Classification: Is the song Spanish, Korean, or Arabic?

Julia Stelman

30/9/2019

Introduction

In this study, I look at a number of audio features of 516 songs and see if I can try to predict the language of the song's lyrics with statistical modeling. I use a multinomial regression approach to formulate my model. The audio features eventually used are

- Danceability (number between 0 and 1)
- Energy (number between 0 and 1)
- Loudness (number between -25 and 0)
- Speechiness (number between 0 and 1)
- Tempo (number between 50 and 250)

The languages I will be looking at today are

- Spanish
- Korean
- Arabic

Thank you to Spotify, Musixmatch, Everynoise.com, and lang-detect for the help I got from your libraries, websites, and APIs in the data collection and cleaning phase of this project, which I did in Python.

Also thank you to the R libraries quanteda, tidyverse, nnet, DescTools, caret, leaps, and car.

Data

A preview of the data

```
##     danceability energy loudness speechiness acousticness liveness   tempo
## 129        0.647  0.489  -11.058      0.0330        0.730    0.131  94.967
## 256        0.547  0.797   -5.378      0.0472        0.047    0.193 139.884
## 387        0.732  0.510   -6.192      0.2600        0.111    0.102  87.837
##     lang
## 129   ko
## 256   ar
## 387   es
```

Methods

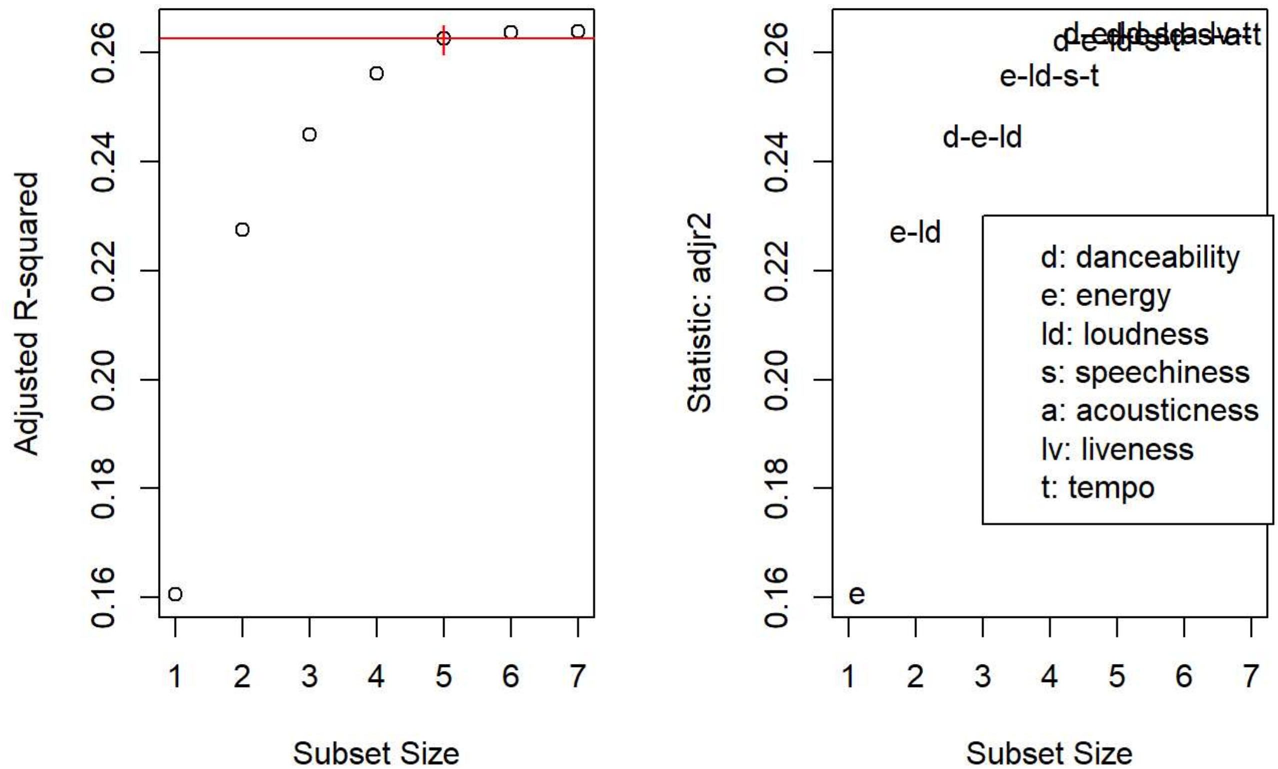
I used R to fit a multinomial model to the data.

Here is the model I ended up using

```
## # weights:  21 (12 variable)
## initial  value 425.162956
## iter  10 value 343.533374
## iter  20 value 342.512782
## final  value 342.512737
## converged
```

```
## Call:
## multinom(formula = lang ~ danceability + energy + loudness +
##     speechiness + tempo, data = train_ska_df)
##
## Coefficients:
##    (Intercept) danceability    energy    loudness speechiness       tempo
## es   -2.494691     2.559326   0.51073 -0.01022033   -6.880827 0.007887857
## ko    9.116123    -2.426092 -10.35331  0.39921908   -4.592110 0.012803649
##
## Residual Deviance: 685.0255
## AIC: 709.0255
```

I deducted that model from the original 7-variable model (which also included *acousticness* and *liveness*) using several handy R packages (which I have listed at the bottom of the intro) to find the set of predictor variables that would minimize the Adjusted R-squared.



The plot on the left, uses an Adjusted R-squared maximizer to decide when to stop adding variables. We see here that five variables, *danceability, energy, loudness, speechiness,* and *tempo* should be kept, and the other two *acousticness* and *liveness* should be dropped.

Results

Confusion Matrix

	ar	es	ko
ar	15	22	6
es	10	28	5
ko	1	3	39

```
##       Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull
##   6.356589e-01   4.534884e-01   5.463743e-01   7.185628e-01   4.108527e-01
## AccuracyPValue  McnemarPValue
##   2.199938e-07   3.556654e-02
```

I did not expect this kinds of results, but I like what I see. The model has a 63.6% accuracy rate, the p-value for the one-tailed test of whether or not the model predicts the a song's lyric language better than no information is very low (0.00000022), and the Mcnemar's Test p-value is 0.035. That's two statistically significant p-values! Well, it's predictive power is not great, but it's significantly better than random guessing.

Discussion

It was a small sample size, yet the results worked out nicely somehow. I chose this trio completely at random, and I plan to explore other combinations next. Maybe I will find that this set of languages was the most difficult, or maybe I'll find that I picked a really lucky trifecta this time around, and no other three languages are as easy to explore through audio features as this one. My guess is that thsi one lies somewhere in the middle. As always, I hope to keep exploring this awesome dataset as time allows. My next idea is to look at bigger groups of languages.

Appendix

```
# Prepare to do a classication training and then testing.

## take an equal random sample from all three languages of interest
eS_ids <- subset(x=df,subset = lang == 'es')$sid
## n = 172 because there are exactly 174 songs in Arabic, the language with the fewest in the th
e trio (Spanish, Korean, Arabic)
eS_ids <- sample(eS_ids,172)
Ar_ids <- subset(x=df,subset = lang == 'ar')$sid
Ar_ids <- sample(Ar_ids,172)
Ko_ids <- subset(x=df,subset = lang == 'ko')$sid
Ko_ids <- sample(Ko_ids,172)

## take the subset of data with only those 172*3 songs and call it a new name
ska_df <- subset(x = df,select = names(df),subset = sid %in% c(eS_ids,Ar_ids,Ko_ids))

## take 1/4 of the song ids sampled from each language and put them aside for test data
test_ska_ids <- c(
  as.character(ska_df[ska_df$sid %in% sample(eS_ids,length(eS_ids) %/% 4),'sid']),
  as.character(ska_df[ska_df$sid %in% sample(Ar_ids,length(Ar_ids) %/% 4),'sid']),
  as.character(ska_df[ska_df$sid %in% sample(Ko_ids,length(Ko_ids) %/% 4),'sid']))

## the rest will be the training data
```

```
## use the test ids to subset a test data frame.
test_ska_df <- subset(x = ska_df, select = names(ska_df), subset = sid %in% test_ska_ids)
## use the remaining ids to subset a training dataframe
train_ska_df <- subset(x = ska_df, select = names(ska_df), subset = !(sid %in% test_ska_ids))

## get rid of the spotify id column, it's not needed anymore
test_ska_df <- select(test_ska_df, - sid)
train_ska_df <- select(train_ska_df, - sid)

## factorize the character columns that are left (there should only be one, language)
test_ska_df <- test_ska_df %>%  mutate_if(is.character, as.factor)
train_ska_df <- train_ska_df %>%  mutate_if(is.character, as.factor)
```

```
train_ska_df[c(129,256,387),]
```

```r
#train the model
#### let's see which ones we really need

## first try all 7
mr_train_fit <- multinom(lang ~ danceability + energy + loudness +
                     speechiness + acousticness + liveness + tempo,
                     data = train_ska_df)
summary(mr_train_fit)
```

```r
#### let's see which ones we really need
AFmatTr <- as.matrix(train_ska_df[,-8])
langVecTr <- train_ska_df[,8]
MSO <- regsubsets(AFmatTr,langVecTr)  #model selection object
regsub <- summary(MSO)
par(mfrow=c(1,2))
plot(1:7,regsub$adjr2,xlab="Subset Size",ylab="Adjusted R-squared")
abline(h = regsub$adjr2[5],col='red')
points(x = 5,y = regsub$adjr2[5],col='red', pch = '|')
subsets(MSO,statistic=c("adjr2"),legend = c(3,0.23))
```

```r
##### Remove the two coefficients that we just cut using the Adjusted R-squared maximizer
###### Refit the model.

mr_train_fitr <- multinom(lang ~ danceability + energy + loudness + speechiness + tempo,
                     data = train_ska_df)

summary(mr_train_fitr)
```

```r
##Now let's see how well it does on our test data

# Next, we create a data based on our fit.
prob_disc <- cbind(test_ska_df, predict(mr_train_fitr, newdata = test_ska_df,
                                  type = "probs", se = TRUE))

labeler <- function(id){
  if (id == 1) 'ar'
  else if (id == 2) 'es'
  else if (id == 3) 'ko'
}

predictions <- c(sapply(max.col(prob_disc[,9:11]),labeler))
truth <- sapply(as.character(prob_disc$lang),paste)

confusion <- c(truth,predictions)
confusion <- as.data.frame(confusion)
confusion <- confusion  %>%  mutate_if(is.character, as.factor)
confusion1 <- cbind(confusion[1:(length(confusion)%/%2)],
                   confusion[((length(confusion)%/%2)+1):length(confusion)])
names(confusion1) <- c("truth","predictions")
rm(confusion)


cm <- confusionMatrix(confusion1$predictions[1:129],
                confusion1$truth[130:258])
knitr::kable(cm$table,caption = "Confusion Matrix")
cm$overall
```