##  [1]  2.5022934  1.3555912  0.2046576  2.7411261  5.2879014  8.0321832
##  [7] 10.3949210 13.6082434 17.2270247 20.8984218 24.7517540
```

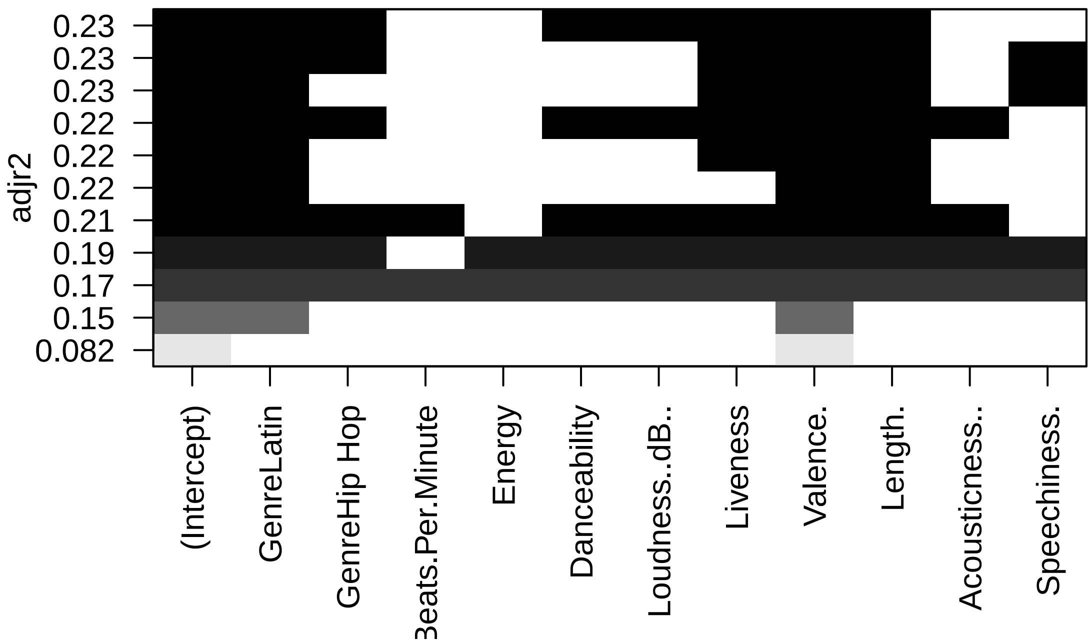
```
which.min(summary(reg.fit)$bic)
```

```
## [1] 3
```

In this I will choose the model with according to the Rˆ2 criterion of variable selection since that model most accurately predicts the response relative to the other models, or in other words has the best fit according to the training data.

Looking at the plot we can visually compared the other models and their adjusted Rˆ2, and see that the model with 7 predictors has the highest Rˆ2 value of 0.23.

```
plot(reg.fit, scale = "adjr2" )
```



The coefficients for the model is below. We can see that only the intercept and whether a song is Pop or Latin is very statistically significant, while the other predictors are not, with $\alpha < 10$.

```
reg.bestfit <- lm(Popularity ~ Genre + Danceability + Loudness..dB.. + Liveness + Valence. + Length., da

summary(reg.bestfit)
```

```
##
## Call:
## lm(formula = Popularity ~ Genre + Danceability + Loudness..dB.. +
##     Liveness + Valence. + Length., data = top50)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.9571  -1.4213  -0.0145   2.3484   7.5334
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    96.19506    5.71113  16.843  < 2e-16 ***
## GenreLatin      6.35060    1.71811   3.696 0.000628 ***
## GenreHip Hop    2.55717    1.75413   1.458 0.152334
## Danceability   -0.06306    0.05426  -1.162 0.251701
## Loudness..dB.. -0.44190    0.32862  -1.345 0.185931
## Liveness        0.07997    0.05428   1.473 0.148151
## Valence.       -0.05879    0.03131  -1.878 0.067331 .
## Length.        -0.03444    0.01745  -1.974 0.054957 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.936 on 42 degrees of freedom
## Multiple R-squared:  0.3417, Adjusted R-squared:  0.2319
## F-statistic: 3.114 on 7 and 42 DF,  p-value: 0.009727
```

```
Yhat.bestfit <- predict(reg.bestfit)
MSE.bestfit <- mean((Yhat.bestfit - Popularity)^2)
MSE.bestfit
```

```
## [1] 13.01549
```

```
reg.full <- lm(Popularity ~ . -X1 -Track.Name -Artist.Name -Popularity,
               data = top50)
Yhat.full <- predict(reg.full)
MSE.full <- mean((Yhat.full - Popularity)^2)
MSE.full
```

```
## [1] 12.68367
```

The prediction MSE for the best fit linear model is 13.01549. The prediciton MSE for the full model was slightly smaller at 12.68, however its R^2 was 0.17 compared to 0.23.

Creating Testing and Training Data

```
set.seed(11)
training = sample(1:n,n/2)
testing <- -training
spotify.training <- top50[training,]
spotify.testing <- top50[testing,]
```

Cross Validation of the Best Fit model found by Exhaustive Search

```
reg.train <- lm(Popularity ~ Genre + Danceability + Loudness..dB.. + Liveness + Valence. + Length., data

Yhat <- predict(reg.train, newx = spotify.testing)
MSEp <- mean((spotify.testing$Popularity - Yhat)^2)
MSEp
```

```
## [1] 17.40967
```

- MSE for exhaustive search is 17.4096661

Using LASSO and Ridge Regression

Create training and testing matrices

```r
spo.mat.training <- model.matrix(Popularity~.-X1 -Track.Name -Artist.Name -Popularity, data=spotify.trai
spo.mat.testing <- model.matrix(Popularity~.-X1 -Track.Name -Artist.Name -Popularity, data=spotify.testi
```

```r
#LASSO
spo.lasso <- cv.glmnet(spo.mat.training, spotify.training$Popularity, alpha=1)
```

```
## Warning: Option grouped=FALSE enforced in cv.glmnet, since < 3 observations per
## fold
```

```r
(lambda <- spo.lasso$lambda.min)  # optimal lambda
```

```
## [1] 1.375505
```

```r
pred.lasso <- predict(spo.lasso, s=lambda, newx=spo.mat.testing)
(err.lasso <- mean((spotify.testing$Popularity - pred.lasso)^2))
```

```
## [1] 15.8992
```

```r
predict(spo.lasso, s=lambda, type="coefficients")
```

```
## 12 x 1 sparse Matrix of class "dgCMatrix"
##                      1
## (Intercept)      87.08
## GenreLatin        .
## GenreHip Hop      .
## Beats.Per.Minute  .
## Energy            .
## Danceability      .
## Loudness..dB..    .
## Liveness          .
## Valence.          .
## Length.           .
## Acousticness..    .
## Speechiness.      .
```

```r
#Ridge Regression
spo.ridge <- cv.glmnet(spo.mat.training, spotify.training$Popularity, alpha=0)
```

```
## Warning: Option grouped=FALSE enforced in cv.glmnet, since < 3 observations per
## fold
```

```r
(lambda <- spo.ridge$lambda.min)
```

```
## [1] 1375.505
```

```r
pred.ridge <- predict(spo.ridge, s=lambda, newx=spo.mat.testing)
(err.ridge <- mean((spotify.testing$Popularity - pred.ridge)^2))
```

```
## [1] 15.8992
```

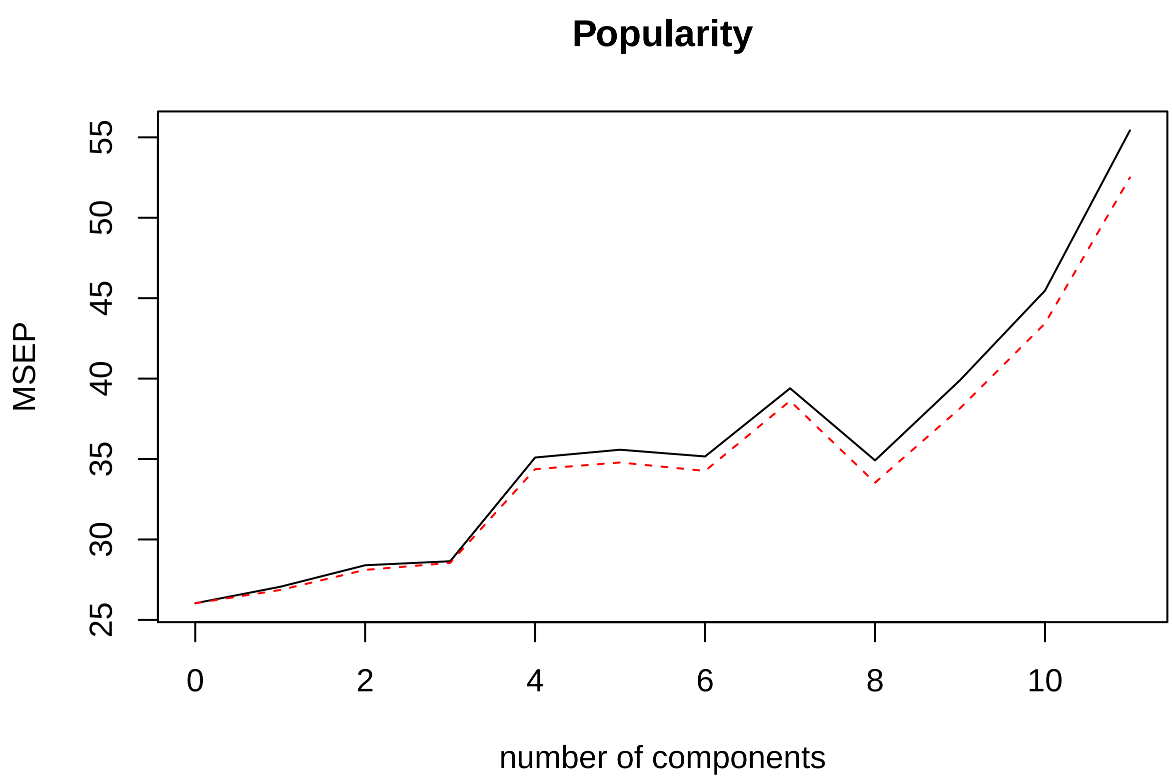
```r
predict(spo.ridge, s=lambda, type="coefficients")
```

```
## 12 x 1 sparse Matrix of class "dgCMatrix"
##                               1
## (Intercept)        8.708000e+01
## GenreLatin         3.094436e-36
## GenreHip Hop       1.406926e-36
## Beats.Per.Minute   7.995687e-39
## Energy            -6.150706e-38
## Danceability       4.069386e-38
## Loudness..dB..    -4.619195e-37
## Liveness           4.705235e-39
## Valence.          -3.129497e-38
## Length.           -6.555672e-39
## Acousticness..    -4.168423e-38
## Speechiness.       9.312137e-38
```

- MSE for Ridge Regression and LASSO methods is 15.9.

Using PCR

```r
reg.pcr <- pcr(Popularity ~ .-X1 -Track.Name -Artist.Name -Popularity, data = spotify.training, scale =
validationplot(reg.pcr, val.type = "MSEP")
```



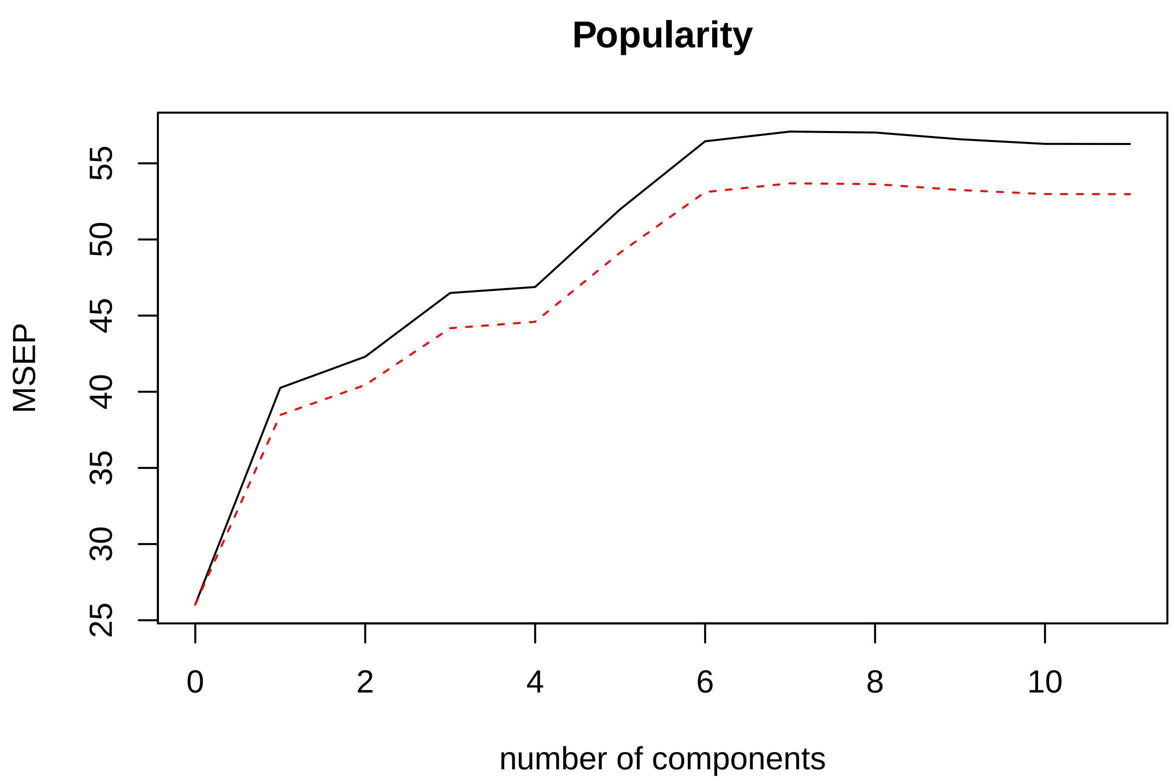
```r
pred.pcr <- predict(reg.pcr, spotify.testing, ncomp = 1)
#Calculate MSE
mean((pred.pcr - spotify.testing$Popularity)^2)
```

```
## [1] 15.44556
```

- MSE for PCR method is 15.9.

Using PLS

```r
reg.pls <- plsr(Popularity ~ .-X1 -Track.Name -Artist.Name -Popularity, data = spotify.training, scale =
validationplot(reg.pls, val.type = "MSEP")
```




```r
pred.pls <- predict(reg.pls, spotify.testing, ncomp = 8)
#Calculate MSE
mean((pred.pls - spotify.testing$Popularity)^2)
```

```
## [1] 18.83678
```

- MSE for PLS method is 18.8.

- The MSE for Ridge, LASSO, and PCR is lower than the MSE and PLS and Exhaustive Search. Also, the screeplots were shaped oddly so I would advise against PLS here in favor of LASSO, Ridge, and PCR.