

Uncertain emotion discrimination differences between musicians and nonmusicians is determined by fine structure association: Hilbert transform psychophysics

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OSF: <https://osf.io/8ws7a>

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Abstract

We perceive musical sound as a complex phenomenon, which is known to induce an emotional response in humans. The cues used to perceive emotion in music have not been unequivocally elucidated. Here, we sought to identify the attributes of sound that confer an emotion to music and determine if professional musicians have different musical emotion perception than nonmusicians. The objective was to determine which sound cues are used to resolve emotional signals. Happy or sad classical music excerpts modified in fine structure or envelope conveyed different degrees of emotional certainty. The psychophysical emotional response of the modified excerpts was measure based on the originals. Certainty was determined by identification of the emotional characteristic presented during a forced-choice discrimination task. Participants were categorized as good or poor performers ($n = 32$, age 21.17 ± 2.63 SD) and in a separate group as musicians in the first or last year of music education at a conservatory ($n = 32$, age 21.97 ± 2.42). We found that temporal fine structure information is essential for correct emotional identification. Non-musically educated individuals used less fine structure information to discriminate emotion in music compared with musically educated individuals. The present psychophysical experiments revealed what cues are used to resolve emotional signals and how they differ between nonmusicians and musically educated individuals.

Code and Methods

The code for **figure 2** and **figure 4** can be found in `Final_figures.R`.

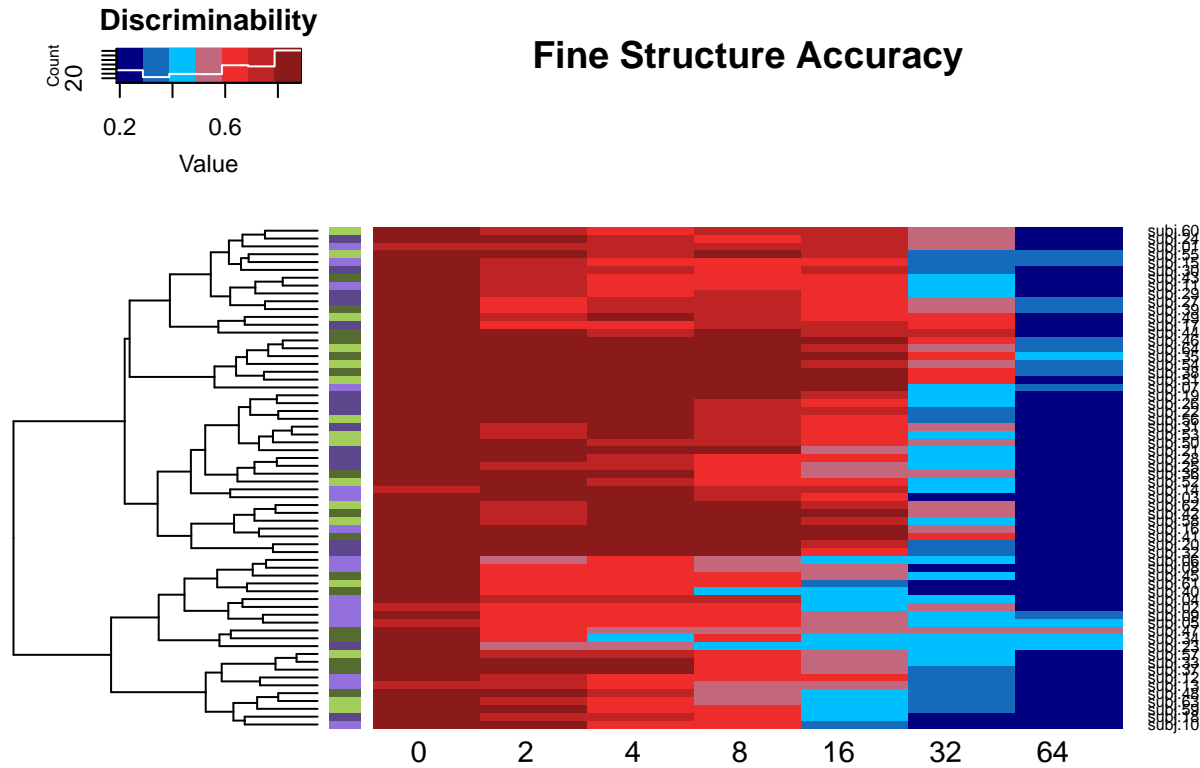
R 3.4.4, required packages

```
library(gplots)
library(gridExtra)
library(MASS)
library(pander)
library(magrittr)
library(dplyr)
library(ggplot2)
library(RCurl)
library(scatterplot3d)
library(klaR)
library(pander)
library(candisc)
```

Group Heatmaps

This was created calculating the accuracy of each subject per stimuli. First, stimuli were binarized based on the answer of **Fine structure emotion**, with 1 if is correct and 0 when wrong. The total was divided by the total amount of stimuli for each category (nb0...nb64).

Accuracy for both emotions: All subjects



Fine Structure Accuracy by Gender

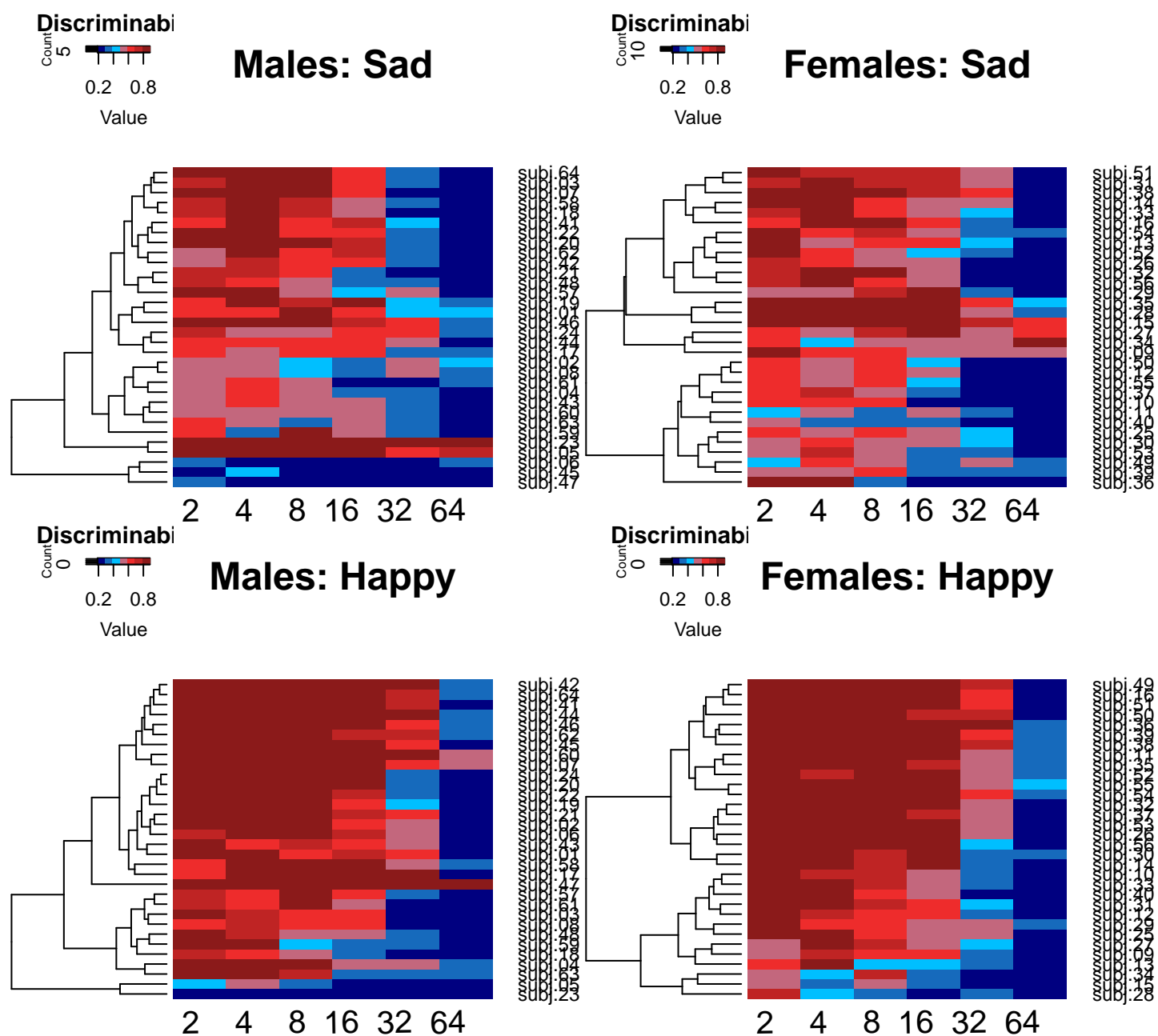
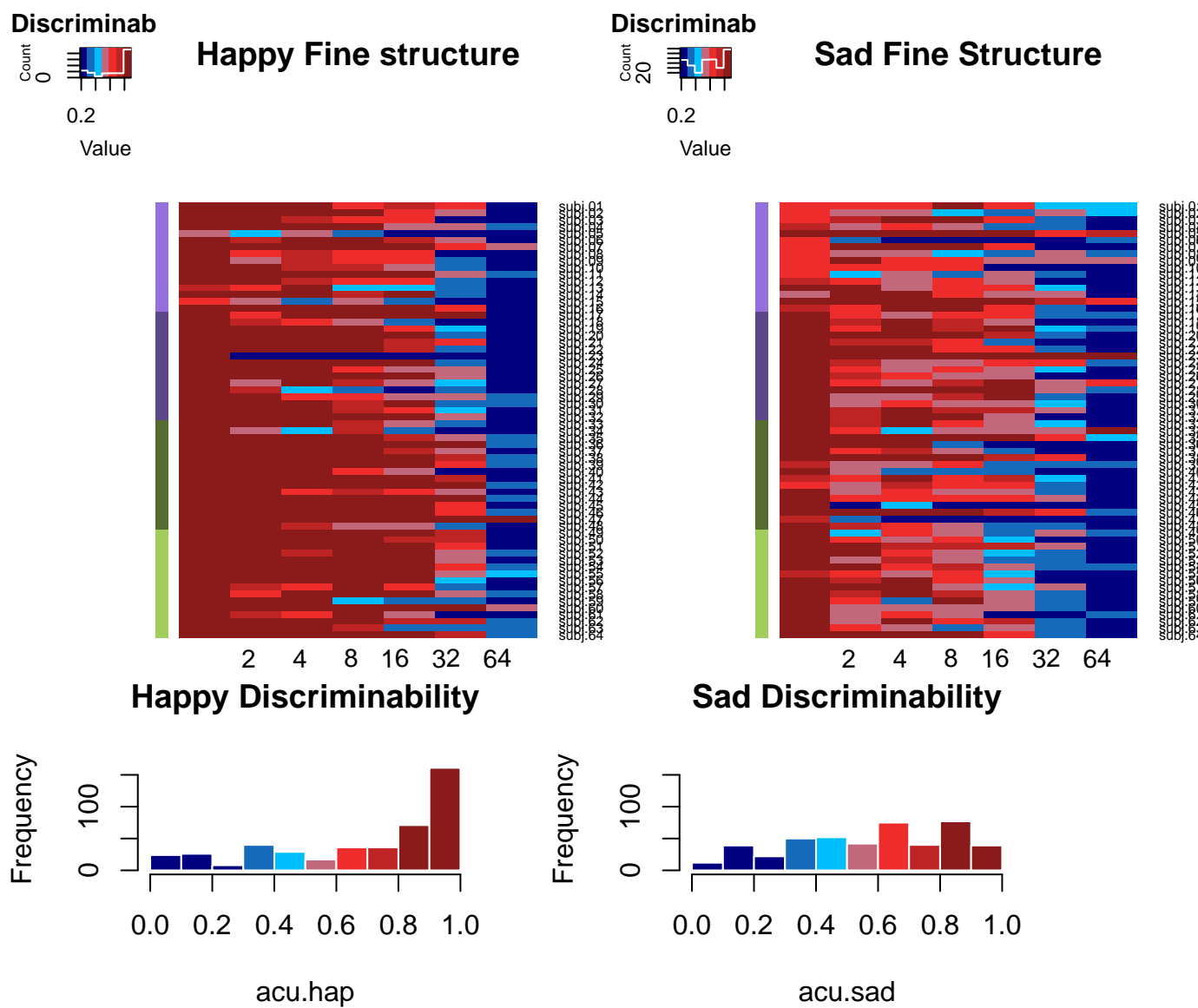
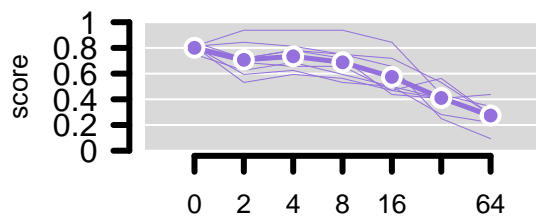


Figure 2. Accuracy and discriminability concerning Happy and Sad

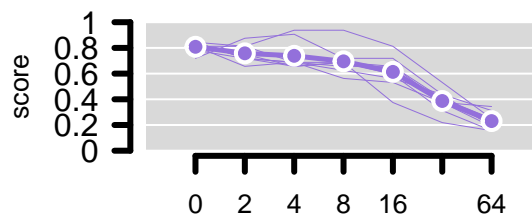


Accuracy calculated by subjects and group

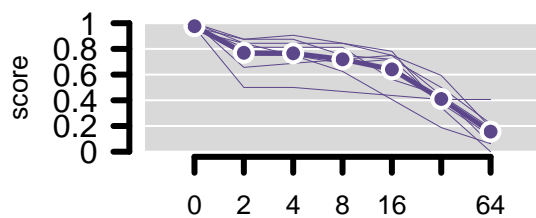
Poor Male



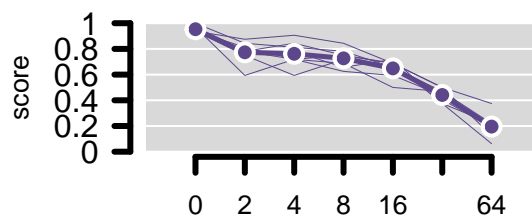
Poor Female



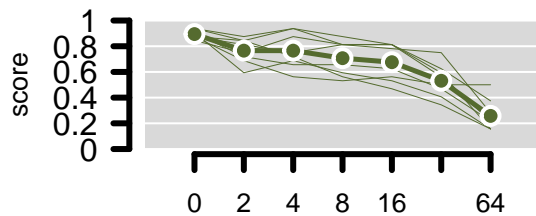
Good Male



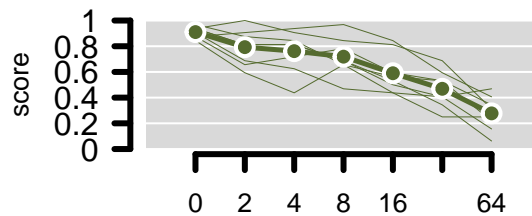
Good Female



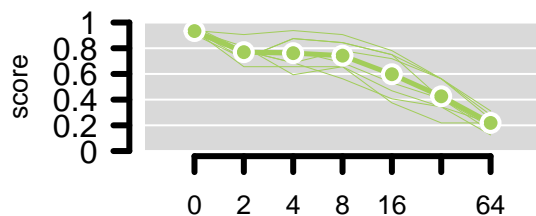
High Male



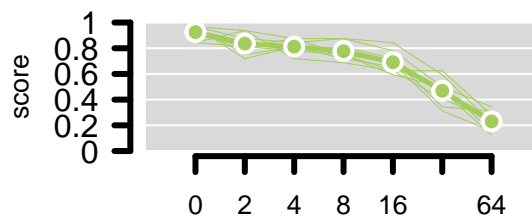
High Female



Low Male



Low Female



ANOVA: Comparisons between groups

Is accuracy in the response given by the class belonging and gender?

Table 1: ANOVA, accuracy by class

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
factor(cases\$class)	3	0.2268	0.0756	60.55	5.292e-18
factor(cases\$gender)	1	6.104e-05	6.104e-05	0.04888	0.8258
Residuals	59	0.07367	0.001249	NA	NA

- **factor(cases\$class):**

	diff	lwr	upr	p adj
high-best	-0.0625	-0.09553	-0.02947	3.147e-05
low-best	-0.03516	-0.06819	-0.002127	0.03271
poor-best	-0.1602	-0.1932	-0.1271	1.795e-11
low-high	0.02734	-0.005686	0.06037	0.1383
poor-high	-0.09766	-0.1307	-0.06463	6.858e-10
poor-low	-0.125	-0.158	-0.09197	1.813e-11

- **factor(cases\$gender):**

	diff	lwr	upr	p adj
M-F	0.001953	-0.01572	0.01963	0.8258

Linear Discriminant Analysis: Happy

$Groupb0 + nb2 + nb4 + nb8 + nb16 + nb32 + nb64$

best	high	low	poor
0.2031	0.1406	0.07812	0.125

Table 5: LDA happy: Observed vs. Predicted Frequencies

	best	high	low	poor	Sum
Predicted best	13	2	4	2	21
Predicted high	1	9	5	2	17
Predicted low	1	4	5	4	14
Predicted poor	1	1	2	8	12
Sum	16	16	16	16	64

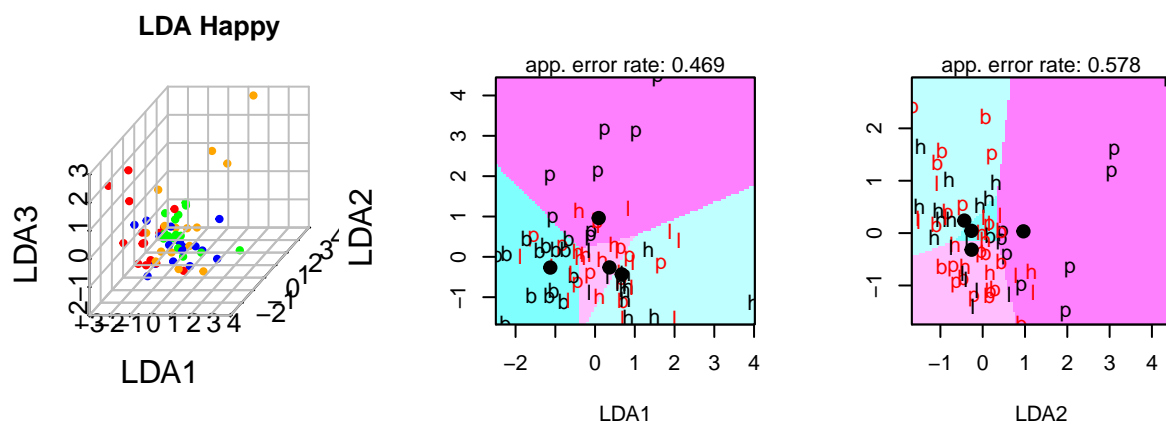
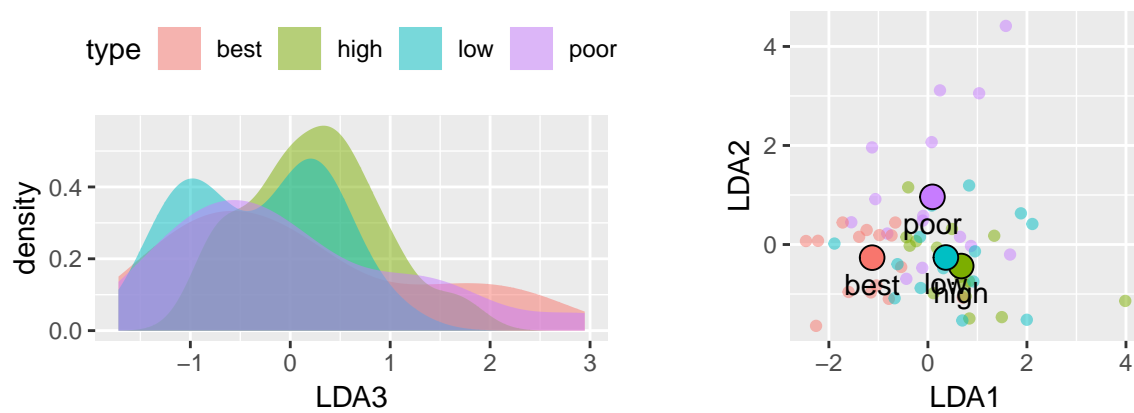
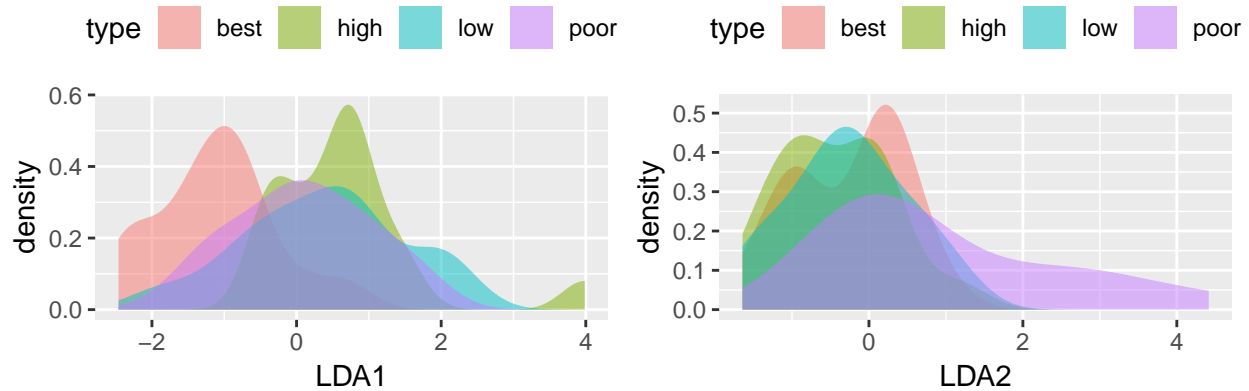
Happy total % correct: 0.546875

Table 6: LDA sad: Observed vs. Predicted Proportions %

	best	high	low	poor	Sum
Predicted best	0.2031	0.03125	0.0625	0.03125	0.3281
Predicted high	0.01562	0.1406	0.07812	0.03125	0.2656
Predicted low	0.01562	0.0625	0.07812	0.0625	0.2188
Predicted poor	0.01562	0.01562	0.03125	0.125	0.1875
Sum	0.25	0.25	0.25	0.25	1

Table 7: Happy: group means by LDA

type	LDA1	LDA2	LDA3
best	-1.126	-0.2657	0.04361
high	0.6722	-0.4348	0.2395
low	0.3626	-0.262	-0.317
poor	0.09148	0.9625	0.03394



Linear Discriminant Analysis: Sad

best	high	low	poor
0.1562	0.125	0.1562	0.2031

Table 9: LDA sad: Observed vs. Predicted Frequencies

	best	high	low	poor	Sum
Predicted best	10	0	1	2	13
Predicted high	2	8	4	0	14
Predicted low	4	4	10	1	19
Predicted poor	0	4	1	13	18
Sum	16	16	16	16	64

Sad total % correct: 0.640625

Table 10: LDA sad: Observed vs. Predicted Proportions %

	best	high	low	poor	Sum
Predicted best	0.1562	0	0.01562	0.03125	0.2031
Predicted high	0.03125	0.125	0.0625	0	0.2188
Predicted low	0.0625	0.0625	0.1562	0.01562	0.2969
Predicted poor	0	0.0625	0.01562	0.2031	0.2812
Sum	0.25	0.25	0.25	0.25	1

Table 11: Happy: group means by LDA

type	LDA1	LDA2	LDA3
best	-1.362	0.4542	0.1613
high	0.04957	-0.4957	0.3254
low	-0.6249	-0.2197	-0.4475
poor	1.937	0.2612	-0.03927

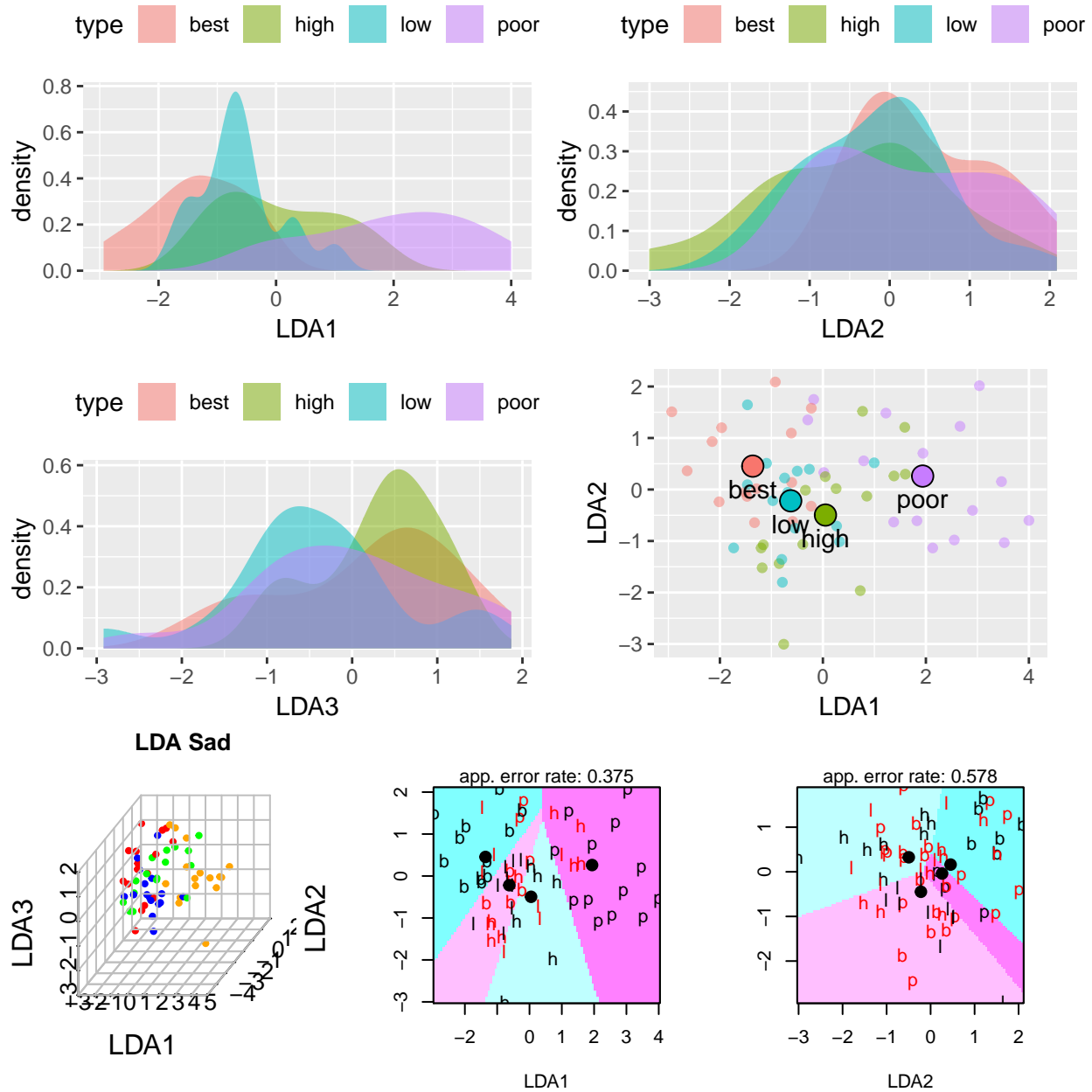


Figure 4. Cannonical Discriminant Analysis (CDA)

Two generalized canonical discriminant analysis was compute using the multivariate linear model:

$$\text{Group } nb0 + nb2 + nb4 + nb8 + nb16 + nb32 + nb64$$

to obtain the canonical scores and vectors, one for HAPPY and the other for SAD. It represents a transformation of the original variables in the scspace of maximal differences for the group. The biplot shows the canonical scores for the groups defined by the term as points and the canonical structure coefficients as vectors from the origin.

Standardized beta coefficients are given for each variable in each discriminant (canonical) function, and the larger the standardized coefficient, the greater is the contribution of the respective variable to the discrimination between groups. However, these coefficients do not tell us between which of the groups the respective functions discriminate.

Happy standardized coefficients

Table 12: Happy CDA standardized coefficients

	Can1	Can2	Can3
nb0	0.6264	0.7113	-0.3907
nb2	-0.1806	0.3608	0.1146
nb4	0.507	-0.6772	-0.4067
nb8	-0.5025	0.3103	-0.6578
nb16	-0.2266	-0.4923	-0.2479
nb32	-0.05239	0.7701	1.224
nb64	-0.7641	-0.08169	-0.24

Sad standardized coefficients

Table 13: Sad CDA standardized coefficients

	Can1	Can2	Can3
nb0	-1.011	-0.05111	0.04974
nb2	-0.01097	-0.1844	0.3217
nb4	0.2952	-0.4591	-0.4602
nb8	-0.08152	0.8909	1.472
nb16	-0.2719	0.5762	-1.304
nb32	0.06616	-0.4042	-0.1513
nb64	0.4193	0.4013	-0.2076

The discriminant function coefficients denote the unique contribution of each variable to the discriminant function, while the structure coefficients denote the simple correlations between the variables and the functions

