INFO523 Decision Trees

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Preprocessing

At first, we are going to make two sets of our spot-data: one only related to the music vaiables and one also including the socio- variables.

Overview

Step 1: build a decision tree to classify countries using social variables. **Step 1B**: Interesting rules for distinguishing countries **Step 2**: use most important variable from Stage 1 to cluster countries (the tree in Step 3 performed better with fewer classes this way) **Step 3**: build a decision tree to classify clustered countries by music variables (dimensions of music taste) **Step 3B**: Interesting rules **Step 4**: Compare performance of decision tree in Step 3 to Random Forest

Step 1. Decision tree

Split Train/Test

We split the spot_music_SOCIO data into training and test data, not using a validation set.

```
##          happiness        density_sqkm percent_internet_users
##          774.80000           681.46667              632.80000
##      percent_urban          median_age                freedom
##          618.13333           574.13333              418.03011
##                gdp    track.popularity           danceability
##          330.99183            41.24946               12.50000
##        speechiness             valence           acousticness
##           12.00000            10.00000                6.00000
##           liveness            loudness
##            3.00000             2.00000
```

```
## error rate:  0
```

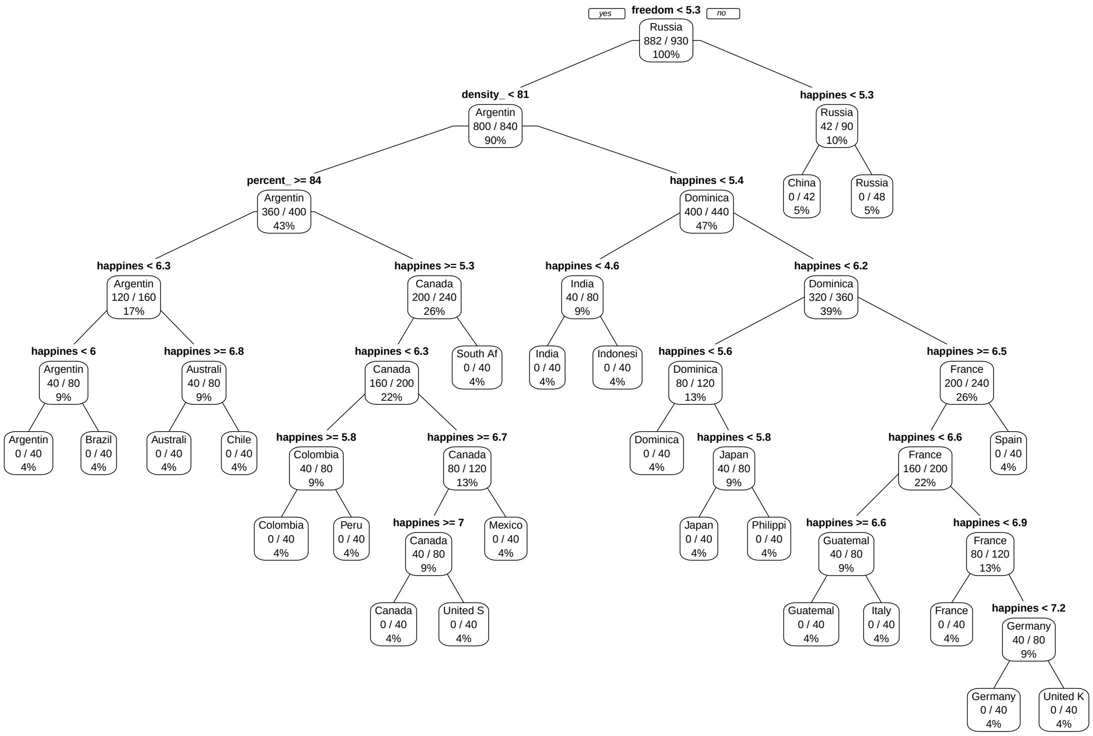


Figure 1. First decision tree: classifying countries by social variables.

Why is the error rate 0?

Seems to good to be true… Let's examine the happiness variable.

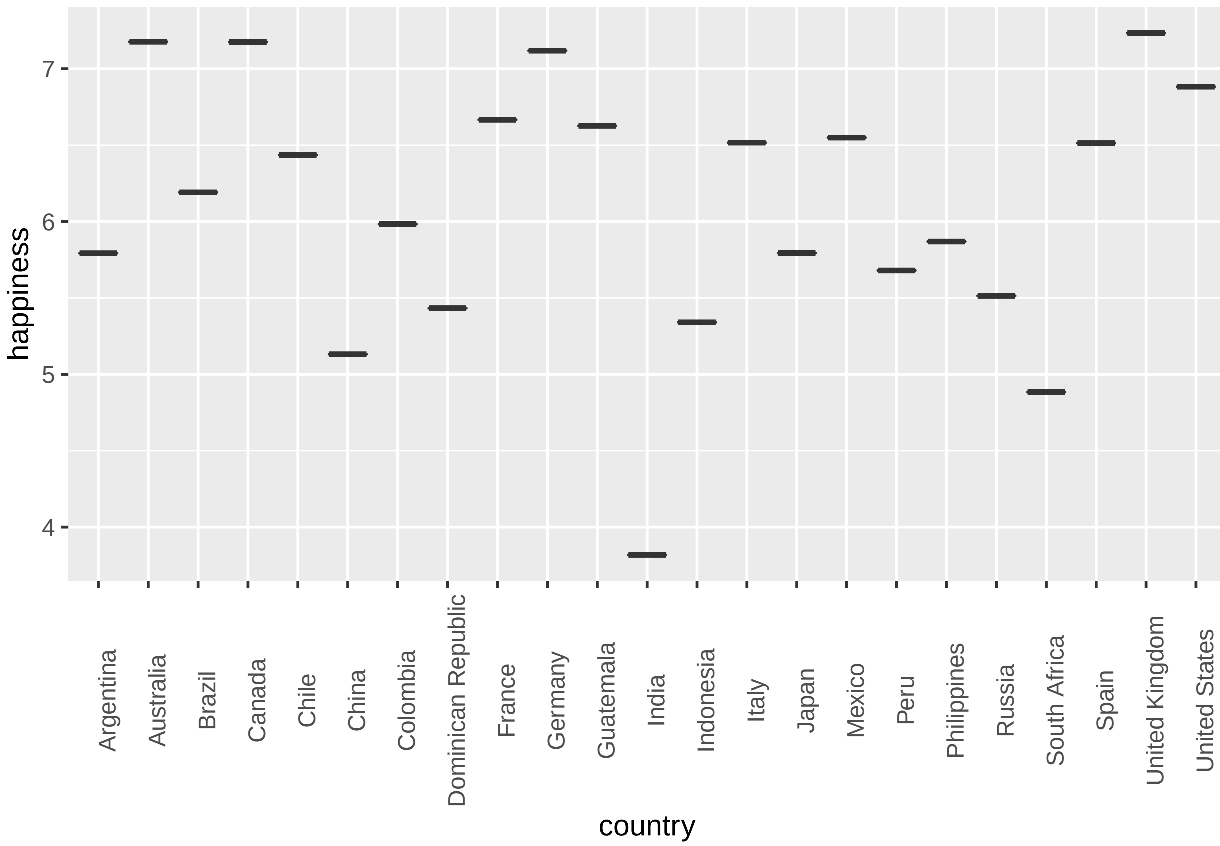


Figure 2. Each country has a single happiness value (boxplot lacks quantiles, etc) spread over each tuple for that country (by virtue of the sociopolitical data source's methods). Therefore, if at least one tuple from each country made it into both the training and test data, this could lead to a perfect error rate.

Solution: Discretize variables and re-run decision tree

```
## Warning: funs() is soft deprecated as of dplyr 0.8.0
## Please use a list of either functions or lambdas:
##
##   # Simple named list:
##   list(mean = mean, median = median)
##
##   # Auto named with `tibble::lst()`:
##   tibble::lst(mean, median)
##
##   # Using lambdas
##   list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
## This warning is displayed once per session.
```

Examine distribution of levels

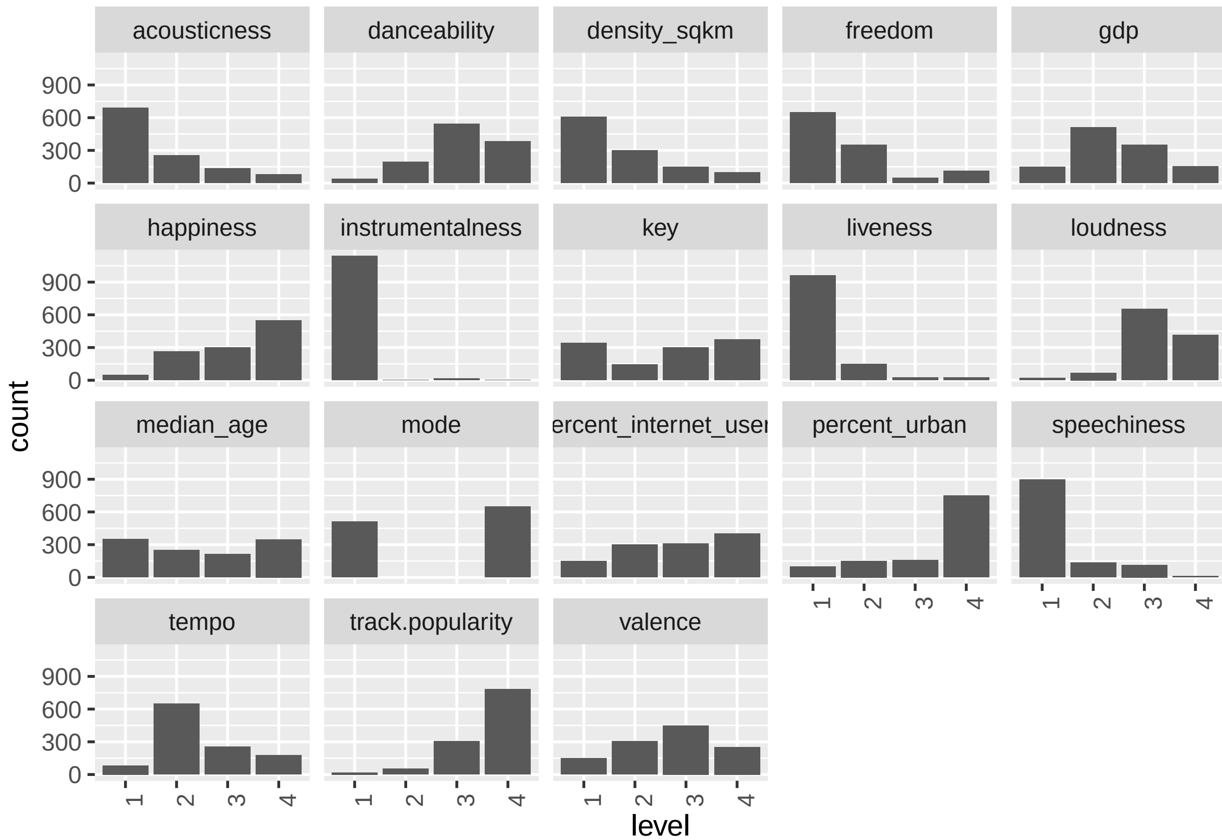


Figure 3. Distribution of discretized levels.

Socio-political tree with discretized variables

```
##              median_age                    gdp               happiness
##              280.966308             240.000000              180.000000
##           percent_urban percent_internet_users                 freedom
##              122.800000             120.000000               96.696774
##             density_sqkm       track.popularity                loudness
##               92.000000              74.172509               66.000000
##             danceability         track.explicit                   tempo
##               58.000000              57.000000               56.166667
##                  valence                   mode             speechiness
##               50.666667              45.933333               43.750000
##             acousticness               liveness                     key
##               41.133333              19.000000               12.000000
##         instrumentalness
##                2.493262
```

```
## error rate (categorical features):  0
```

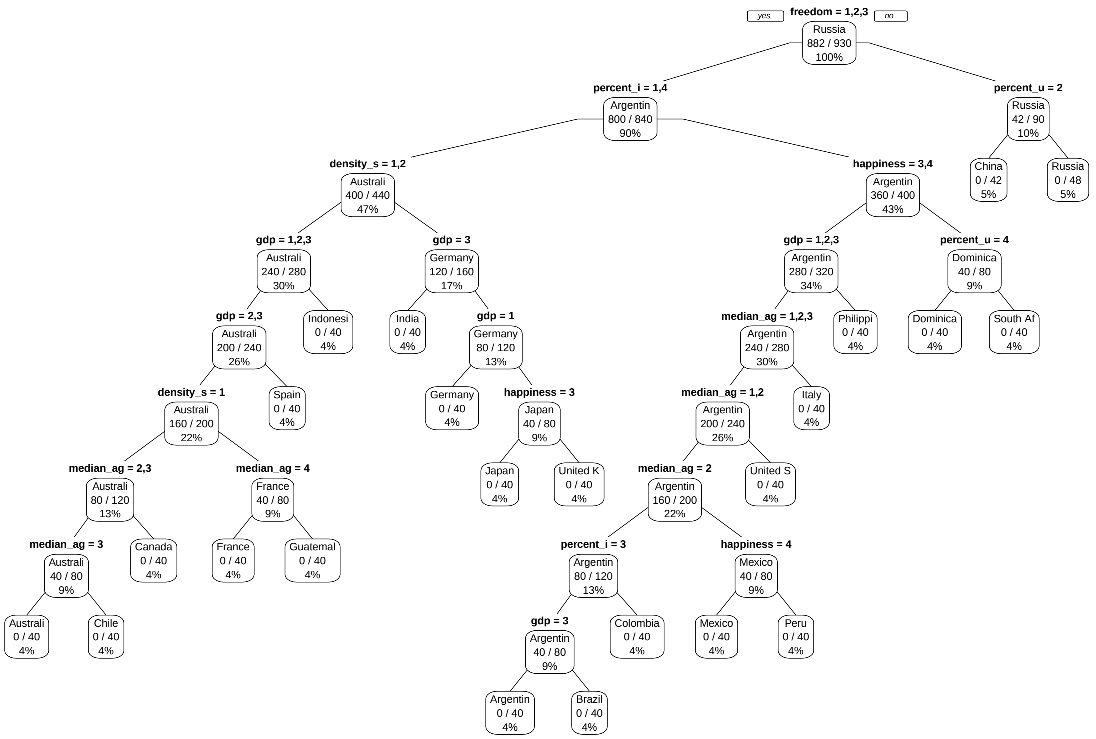


Figure 4. Classification of countries using discretized social variables. We chose not to prune the tree because it already has impeccable performance on the test data. The error rate is still 0.

Step 1B: interesting rules

1. If freedom != 1,2,3 (1 is highest) and percent urban = 2, then country = China
2. If freedom != 1,2,3 (1 is highest) and percent urban != 2, then country = Russia (note: Russia's percent urban is 74.3 (> level 2))
3. If freedom = 1,2,3 (all but lowest), percent internet users != 1,4 (moderate), happiness != 3,4 (below 50th percentile), and percent urban = 4 (highest), then country = Dominican Republic

Step 2. Use important variable from tree in Step 1 to cluster countries

Our goal is to classify countries by music tastes. To make results more interpretable, we clustered countries by the most important variable in the decision tree shown in Fig. 4, *median_age*, for classification (this also improved performance over a previous tree, not shown). We decided to use two k = 2 to get "old" and "young" countries. We then bound the clusters to our solely music-variable data and used this to grow the tree.

In essence, our question is: what are the most important music variables that distinguish 'old' countries' music taste from 'young' countries?


```
##  [1] 1 2 1 2 1 2 1 1 2 2 1 1 1 2 2 1 1 1 2 1 2 2 2
```

```
##               country  age cluster
## 1           Argentina 30.8       1
## 2              Brazil 31.3       1
## 3               Chile 33.7       1
## 4            Colombia 30.1       1
## 5  Dominican Republic 26.1       1
## 6           Guatemala 21.3       1
## 7               India 26.7       1
## 8           Indonesia 28.0       1
## 9              Mexico 27.5       1
## 10               Peru 27.5       1
## 11        Philippines 24.1       1
## 12       South Africa 26.1       1
## 13          Australia 37.4       2
## 14             Canada 40.5       2
## 15              China 37.0       2
## 16             France 41.2       2
## 17            Germany 45.9       2
## 18              Italy 45.9       2
## 19              Japan 46.3       2
## 20             Russia 38.7       2
## 21              Spain 43.2       2
## 22     United Kingdom 40.2       2
## 23      United States 37.6       2
```

```
## track.popularity         loudness     danceability         liveness
##        56.298012        46.181401        40.188362        39.264202
##          valence      speechiness            tempo     acousticness
```

```
##        36.702339        31.893695        31.614387        27.126734
##   track.explicit              key             mode instrumentalness
##        21.803740        13.448384         8.021733         6.615569
```

```
## DT on age clusters error rate:  0.2618026
```

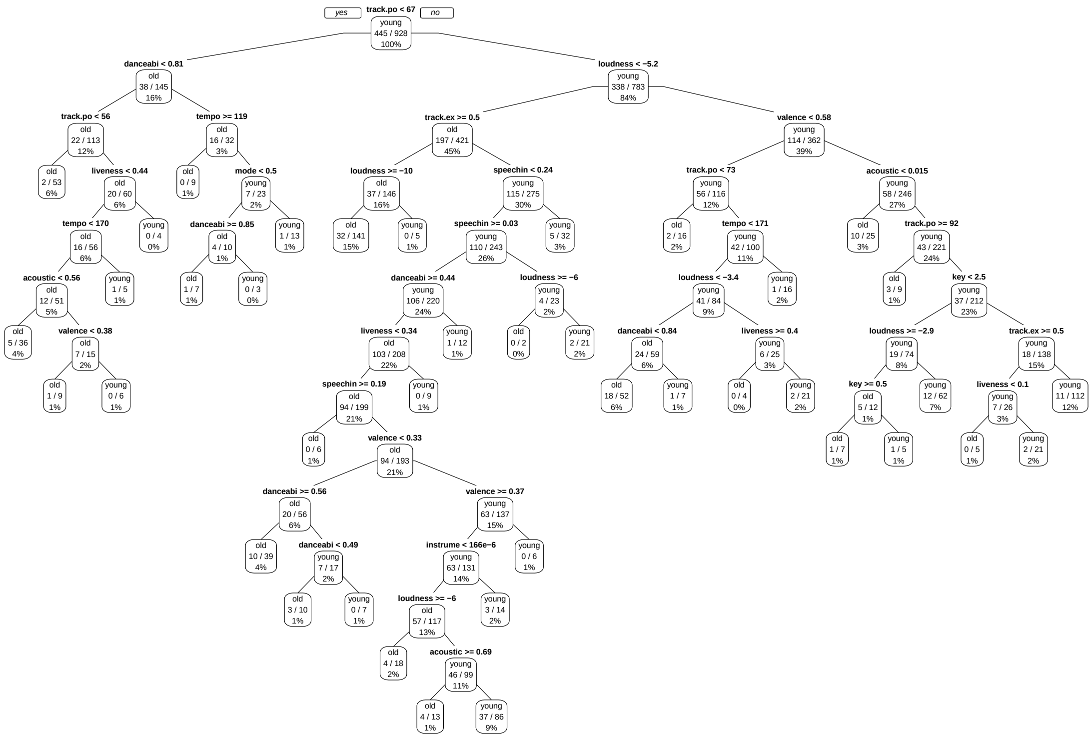


Figure 6. Classification of young and old countries.

Step 3B: interesting rules

1. If track popularity >= 70 (scale 0-100) and speechiness >= 0.046 (range 0.02-0.56 in our data), then people in the country are old.
2. If track popularity <70 then people in the country are young.
3. IF track popularity >70 and speechiness < 0.046 (extremely low), then people in the country are young.

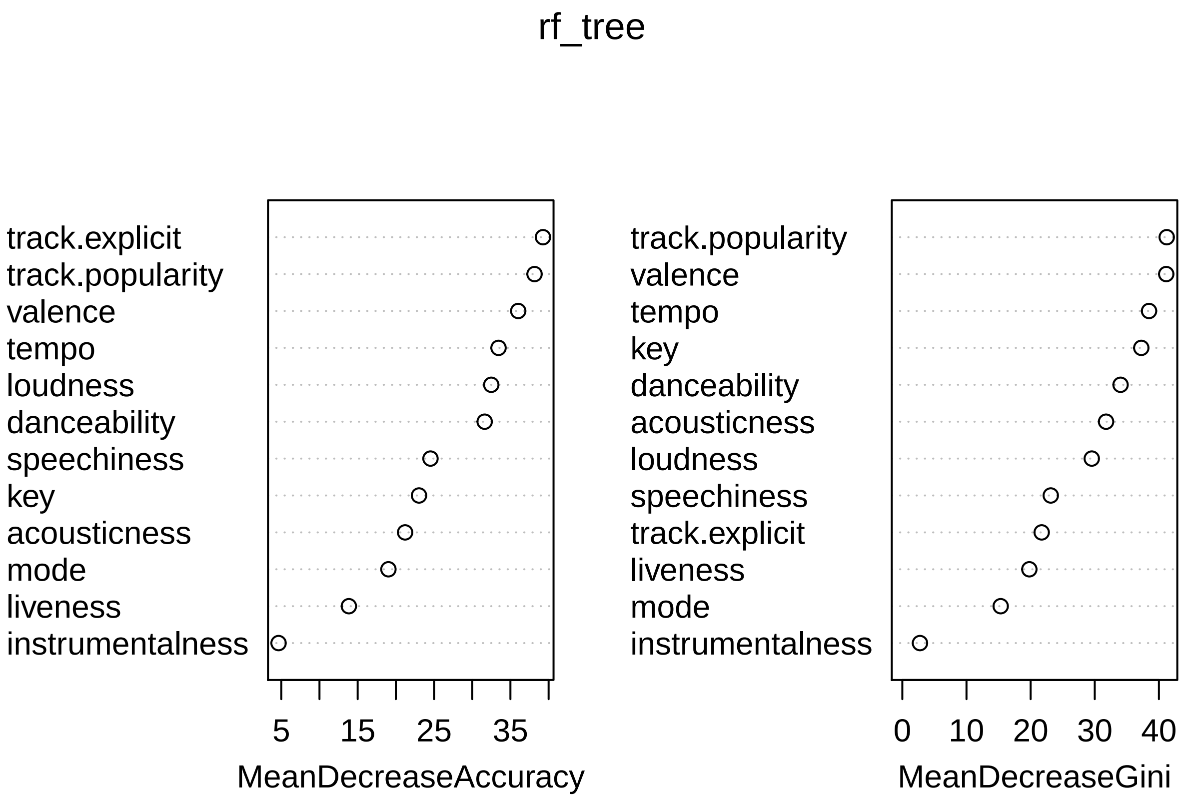
Step 4. Compare performance with Random Forest

```
## error rate of random forest:  0.3061371
```

```
##                         old     young MeanDecreaseAccuracy
## track.popularity 14.8610114 38.536835            38.156838
## track.explicit   26.1189837 28.218747            39.260859
## danceability      6.6209921 31.329210            31.627768
## key               0.3814949 25.155949            23.031012
## loudness         20.0696730 24.866302            32.488752
## mode              3.4348690 18.752703            19.025058
## speechiness       8.8587460 22.417634            24.533138
## acousticness      3.3322197 21.872132            21.210333
## instrumentalness  3.7132997  1.161682             4.643728
## liveness          7.5477464 10.266746            13.846465
## valence           7.3661636 33.532441            36.020983
## tempo             8.4027534 32.876324            33.443795
```

```
##                    MeanDecreaseGini
## track.popularity          41.219844
## track.explicit            21.723402
## danceability              34.020828
## key                       37.256145
## loudness                  29.532470
## mode                      15.334032
## speechiness               23.142324
## acousticness              31.761173
## instrumentalness           2.750786
## liveness                  19.798520
## valence                   41.143108
## tempo                     38.462655
```

```
##                           old        young MeanDecreaseAccuracy
## track.popularity 0.0205116475 0.0527427290         0.0371596379
## track.explicit   0.0403204628 0.0347164965         0.0373467459
## danceability     0.0095001035 0.0501888096         0.0305905640
## key              0.0005122247 0.0401616204         0.0210420559
## loudness         0.0308169769 0.0365875559         0.0337248980
## mode             0.0040735301 0.0235115733         0.0141087717
## speechiness      0.0079679666 0.0227406534         0.0155535272
## acousticness     0.0042688935 0.0271475209         0.0161161694
## instrumentalness 0.0011389665 0.0002532277         0.0006699091
## liveness         0.0061082189 0.0082612429         0.0072204467
## valence          0.0109830882 0.0678681232         0.0404535990
## tempo            0.0110016668 0.0502082969         0.0312828891
##                    MeanDecreaseGini
## track.popularity          41.219844
## track.explicit            21.723402
## danceability              34.020828
## key                       37.256145
## loudness                  29.532470
## mode                      15.334032
## speechiness               23.142324
## acousticness              31.761173
## instrumentalness           2.750786
## liveness                  19.798520
## valence                   41.143108
## tempo                     38.462655
```



How did Random Forest stack up against the decision tree?

With an error rate of ~.4, random forest performed *slightly* better than our single decision tree, which yielded an error rate of ~0.43. Surprisingly, variable importance changed: track.popularity is still most important, but speechiness is relatively unimportant in the random forest model; instead, the second most important variable here is whether music is explicit.