Songs Analysis

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Abstract

An analysis of songs

With the increasing popularity of the field known as "Big Data" we ask ourselves if by collecting information about songs, we can predict which song will be the next hit that will be listened all over the world. Can record labels use machine learning and big data to discover or create the next hit? By downloading a dataset known as the million songs dataset, I am trying to get an answer to this question.

Contents

1 Introduction

Music has had an important role in our culture troughout human history. As a result of this importance, follows a billion dollar industry. In 2014 alone, this industry generated 15 billion dollars [1]. Most of the income is made from mainstream popular songs and goes straight to the hands of record labels companies. Having a good understanding and of songs is a valuable skillset to have in this industry. . of what song will get popular is a valuable skillset to have in this industry, not only making the record labels rich [2], but also attracting listeners to radio station, making artists famous and help digital and physical music marketplaces.

This project will try to see if the next hit can be predicted from a given set of features.

2 Related Work

A similar project is done by three students at Stanford University that did a song popularity prediction with a computer science view [6]. In their work they

An example track description is available at: http://labrosa.ee.columbia.edu/millionsong/pages/example-track-description.

3 Dataset

3.1 Data

The million songs dataset is a data set with information about a million different songs [3]. The total dataset, with all the information included, as a size of 280GB. I do not have enough space on my computer to store a so big data set. Therefore I have focused on working on subset of the data set. For this project I am working with two different subset of the dataset. One is a subset with all the information included, but reduced to 10 000 songs instead of a million. This dataset has the perk of having all the information and am therefore able to work with the dataset as I please. I also came cross another subset of the dataset, that had reduced the informations, or the features from the dataset and added another feature called genre. This dataset I will also use in order to predict genre, and has a total of 59 600 songs.

3.2 Features

The dataset can be split into two different parts. The first part contains the track data, and the second the sequenced data. From the track data we have features such as duration, tempo, loudness, confidence, song hotttnesss, tempo and year. From the sequence data we have timing information (start, duration of sequence) as well as loudness, pitch and timbre features in each sequence. For this project I will not include the sequenced data in my work, because using the sequenced data I will be trying to figure out a deep psychological patterns in what kind of music appeals to people. Using only the track data, it will therefore be easier to read and understand the results we are getting.

For more information about the sequenced data, I suggest reading the echonest Analyser documentation [8].

3.3 Statistical Distribution

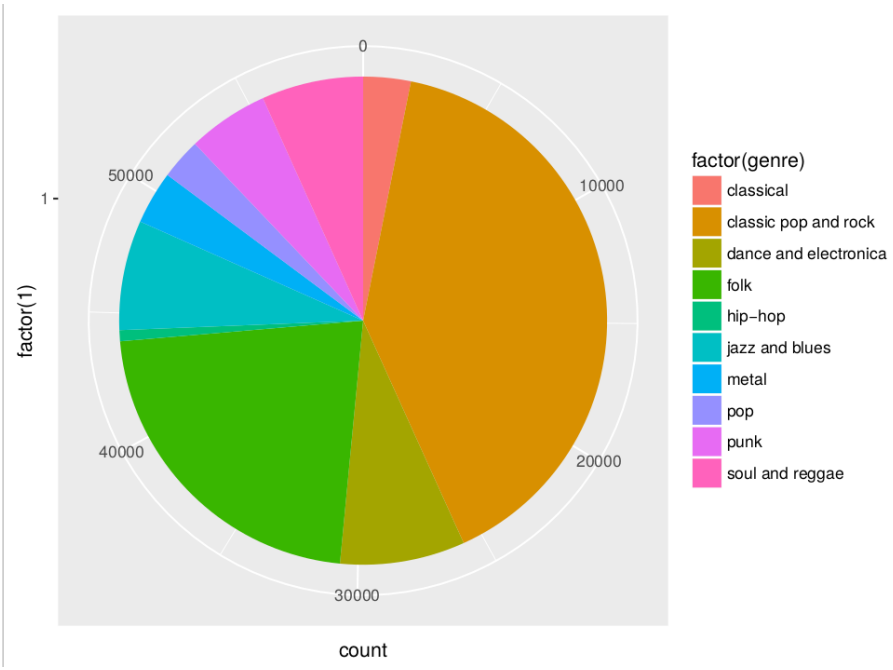

Figure 1: Distribution of the genres in the genre data set

From figure 1, we can see the distrubution between the different genres in the data set. There is clearly a majority of the classic pop and rock genre, while the simple pop genre have few samples. This is a typical problem in data sets that one class have more samples than the other classes, and can lead to a bad results. One solution can be to merge together genres to create fewer and bigger classes, or keep on increasing the total samples with more tracks of the classes with low samples.

4 Methods and Quantitative Results

4.1 Exploratory Data Analysis

One thing I wanted to analyse, was to try and find a correlation between different variables.

From figure 2 we see the correlation between genre classes and loudness values. Not surpirsingly, the metal genre is the loudest genre with most of the samples close to 0 and the punk genre has the second highest loudness value. The figure also makes it clear that it will be hard to predict genre just by loudness value, and each of the genres have a samples with many different values.

4.2 Predictive Analytics Model

This project have focused on predicting three different problems. The first problem is to predict a songs popularity. When predicting the popularity, I used the 25% hottest song (top 25% of the

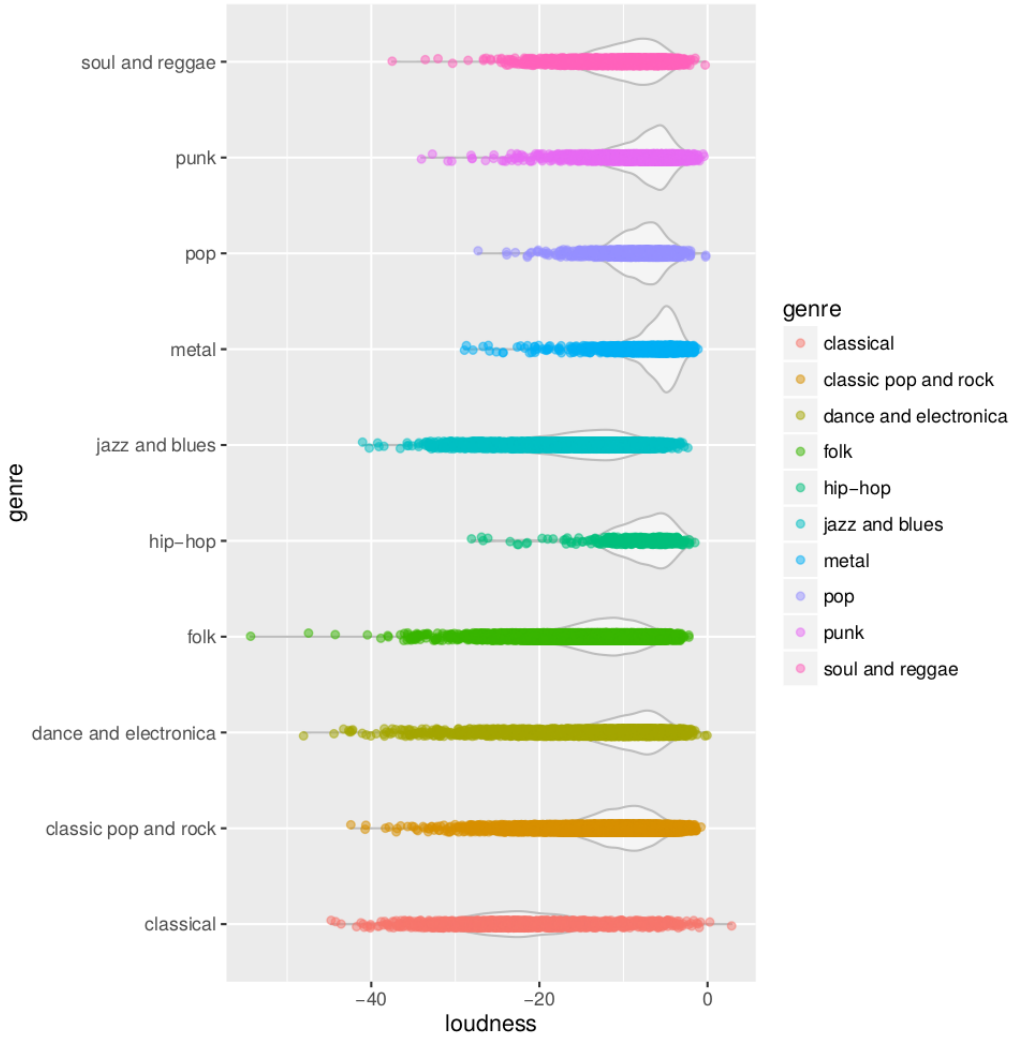

Figure 2: The correlation between Genre class and loudness

feature song hotttnesss). The second is predicting which year a song is from. Last, we predicted the genre of the song. To classify these three problems we used two different dataset. One was the one percentage subset of the million song dataset, and the other was a genre dataset that had already genre as a value. The genre dataset was larger than the one percentage subset, but missed year and song hottness.

For predictive analysis, this project have used three different classification methods. This is used becuase often different classification models can be better for different kinds of problems. By using several different models, we have a better chance of getting a better total results. The three different methods used is **Decision Tree**, **Support Vector Machine (SVM)** and **Random Forest**.

4.2.1 Predicting if a song is popular

4.2.2 Predicting a song release year

4.2.3 Predicting a song genre

4.3 Testing and evaluating the Models

Table 1: Scores on testset for each learning algorithm by problem

Model	Popular	Year	Genre	MEAN
DT	0.846	0.816	0.989	**0.959**
RF	0.847	**0.818**	0.985	0.946
SVM	0.781	0.786	**0.990**	0.958

From table 1 we can see

4.3.1 Predicting if a song is popular

4.3.2 Predicting a song release year

4.3.3 Predicting a song genre

5 Conclusion

6 Acknowledgement

Many thanks to Professor Roger Bohn for providing me with his guidance and advise throughout the project.

References

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[2] Mike Masnick, Yes, "Major Record Labels Are Keeping Nearly All The Money They Get From Spotify, Rather Than Giving It To Artists", Feb 5th 2015, available at: https://www.techdirt.com/articles/20150204/07310329906/yes-major-record-labels-are-keeping-nearly-all-money-they-get-spotify-rather-than-giving-it-to-artists.shtml

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[7] Derek Thompson. "The Shazam Effect". The Atlantic (2014). http://www.theatlantic.com/magazine/archive/2014/12/the-shazam-effect/382237/

[8] Tristan Jehan and David DesRoches. "Analyzer Documentation". The Echonest http://developer.echonest.com/docs/v4/$_s$*tatic/AnalyzeDocumentation.pdf*

[9] dede

Appendices

Project code

```
##
## Thomas Astad Sve
##
##

## Create new environment, classification
cls <- new.env()

##
## Load dataset
##

## Predict popularity
#cls$dt <- read.csv("msd_mean_pop.csv")

## Predict genre
cls$dt <- read.table(file = "../datasets/msd_genre_dataset.txt", header = TRUE, sep = ",", comment = "#", quote=NULL, fill=TRUE)

## Build the training/validate/test datasets.
## Split into 70/15/15 train/test/val
val <- 0.15
test <- 0.15
train <- 0.7

cls$nrow <- nrow(cls$dt)
cat(paste("Number_of_rows:_", cls$nrow, "\n"))

cls$sample <- cls$train <- sample(cls$nrow, train*cls$nrow)
cls$validate <- sample(setdiff(seq_len(cls$nrow), cls$train), val*cls$nrow)
cls$test <- setdiff(setdiff(seq_len(cls$nrow), cls$train), test*cls$nrow)

##cat(paste("Distribution: ", cls$train ,"/", cls$validate ,"/", cls$test, "\n"))


## The following variable selections have been noted.

cls$input <- c("loudness", "tempo", "time_signature", "key", "mode", "duration")

cls$numeric <- c("loudness", "tempo", "time_signature", "key", "mode", "duration")

#cls$target  <- "popular"
cls$target <- "genre"
cls$ident   <- "track_id"
#cls$ignore  <- c("artist_name", "title", "energy", "danceability", "song_hotttnesss")

##
## Decision Tree
##

library(rpart, quietly=TRUE)

## Build the Decision Tree model.
cat(paste("Classifying_a_decision_tree_\n"))
cls$dtfit <- rpart(genre ~ .,
    data=cls$dt[cls$train, c(cls$input, cls$target)],
    method="class")


## Predict on test-set
printcp(cls$dtfit)
##cls$dtpred <- predict(cls$dtfit, newdata = cls$dt[cls$test, c(cls$input, cls$target)], type = "prob")
##cat(paste("Decision tree results: ", cls$dtpred, "\n"))

##
## Support vector machine.
##

##library(kernlab, quietly=TRUE)

## Build a Support Vector Machine model.
##cls$ksvm <- ksvm(as.factor(genre) ~ .,
##       data=cls$dt[cls$train,c(cls$input, cls$target)],
##       kernel="rbfdot",
##       prob.model=TRUE)

## Generate a textual view of the SVM model.

##
## Evaluate results
##

library(ggplot2)
```

```
library(plyr)


## plot tree
cat(paste("Saving a plot of the decision Tree \n"))
jpeg('dt_plot.jpg')
plot(cls$dtfit, uniform=TRUE,
     main="Classification Tree for genre")
text(cls$dtfit, use.n=TRUE, all=TRUE, cex=.8)
dev.off()

## Generate a Confusion Matrix
cat(paste("Saving a confusion Matrix of the decision Tree \n"))
jpeg('dt_confusion_matrix.jpg')
plot(cls$dtfit, uniform=TRUE,
     main="Classification Tree for genre")
text(cls$dtfit, use.n=TRUE, all=TRUE, cex=.8)
dev.off()

## Plot count of genre distribution
##distribution <- count(cls$dt, "genre")

##g1<-ggplot(cls$dt, aes(x=factor(1), fill=factor(genre))) + geom_bar(width = 1)

##plot(g1 + coord_polar(theta="y"))

##plot(g1+geom_violin(alpha=0.5, color="gray")+geom_jitter(alpha=0.5, aes(color=genre),
##     position = position_jitter(width = 0.1))+coord_flip())


## Plot relation between loudness and genre
##g<-ggplot(cls$dt, aes(x=genre, y=loudness))

##plot(g+geom_violin(alpha=0.5, color="gray")+geom_jitter(alpha=0.5, aes(color=genre),
##     position = position_jitter(width = 0.1))+coord_flip())


##
## Thomas Astad Sve
##
##

## -- Load dataset --
print("Loading dataset...")
file <- "msd_seg_mean.csv"
MSongs <- read.csv(file, header = TRUE)

## Removing duplicates
MSongs <- MSongs[!duplicated(MSongs[,c('artist_name', 'title')]),]

## Sort data by hotness
print("Sorting dataset by hottnesss")
MSongs <- na.omit(MSongs[order(-MSongs$song_hotttnesss),])

## Insert new value with the most popular songs as 1, rest 0
print("Adding new variable, popular")

## Take top 25% of the hottest songs as popular
n = 25
MSongs$popular <- ifelse(MSongs$song_hotttnesss < quantile(MSongs$song_hotttnesss,prob=1-n/100),0,1)

print(paste("Num samples: ", nrow(MSongs)))

numUnPop <- length(MSongs$popular[MSongs$popular == 0])
numPop <- length(MSongs$popular[MSongs$popular == 1])

print(paste("Num Popular: ", numPop, " Num unPopular: ", numUnPop))

## Save dataset
write.csv(MSongs, "msd_mean_pop.csv")

warnings()


##
## Thomas Astad Sve
## Script to clear the year dataset, so there is no samples with NA or 0 value in year
##

## -- Load dataset --
print("Loading dataset...")
MSongs <- read.csv("../datasets/msd_simple.csv", header = TRUE)

## Removing duplicates
print("Removing duplicates...")
MSongs <- MSongs[!duplicated(MSongs[,c('artist_name', 'title', 'track_id')]),]

## Remove columns where year is zero, year has column 11
print("Removing columns where year is 0...")
cleanYMS <- MSongs[apply(MSongs[11], 1, function(z) any(z!=0)),]

print("Saving new clean dataset...")
```

```
write.csv(cleanYMS, "../datasets/msd_year.csv")
print("Saved!")
```