

# Team 5 Codebook - Baby Cry Project

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## Libraries:

```
library(tidyverse)
library(readxl)
library(dplyr)
library(ggplot2)
library(ggpubr)
library(janitor)
library(randomForest)
library(mice)
library(caret)
library(xgboost)
library(MLmetrics)
library(reshape2)
library(pROC)
library(factoextra)
library(e1071)
library(stats)
library(igraph)
library(kernlab)
library(dbSCAN)
library(knitr)
library(mclust)
library(cluster)
library(nnet)
library(GGally)
library(skimr)
```

```
full_data_odd <- read_csv("../Data/filtered_full_data_odd.csv")
```

Rows: 1250 Columns: 27

-- Column specification -----

Delimiter: ",",

chr (2): ParentFile, Filename

dbl (25): shimmerLocaldB\_sma3nz\_stddevNorm, loudness\_sma3\_percentile20.0, F3...

i Use `spec()` to retrieve the full column specification for this data.

i Specify the column types or set `show\_col\_types = FALSE` to quiet this message.

```
demographics <- read_csv("../Data/demographics_students.csv")
```

Rows: 2500 Columns: 6

-- Column specification -----

Delimiter: ","

chr (4): ID, Reason, Age, Gender

dbl (2): Date, sample

i Use `spec()` to retrieve the full column specification for this data.

i Specify the column types or set `show\_col\_types = FALSE` to quiet this message.

## Cleaning:

Find the groups of demographics dataset:

```
demographics %>%  
  group_by(Reason) %>%  
  summarise(count = n())
```

```
# A tibble: 5 x 2  
  Reason      count  
  <chr>      <int>  
1 Diaper-Change    500  
2 Fussy            500  
3 Hungry           500  
4 Pain             500  
5 Tired            500
```

I see some no email and no gender and no age. clean the demographics data

```
# demographics <- demographics %>%  
#   filter(ID != 'NO-EMAIL', Age != 'NO-AGE', Gender != 'NO-GENDER')  
#  
# demographics %>%  
#   group_by(Reason) %>%  
#   summarise(count = n())
```

```
full_data_odd %>%  
  group_by(ParentFile) %>%  
  summarise(count = n())
```

```
# A tibble: 5 x 2  
  ParentFile      count  
  <chr>          <int>  
1 gemaps_part_diaper.csv    250  
2 gemaps_part_fussy.csv    250  
3 gemaps_part_hungry.csv    250  
4 gemaps_part_pain.csv      250  
5 gemaps_part_tired.csv     250
```

```
demographics %>%  
  group_by(Reason) %>%  
  summarise(count = n())
```

```
# A tibble: 5 x 2
  Reason      count
  <chr>      <int>
1 Diaper-Change 500
2 Fussy         500
3 Hungry        500
4 Pain          500
5 Tired         500
```

Join the two datasets:

```
# # Filter out email and no email separately
# demographics_no_em <- demographics %>%
#   filter(ID == "NO-EMAIL")
# demographics_em <- demographics %>%
#   filter(ID != "NO-EMAIL")

# full_data_no_em <- full_data_odd %>%
#   filter(str_detect(Filename, "^NO-EMAIL"))
# full_data_em <- full_data_odd %>%
#   filter(!str_detect(Filename, "^NO-EMAIL"))

# For the email, join by ID
full_data_mod <- full_data_odd %>%
  #mutate(ID = str_split(Filename, "_")[1]) %>%
  separate(Filename, into = paste0("Comp", 1:8), sep = "_") %>%
  relocate(paste0("Comp", 1:8), .before = ParentFile) %>%
  rename(ID = `Comp1`, Reason = Comp2, Age = Comp3, Gender = Comp4, Date = Comp5, Sample = Comp6)
  ↪ %>%
  select(-Comp7, -Comp8)

# join_em <- left_join(full_data_em, demographics_em)

# For the no email, join by the sample ID plus date

# write_csv(full_data_mod, "full_data_mod.csv")
```

## Question 1: EDA

```
# reading in data
full_data_odd <- read.csv("../Data/filtered_full_data_odd.csv", header = TRUE)
demographics <- read.csv("../Data/demographics_students.csv", header = TRUE)
```

```
# analyze rows
head(demographics)
```

	ID	Reason	Age	Gender	Date
1	bfb4662ea7ea4b8468d74c7ad1909ef1	Diaper-Change	49	female	181002
2	79eb1cf511da7ca57dd1996f0e0dca9e	Diaper-Change	122	female	210811
3	1bb7c3a247deb74ec63b50048d97295b	Diaper-Change	NO-AGE	male	210609

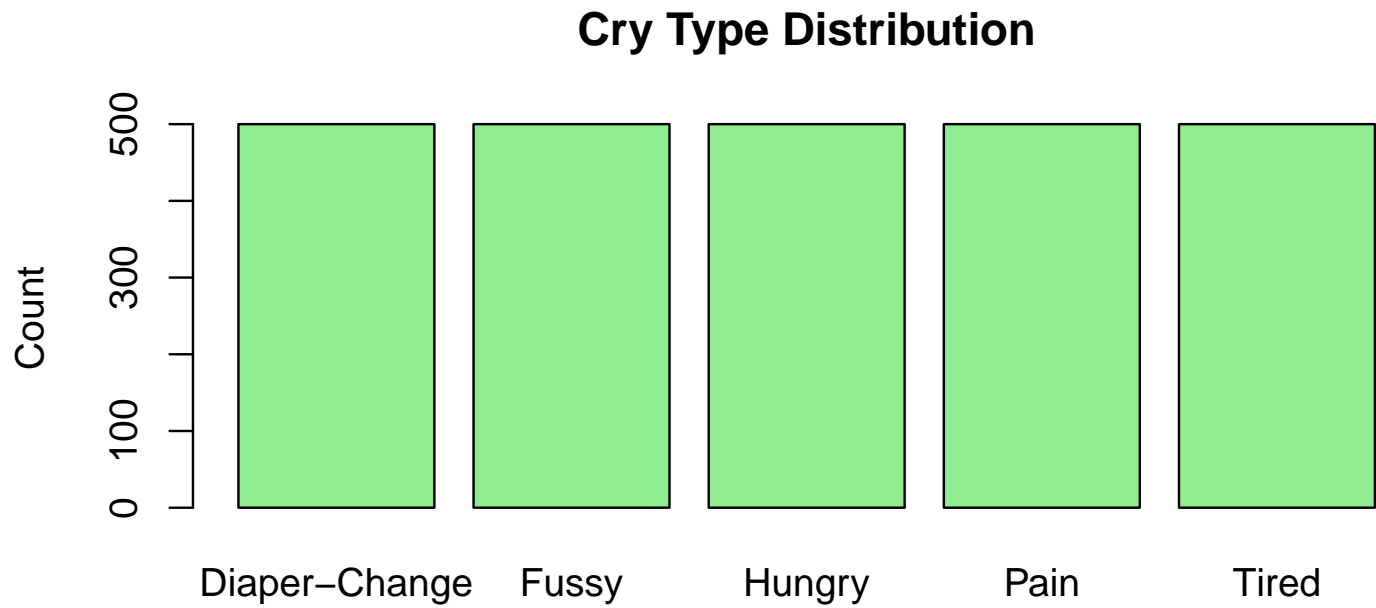
```
4 aefc074bf9d634beeb762f45600060b7 Diaper-Change NO-AGE female 220223
5 NO-EMAIL Diaper-Change NO-AGE NO-GENDER 181223
6 5c78e65a7f0c779bc56ef188171ec829 Diaper-Change 241 female 180810
sample
1 340074
2 1099184
3 1048016
4 1306174
5 402716
6 283764
```

Reason Distribution Bar Plot

```
# see how the distributions stack up
table(demographics$Reason)
```

Diaper-Change	Fussy	Hungry	Pain	Tired
500	500	500	500	500

```
barplot(table(demographics$Reason),
  col = "lightgreen",
  main = "Cry Type Distribution",
  ylab = "Count")
```

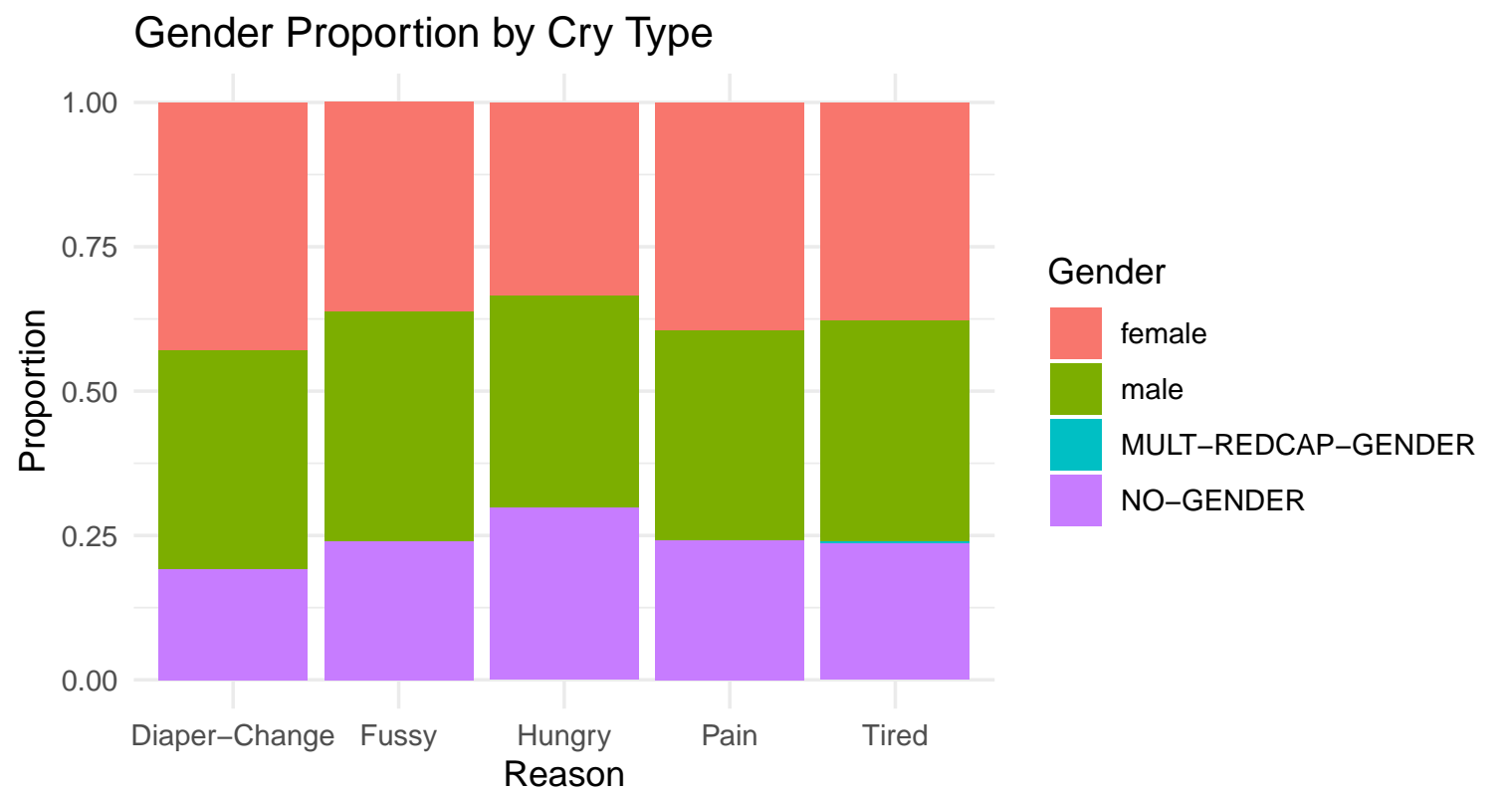


## Reason with Gender Proportion

```
# see how the reasons vary with gender
table(demographics$Gender, demographics$Reason)
```

	Diaper-Change	Fussy	Hungry	Pain	Tired
female	215	181	167	198	189
male	189	199	184	181	191
MULT-REDCAP-GENDER	0	0	0	0	2
NO-GENDER	96	120	149	121	118

```
library(ggplot2)
ggplot(demographics, aes(x = Reason, fill = Gender)) +
  geom_bar(position = "fill") +
  labs(title = "Gender Proportion by Cry Type", y = "Proportion") +
  theme_minimal()
```



## Chi-Square

```
# chi square test between gender and reason
chisq.test(table(demographics$Gender, demographics$Reason))
```

Warning in stats::chisq.test(x, y, ...): Chi-squared approximation may be incorrect

Pearson's Chi-squared test

```
data: table(demographics$Gender, demographics$Reason)
X-squared = 27.608, df = 12, p-value = 0.00631
```

## ANOVA w/ removed missing ages

```
# anova between age and reason
# convert missing ages to NA
demographics$Age[demographics$Age == "NO-AGE"] <- NA
demographics$Age <- as.numeric(demographics$Age)
```

Warning: NAs introduced by coercion

```
anova_result <- aov(Age ~ Reason, data = demographics)
summary(anova_result)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Reason	4	3832052	958013	3.648	0.00575 **
Residuals	1761	462429901	262595		

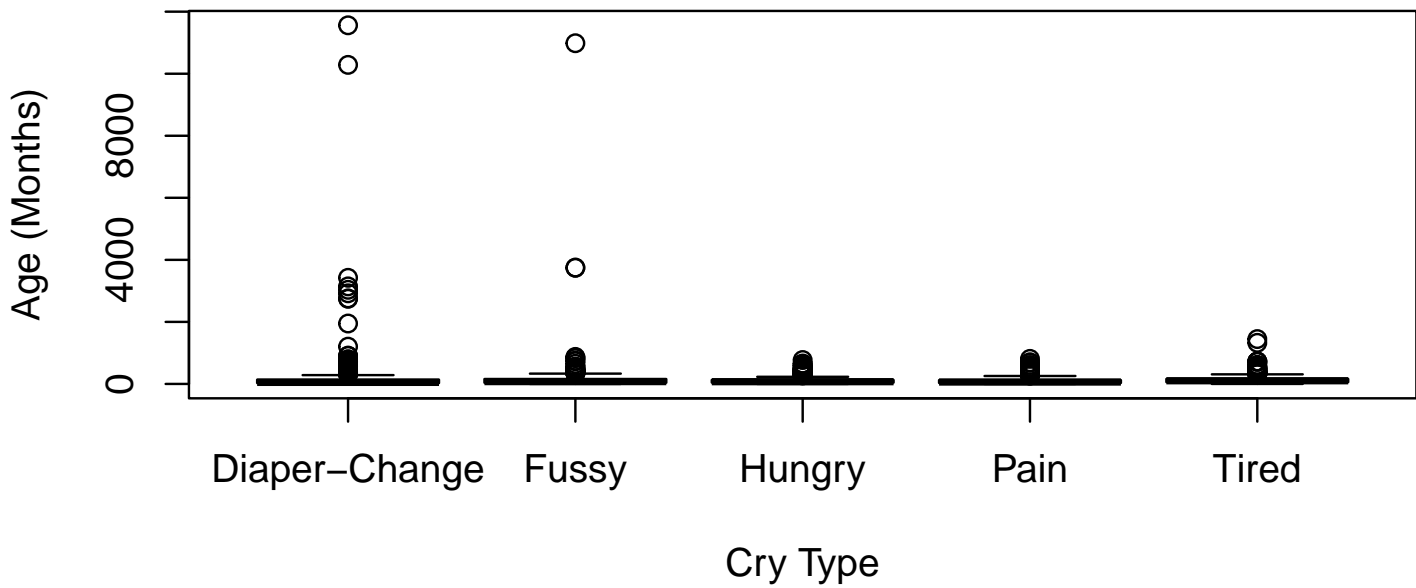
---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

734 observations deleted due to missingness

```
# visually see age by reason
boxplot(Age ~ Reason, data = demographics,
        main = "Age Distribution by Cry Type",
        xlab = "Cry Type",
        ylab = "Age (Months)",
        col = "lightgreen")
```

## Age Distribution by Cry Type

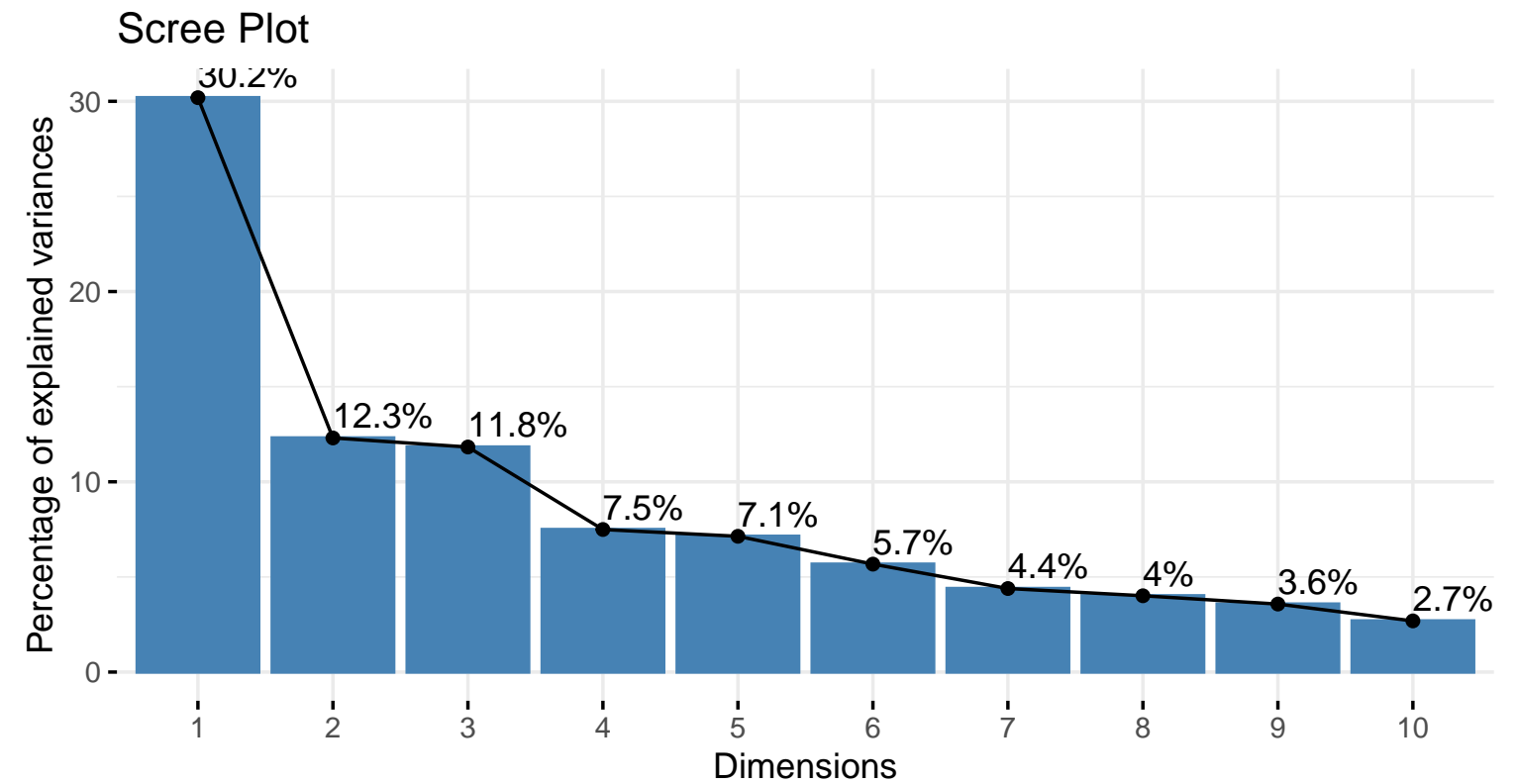


## Scree Plot by Cry Acoustics Dimensions

```
# see how the acoustic features measure
library(factoextra)
# get numeric only
acoustic_features <- full_data_odd %>%
  select(where(is.numeric)) %>%
  na.omit()

#scale for scree plot
scaled_features <- scale(acoustic_features)
pca <- prcomp(scaled_features, center = TRUE, scale. = TRUE)

# plot the scree plot
fviz_eig(pca, addlabels = TRUE, barfill = "steelblue") +
  labs(title = "Scree Plot")
```



### Summary Statistics

```
data6 <- read.csv("full_data_cleaned_without_nas.csv", header=TRUE) #loading data
data <- data6

# Summary stats variables
skim(data6)
```

Table 1: Data summary

Name	data6
Number of rows	868
Number of columns	33
Column type frequency:	
character	4
numeric	29
Group variables	None

### Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
ID	0	1	32	32	0	822	0
Reason	0	1	4	13	0	5	0
Gender	0	1	4	6	0	2	0
ParentFile	0	1	4	6	0	5	0



## Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
newID	0	1	620.69	361.92	1.00	309.50	618.00	941.25	1250.00	
Age	0	1	173.88	689.98	-1.00	37.00	73.50	139.00	11561.00	
Date	0	1	189951.12	3503.70	180516.00	180628.00	180825.50	195667.75	220307.00	
Sample	0	1	471968.45	108597.23	14262.00	153291.75	305825.00	667055.75	1321011.00	
shimmerLocaldB_sma3nz_stddevNorm	0	1	0.74	0.23	0.00	0.59	0.72	0.88	1.76	
loudness_sma3_percentile20.0	0	1	0.31	0.26	0.01	0.13	0.23	0.43	2.63	
F3amplitudeLogRelF0_sma3nz_amean	0	1	-96.11	41.59	-	-	-89.53	-65.08	-4.44	
					201.00	125.00				
loudness_sma3_percentile50.0	0	1	0.85	0.62	0.02	0.35	0.71	1.20	3.74	
loudness_sma3_amean	0	1	0.98	0.53	0.07	0.55	0.92	1.30	3.35	
F2amplitudeLogRelF0_sma3nz_amean	0	1	-94.68	42.17	-	-	-88.53	-63.58	-0.75	
					201.00	124.14				
F3amplitudeLogRelF0_sma3nz_stddevNorm	1	1	-1.11	0.79	-15.33	-1.33	-1.02	-0.72	0.00	
MeanUnvoicedSegmentLength	0	1	0.33	0.38	0.03	0.16	0.23	0.38	4.93	
F2amplitudeLogRelF0_sma3nz_stddevNorm	1	1	-1.26	3.27	-95.48	-1.40	-1.06	-0.74	0.00	
F0semitoneFrom27.5Hz_sma3nz_percentile80.0	1	1	49.94	4.40	0.00	47.77	49.63	51.64	62.20	
F1amplitudeLogRelF0_sma3nz_amean	1	1	-	44.14	-	-	-	-71.78	-12.54	
			105.95		201.00	140.67	100.39			
F0semitoneFrom27.5Hz_sma3nz_percentile0.2	1	1	6.75	6.53	0.00	3.11	4.67	7.96	47.69	
alphaRatioV_sma3nz_stddevNorm	0	1	1.24	80.10	-	-1.34	0.34	1.57	2138.09	
					725.55					
StddevUnvoicedSegmentLength	0	1	0.27	0.24	0.00	0.11	0.19	0.33	1.86	
loudness_sma3_stddevNorm	0	1	0.76	0.25	0.25	0.59	0.72	0.87	1.98	
loudness_sma3_percentile80.0	0	1	1.62	0.89	0.10	0.88	1.56	2.18	5.22	
shimmerLocaldB_sma3nz_amean	0	1	1.05	0.34	0.00	0.80	1.01	1.25	2.58	
F0semitoneFrom27.5Hz_sma3nz_stddevNorm	1	1	0.11	0.08	0.00	0.06	0.09	0.13	0.68	
F0semitoneFrom27.5Hz_sma3nz_percentile50.0	1	1	47.26	4.46	0.00	45.66	47.52	49.20	59.41	
HNRdBACF_sma3nz_amean	0	1	7.72	3.12	-2.41	5.59	7.85	9.93	16.11	
slopeV500.1500_sma3nz_amean	0	1	0.00	0.01	-0.04	-0.01	0.00	0.01	0.05	
loudness_sma3_meanRisingSlope	0	1	7.96	5.34	-1.54	4.03	6.87	10.52	34.88	
alphaRatioV_sma3nz_amean	0	1	0.36	8.08	-27.30	-5.38	0.22	5.71	24.36	
F0semitoneFrom27.5Hz_sma3nz_percentile20.0	1	1	43.19	6.94	0.00	41.92	44.81	46.79	56.82	
F1amplitudeLogRelF0_sma3nz_stddevNorm	1	1	-1.05	0.58	-5.03	-1.32	-0.98	-0.65	0.00	

## Histogram of Features

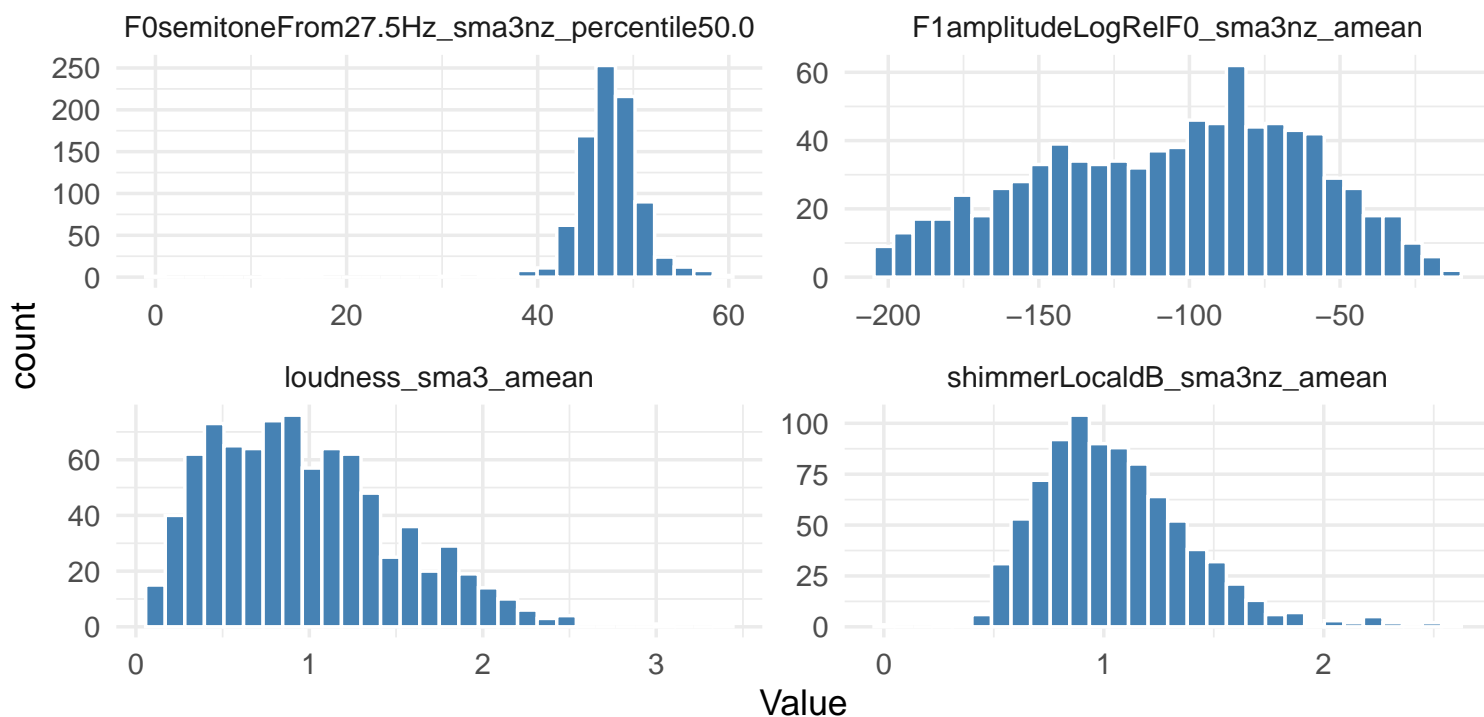
```
# Histograms of some acoustic features
acoustic_subset <- data6 %>%
  select(loudness_sma3_amean,
         F0semitoneFrom27.5Hz_sma3nz_percentile50.0,
         shimmerLocaldB_sma3nz_amean,
         F1amplitudeLogRelF0_sma3nz_amean)

# histogram setup
acoustic_long <- acoustic_subset %>%
  pivot_longer(everything(), names_to = "Feature", values_to = "Value")

# create histograms
ggplot(acoustic_long, aes(x = Value)) +
```

```
geom_histogram(bins = 30, fill = "steelblue", color = "white") +
facet_wrap(~ Feature, scales = "free", ncol = 2) +
theme_minimal() +
labs(title = "Distribution of Selected Acoustic Features")
```

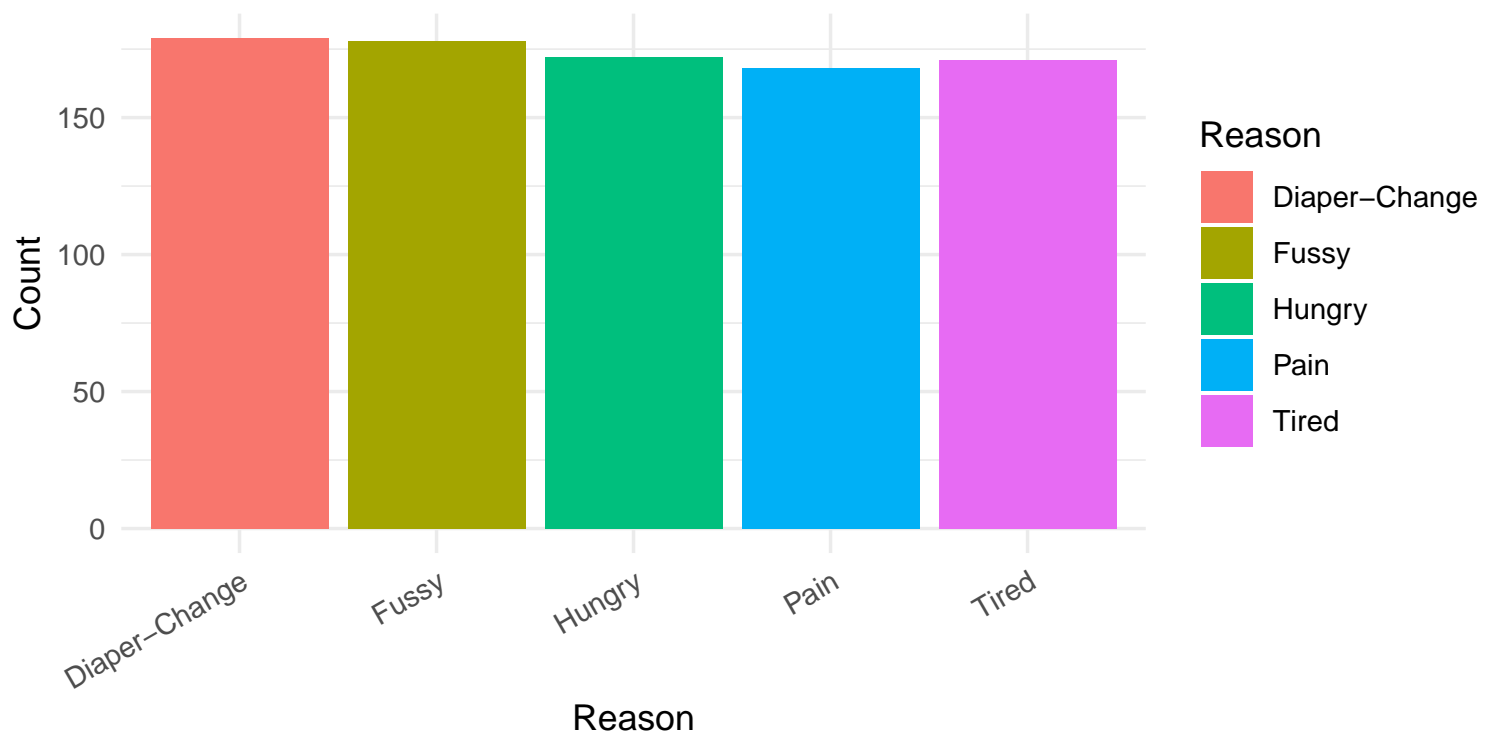
## Distribution of Selected Acoustic Features



## Distribution After Cleaning Data:

```
# eda: dist after cleaing data
ggplot(data6, aes(x = Reason, fill = Reason)) +
geom_bar() +
theme_minimal() +
labs(title = "Distribution of Parent-Labeled Cry Reasons", x = "Reason", y = "Count") +
theme(axis.text.x = element_text(angle = 30, hjust = 1))
```

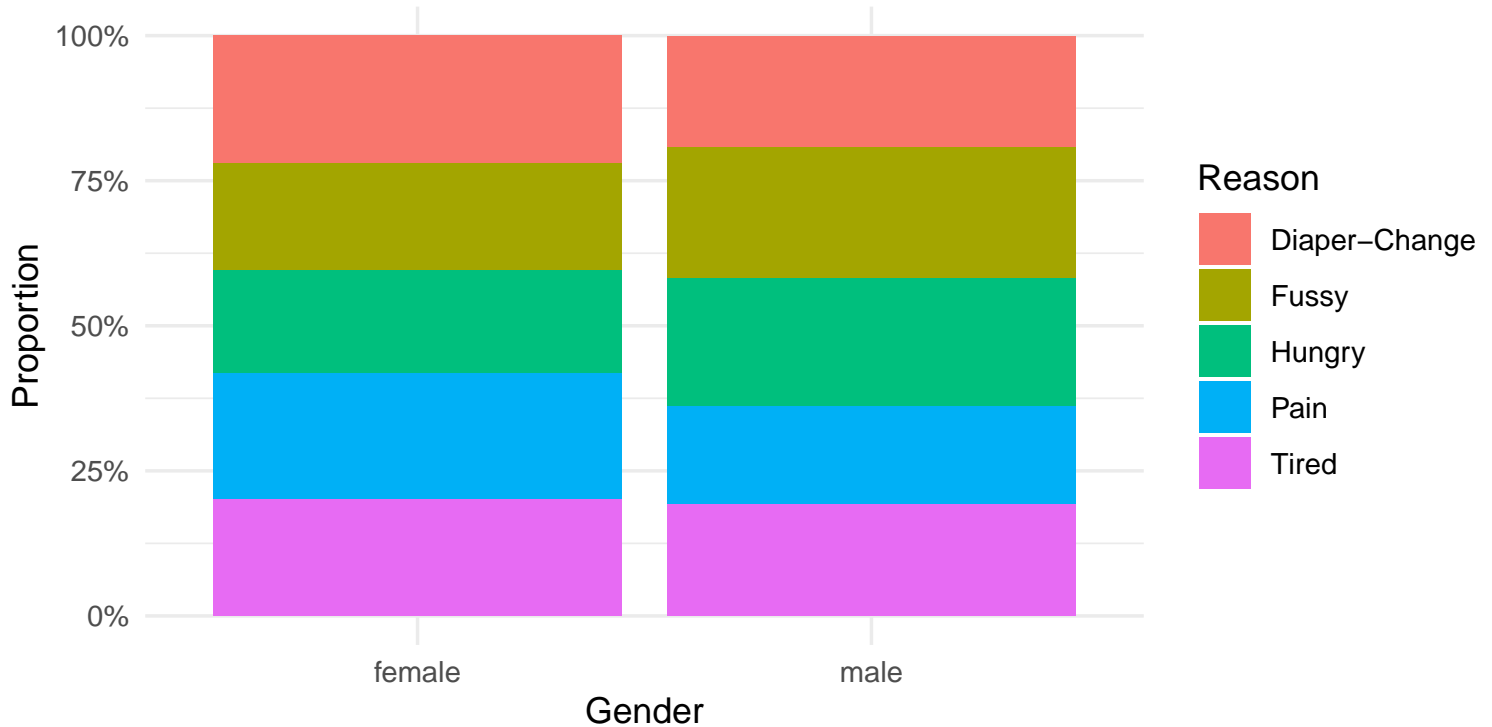
## Distribution of Parent-Labelled Cry Reasons



## Reason by Gender Plot

```
# reason by gender plot
ggplot(data6, aes(x = Gender, fill = Reason)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(title = "Cry Reasons by Gender (Proportion)", y = "Proportion") +
  theme_minimal()
```

## Cry Reasons by Gender (Proportion)



## PCA Components

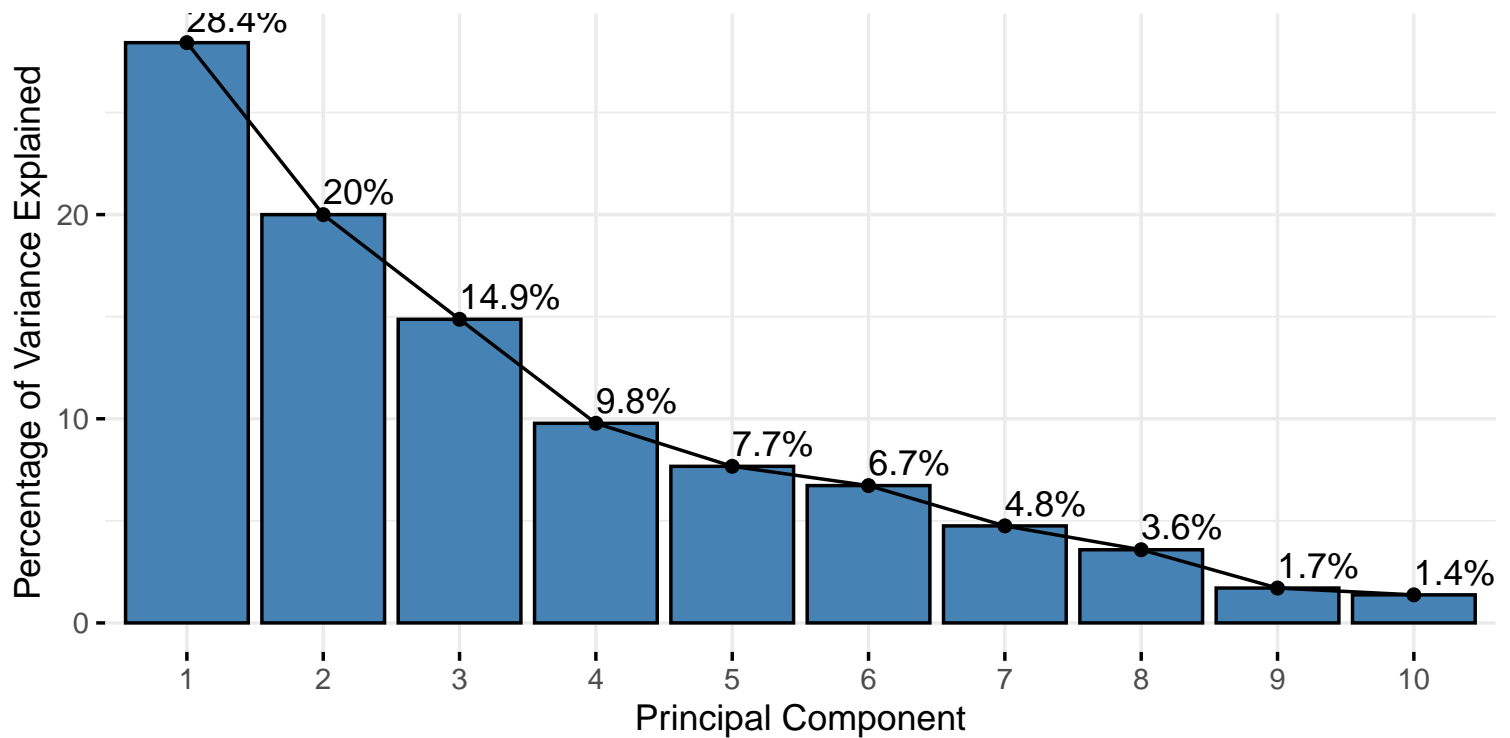
```
pca_data <- data %>% # obtain pca data for narrowing variables
  select(starts_with("shimmer"),
         starts_with("F0"),
         starts_with("alpha"),
         starts_with("F1"),
         starts_with("F2")) %>%
  na.omit()

scaled_pca_data <- scale(pca_data) # scaling data

pca <- prcomp(scaled_pca_data, center = TRUE, scale. = TRUE)

# plot the pca
fviz_eig(pca,
         addlabels = TRUE,
         barfill = "steelblue",
         barcolor = "black") +
  labs(title = "Scree Plot: Variance Explained by Principal Components",
       x = "Principal Component",
       y = "Percentage of Variance Explained")
```

# Scree Plot: Variance Explained by Principal Components



```
head(pca$rotation)
```

	PC1	PC2	PC3
shimmerLocaldB_sma3nz_stddevNorm	0.14060167	-0.2277505	0.1181830
shimmerLocaldB_sma3nz_amean	-0.19888243	0.2829413	-0.2517309
F0semitoneFrom27.5Hz_sma3nz_percentile80.0	0.08453555	0.3675123	-0.4520854
F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	-0.31991083	-0.1730493	-0.4920759
F0semitoneFrom27.5Hz_sma3nz_stddevNorm	-0.33579359	-0.2221301	-0.3931566
F0semitoneFrom27.5Hz_sma3nz_percentile50.0	0.19478719	0.4187253	-0.2476559
	PC4	PC5	PC6
shimmerLocaldB_sma3nz_stddevNorm	0.6113230	-0.078572404	-0.154634749
shimmerLocaldB_sma3nz_amean	-0.4048324	0.009026781	0.155641722
F0semitoneFrom27.5Hz_sma3nz_percentile80.0	0.3462639	-0.047279228	0.052364008
F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	0.1456982	-0.030310265	0.025561808
F0semitoneFrom27.5Hz_sma3nz_stddevNorm	0.1045340	-0.012357769	0.006258527
F0semitoneFrom27.5Hz_sma3nz_percentile50.0	0.3490690	-0.034529828	0.038692272
	PC7	PC8	PC9
shimmerLocaldB_sma3nz_stddevNorm	-0.41584646	0.57751810	0.05605189
shimmerLocaldB_sma3nz_amean	0.13664452	0.77599034	0.05747031
F0semitoneFrom27.5Hz_sma3nz_percentile80.0	0.10803950	-0.04580176	-0.21182055
F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	-0.04104088	-0.10468064	0.34650253
F0semitoneFrom27.5Hz_sma3nz_stddevNorm	-0.10110678	-0.04419690	-0.65588479
F0semitoneFrom27.5Hz_sma3nz_percentile50.0	0.15347305	-0.11672533	0.38471018
	PC10	PC11	
shimmerLocaldB_sma3nz_stddevNorm	0.003899279	0.01308935	
shimmerLocaldB_sma3nz_amean	-0.063155752	-0.02233004	
F0semitoneFrom27.5Hz_sma3nz_percentile80.0	0.538763936	0.03771055	
F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	0.280639918	-0.06396673	
F0semitoneFrom27.5Hz_sma3nz_stddevNorm	-0.450214466	0.16147718	
F0semitoneFrom27.5Hz_sma3nz_percentile50.0	-0.644141475	-0.02395427	

	PC12	PC13
shimmerLocaldB_sma3nz_stddevNorm	-0.028435276	1.570508e-08
shimmerLocaldB_sma3nz_amean	-0.014266926	2.495110e-08
F0semitoneFrom27.5Hz_sma3nz_percentile80.0	0.049052825	4.192829e-01
F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	0.002301818	-6.222620e-01
F0semitoneFrom27.5Hz_sma3nz_stddevNorm	0.032875355	-1.672766e-08
F0semitoneFrom27.5Hz_sma3nz_percentile50.0	0.013501964	2.981236e-08

## Question 2: Unsupervised learning

### K-means Clustering Attempt 1

```
data <- read.csv("./full_data_cleaned_without_nas.csv", header=TRUE) #loading data
data2 <- data
data2$Reason <- as.factor(data$Reason) # factor data

set.seed(333) # set up training data
trainIndex <- createDataPartition(data2$Reason, p = 0.8, list = FALSE)
trainData <- data2[trainIndex, ]
testData <- data2[-trainIndex, ]

ctrl <- trainControl(method = "cv", number = 10, verboseIter = FALSE)
```

```
# tart fresh
data5 <- data

# only acoustic data
acoustic_numeric <- data5 %>%
  select(where(is.numeric))

# Scale the features
acoustic_scaled <- scale(acoustic_numeric)

#k-means clustering (k=5)
set.seed(123)
k <- 5
kmeans_res <- kmeans(acoustic_scaled, centers = k, nstart = 25)

# add cluster labels to data5
data5$Cluster <- factor(kmeans_res$cluster)

#print results
table(Cluster = data5$Cluster, Reason = data5$Reason)
```

	Reason					
Cluster	Diaper-Change	Fussy	Hungry	Pain	Tired	
1	45	22	50	56	28	
2	45	34	76	47	61	
3	48	70	41	28	40	
4	9	8	5	7	7	
5	32	44	0	30	35	

```

data5$Cluster <- factor(data5$Cluster) # facotr data

#prepare dataset for classification
dataset_for_cluster_pred <- data5 %>%
  select(-Reason, -Gender, -Age, -newID, -Date, -Sample) # keep acoustic + Cluster

# 10-fold cross-validation
set.seed(123)
ctrl <- trainControl(method = "cv", number = 10, verboseIter = FALSE)

# rando forest to predict clusters from features
invisible(capture.output({
  suppressMessages({
    suppressWarnings({
      cluster_pred_model <- train(
        Cluster ~ .,
        data = dataset_for_cluster_pred,
        method = "rf",
        trControl = ctrl
      )
    })
  })
}))

# CV accuracy for predicting clusters
mean(cluster_pred_model$resample$Accuracy)

```

```
[1] 0.7799013
```

## K means Clustering w/ PCA

```

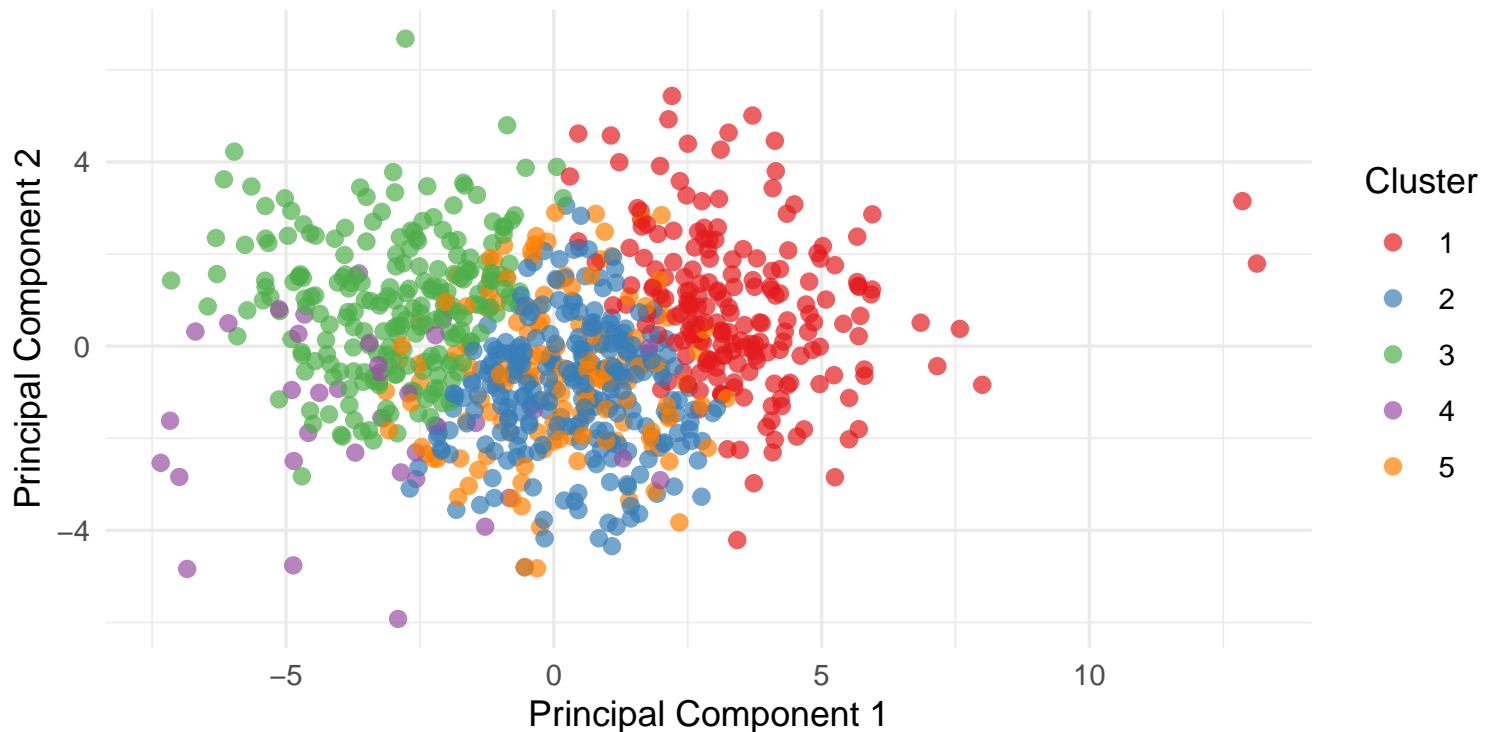
# PCA
pca_kmeans <- prcomp(acoustic_scaled)

# fist two PCs
pca_df <- as.data.frame(pca_kmeans$x[, 1:2])
pca_df$Cluster <- factor(data5$Cluster)

# Plot
ggplot(pca_df, aes(x = PC1, y = PC2, color = Cluster)) +
  geom_point(alpha = 0.7, size = 2) +
  labs(title = "K-means Clustering of Baby Cries (PCA Projection)",
       x = "Principal Component 1",
       y = "Principal Component 2") +
  theme_minimal() +
  scale_color_brewer(palette = "Set1")

```

## K-means Clustering of Baby Cries (PCA Projection)



```
# table for prediciting clusters
table(Cluster = data5$Cluster, Reason = data5$Reason)
```

	Reason				
Cluster	Diaper-Change	Fussy	Hungry	Pain	Tired
1	45	22	50	56	28
2	45	34	76	47	61
3	48	70	41	28	40
4	9	8	5	7	7
5	32	44	0	30	35

```
data7 <- data
# ACOUSTIC ONLY AGAIN
acoustic_only2 <- data7 %>%
  select(-Reason, -Gender, -Age, -newID, -ID, -Date, -Sample, -ParentFile)

acoustic_scaled <- scale(acoustic_only2)

# K-means clustering
set.seed(123)
kmeans_model <- kmeans(acoustic_scaled, centers = 5, nstart = 25)

# Add cluster labels
data7$Cluster <- as.factor(kmeans_model$cluster)
```

```
set.seed(123)

ctrl <- trainControl(method = "cv", number = 10, verboseIter = FALSE)
```



```
# RF model using only Cluster to predict Reason
invisible(capture.output({
  suppressMessages({
    suppressWarnings({
      rf_cluster_model <- train(
        Reason ~ Cluster,
        data = data7,
        method = "rf",
        trControl = ctrl
      )
    })
  })
}))

# average cross-validated accuracy
mean(rf_cluster_model$resample$Accuracy)
```

```
[1] 0.2499599
```

```
# table for results
table_cluster_reason <- table(data7$Cluster, data7$Reason)
table_cluster_reason
```

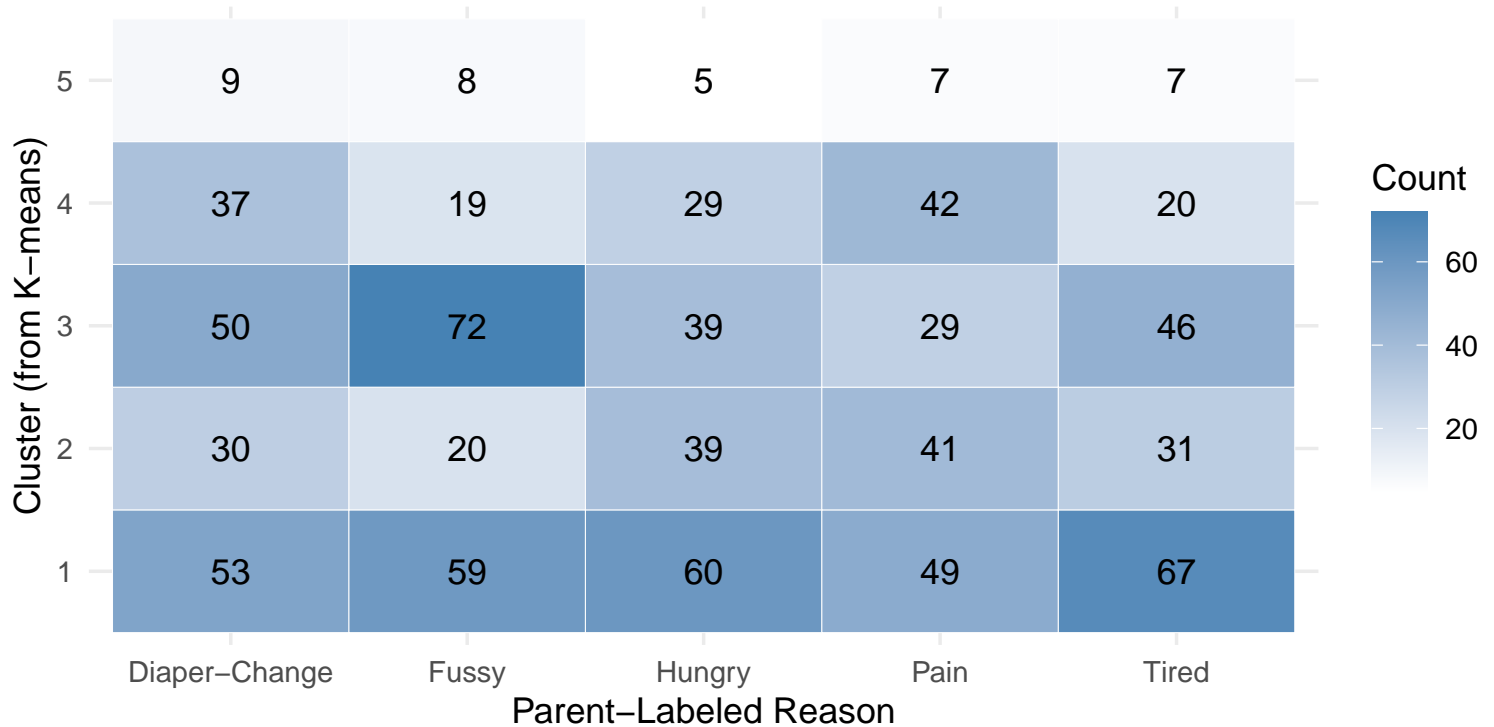
	Diaper-Change	Fussy	Hungry	Pain	Tired
1	53	59	60	49	67
2	30	20	39	41	31
3	50	72	39	29	46
4	37	19	29	42	20
5	9	8	5	7	7

```
# Convert to data frame for plotting

conf_df <- as.data.frame(table_cluster_reason)
colnames(conf_df) <- c("Cluster", "Reason", "Count")

ggplot(conf_df, aes(x = Reason, y = Cluster, fill = Count)) +
  geom_tile(color = "white") +
  geom_text(aes(label = Count), color = "black", size = 4) +
  scale_fill_gradient(low = "white", high = "steelblue") +
  labs(title = "Cluster vs Reason Heatmap",
       x = "Parent-Labeled Reason",
       y = "Cluster (from K-means)") +
  theme_minimal()
```

## Cluster vs Reason Heatmap



```
# Create a contingency table
table(data7$Cluster, data7$Reason)
```

```
Diaper-Change Fussy Hungry Pain Tired
1      53      59      60      49      67
2      30      20      39      41      31
3      50      72      39      29      46
4      37      19      29      42      20
5       9       8       5       7       7
```

```
# data frame too
cluster_reason_df <- as.data.frame(table(data7$Cluster, data7$Reason))
print(cluster_reason_df)
```

```
Var1 Var2 Freq
1    1 Diaper-Change 53
2    2 Diaper-Change 30
3    3 Diaper-Change 50
4    4 Diaper-Change 37
5    5 Diaper-Change  9
6    1      Fussy 59
7    2      Fussy 20
8    3      Fussy 72
9    4      Fussy 19
10   5      Fussy  8
11   1      Hungry 60
12   2      Hungry 39
13   3      Hungry 39
```

14	4	Hungry	29
15	5	Hungry	5
16	1	Pain	49
17	2	Pain	41
18	3	Pain	29
19	4	Pain	42
20	5	Pain	7
21	1	Tired	67
22	2	Tired	31
23	3	Tired	46
24	4	Tired	20
25	5	Tired	7

```
# show proportions within each cluster
prop.table(table(data7$Cluster, data7$Reason), margin = 1)
```

	Diaper-Change	Fussy	Hungry	Pain	Tired
1	0.1840278	0.2048611	0.2083333	0.1701389	0.2326389
2	0.1863354	0.1242236	0.2422360	0.2546584	0.1925466
3	0.2118644	0.3050847	0.1652542	0.1228814	0.1949153
4	0.2517007	0.1292517	0.1972789	0.2857143	0.1360544
5	0.2500000	0.2222222	0.1388889	0.1944444	0.1944444

## K-means Clustering Attempt 2

```
# loading incomplete and complete data into R
data_with_nas <- read.csv("full_data_cleaned_include_nas.csv")
data_complete <- read.csv("full_data_cleaned_without_nas.csv")

# removing columns (newID, ID, Date, Sample, ParentFile)
rf_with_nas <- read.csv("full_data_cleaned_include_nas.csv")[, -c(1, 2, 6:8)]
rf_complete <- read.csv("full_data_cleaned_without_nas.csv")[, -c(1, 2, 4:8)]
rf_with_nas$Reason <- as.factor(rf_with_nas$Reason)
rf_complete$Reason <- as.factor(rf_complete$Reason)

# create method vector for mice
methods <- make.method(rf_with_nas)
rf_with_nas$Gender[rf_with_nas$Gender == "MULT-REDCAP-GENDER"] <- NA
rf_with_nas$Gender <- as.factor(rf_with_nas$Gender)
init <- mice(rf_with_nas, maxit = 0)
methods <- init$method
methods["Reason"] <- ""
methods["Gender"] <- "logreg" # or "polyreg" if >2 levels

# impute missing values using mice
imputed_data <- mice(rf_with_nas, m = 1, method = methods, seed = 605794011)
```

```
iter imp variable
1 1 Age Gender
2 1 Age Gender
```

```
3 1 Age Gender
4 1 Age Gender
5 1 Age Gender
```

Warning: Number of logged events: 10

```
data_imputed <- complete(imputed_data, action = 1)

# ensure target and gender are factors
data_imputed$Reason <- as.factor(data_imputed$Reason)
data_imputed$Gender <- as.factor(data_imputed$Gender)

# set seed for reproducibility
set.seed(605794011)

# train/test split
train_index2 <- createDataPartition(data_imputed$Reason, p = 0.8, list = FALSE)
train_imputed <- data_imputed[train_index2, ]
test_imputed <- data_imputed[-train_index2, ]
```

```
# remove categorical columns
clust_data <- data_imputed %>%
  select_if(is.numeric)

# scale (standardize) the data
clust_data_scaled <- scale(clust_data)[, -1]

# set seed for reproducibility
set.seed(605794011)

# establish k as number of groups
k <- 5

# run k-means variable
kmeans_result <- kmeans(clust_data_scaled, centers = k, nstart = 25)
print(kmeans_result)
```

K-means clustering with 5 clusters of sizes 388, 489, 53, 1, 319

Cluster means:

	shimmerLocaldB_sma3nz_stddevNorm	loudness_sma3_percentile20.0
1	-0.32181019	-0.5481103
2	0.32973971	-0.2367317
3	-0.44991143	-0.1268494
4	-0.08906947	0.8788965
5	-0.03901565	1.0478769

	F3amplitudeLogRelF0_sma3nz_amean	loudness_sma3_percentile50.0
1	-1.0652047	-0.8046027
2	0.3356373	-0.1738951
3	-0.8886649	-0.4146459
4	2.2333977	-0.1016758
5	0.9217512	1.3144153

	loudness_sma3_amean	F2amplitudeLogRelF0_sma3nz_amean
1	-0.73942615	-1.0698033

2	-0.19241236	0.3486303
3	-0.43838587	-0.8814712
4	0.04614704	2.2534950
5	1.26700719	0.9061691
	F3amplitudeLogRelF0_sma3nz_stddevNorm	MeanUnvoicedSegmentLength
1	0.63608777	0.6048689
2	-0.02150155	-0.2439456
3	0.63161267	0.4773037
4	-19.17557759	-0.7801443
5	-0.78554135	-0.4386102
	F2amplitudeLogRelF0_sma3nz_stddevNorm	
1	0.21075295	
2	0.01651836	
3	0.20453175	
4	-34.05784428	
5	-0.20887761	
	F0semitoneFrom27.5Hz_sma3nz_percentile80.0	F1amplitudeLogRelF0_sma3nz_amean
1	0.09795817	-1.0711121
2	-0.13437268	0.4149819
3	-1.26674525	-0.7709568
4	2.17632572	1.7622032
5	0.29047538	0.7892284
	F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	alphaRatioV_sma3nz_stddevNorm
1	-0.06616199	-0.017495302
2	-0.20140314	-0.048697149
3	3.25423181	-0.025148063
4	0.16305650	-0.005821306
5	-0.15197604	0.100124613
	StddevUnvoicedSegmentLength	loudness_sma3_stddevNorm
1	0.85781251	0.66657536
2	-0.30024284	-0.12508868
3	-0.04802405	-0.01923197
4	-1.00374957	-0.43289505
5	-0.57198583	-0.61445357
	loudness_sma3_percentile80.0	shimmerLocaldB_sma3nz_amean
1	-0.6673099	0.4222571
2	-0.1604694	-0.4704828
3	-0.4741000	0.5366185
4	-0.2659146	-0.1858470
5	1.1372382	0.1190452
	F0semitoneFrom27.5Hz_sma3nz_stddevNorm	
1	-0.01272255	
2	-0.18455482	
3	3.13545130	
4	-0.33707109	
5	-0.22149904	
	F0semitoneFrom27.5Hz_sma3nz_percentile50.0	HNRdBACF_sma3nz_amean
1	0.08706357	-0.3489994
2	-0.04038745	0.5741044
3	-2.00237605	-1.1221022
4	1.71690887	0.5132584
5	0.28331605	-0.2707432
	slopeV500.1500_sma3nz_amean	loudness_sma3_meanRisingSlope
1	0.09406474	-0.3101952
2	-0.34319895	-0.2268026

3	-0.38939617	-0.2230488
4	2.18205869	1.1166997
5	0.46953952	0.7585175
alphaRatioV_sma3nz_amean F0semitoneFrom27.5Hz_sma3nz_percentile20.0		
1	0.0601328	0.12636406
2	-0.4186523	0.09343233
3	-1.1745944	-3.82428437
4	2.9566687	1.31635629
5	0.7545025	0.33433558
FlamplitudeLogRelF0_sma3nz_stddevNorm		
1	0.5483013	
2	-0.1205928	
3	0.4802127	
4	-2.4176686	
5	-0.5542464	

Clustering vector:

```

[1] 1 1 1 2 5 2 1 2 5 5 1 1 2 5 1 1 2 3 2 2 1 2 2 2 2 5 5 2 1 5 2 2 1 2 2 3 2
[38] 1 5 1 1 5 1 5 2 2 5 2 1 5 2 5 2 1 2 3 1 2 2 5 5 5 1 5 1 2 1 5 2 1 2 2 1 3
[75] 2 5 5 1 2 3 1 1 5 2 3 5 1 5 1 1 5 2 2 2 5 1 2 2 1 2 1 1 2 5 5 1 2 1 1 1 2
[112] 1 2 1 1 5 2 2 5 2 1 1 2 5 1 2 2 2 3 3 5 1 5 2 1 2 2 1 5 5 5 5 1 1 1 1 2 5
[149] 1 1 2 1 2 1 1 2 1 1 1 1 2 5 1 1 2 2 2 2 2 1 1 2 1 5 2 5 1 5 3 5 2 5 2 1 5
[186] 1 2 1 1 5 5 3 3 5 5 2 2 3 1 5 1 2 2 1 2 5 5 4 2 1 2 2 5 1 1 2 5 1 5 5 1 5
[223] 1 2 2 1 2 3 5 1 1 2 5 1 5 2 2 2 1 2 5 1 2 1 5 1 5 1 5 1 2 1 1 1 2 2 1 1 2
[260] 1 1 1 2 2 2 5 5 1 5 1 2 1 1 2 1 1 2 5 1 1 3 2 2 2 5 1 5 2 5 5 2 5 1 2 2 1
[297] 2 1 1 1 1 1 3 2 3 2 2 1 2 1 1 1 1 1 5 2 2 5 2 2 1 5 2 5 1 2 1 1 1 1 5 1 1
[334] 2 1 2 1 1 1 2 1 2 2 1 2 1 1 2 2 2 5 2 1 2 1 5 1 5 2 1 2 1 1 1 1 1 1 5 3 1
[371] 5 2 3 1 2 1 1 1 3 1 2 1 5 2 1 5 2 1 1 2 1 2 1 5 1 1 2 2 2 2 1 1 1 1 5 2 5
[408] 1 1 1 2 1 5 1 1 2 5 2 2 5 1 1 5 2 1 1 2 2 1 1 1 2 1 5 2 2 2 2 1 5 2 2 1 3
[445] 5 1 2 1 1 2 1 1 1 2 2 1 2 3 1 2 1 2 2 5 2 1 5 2 1 2 2 2 3 1 1 5 1 2 5 1 5
[482] 1 1 2 3 2 2 5 2 2 2 2 2 1 2 1 2 1 1 1 5 5 2 5 2 5 5 1 2 2 1 5 5 2 1 5 2 2
[519] 1 1 1 1 5 1 2 1 1 1 2 2 1 2 2 1 2 1 1 2 5 1 5 1 1 2 5 5 1 1 2 5 5 5 2 2 5
[556] 5 2 1 2 5 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 5 5 2 5 2 1 5 2 5 5 1 2 5 5 2 2 2
[593] 5 1 1 2 1 5 1 5 2 5 1 1 5 2 5 2 5 5 5 1 5 2 2 5 1 5 1 2 5 1 2 5 5 1 2 2 2
[630] 2 5 2 5 3 5 5 2 1 2 2 3 2 1 2 3 2 5 5 1 2 5 5 2 1 5 1 5 5 2 2 2 5 2 5 1 1
[667] 5 2 1 2 2 5 5 5 2 2 5 2 1 5 5 2 1 5 5 1 2 5 5 5 5 1 5 1 1 5 2 5 2 1 5 5 1
[704] 5 5 1 2 2 5 1 1 2 1 1 2 1 1 2 2 1 3 2 5 3 1 2 5 2 1 3 1 2 2 2 2 2 1 2 2 2
[741] 2 1 2 3 2 3 5 2 2 2 3 2 5 1 2 1 1 5 5 1 2 2 2 1 2 2 5 5 5 5 2 2 5 5 2 1 1
[778] 2 1 2 1 5 2 2 1 5 2 1 1 1 3 2 5 2 5 5 5 3 2 2 5 5 2 2 2 5 5 5 5 5 2 3 1 5
[815] 2 1 1 5 1 2 5 2 2 2 5 5 1 2 1 5 2 5 2 5 2 1 2 2 2 2 1 1 2 5 2 1 5 1 2 5 5
[852] 2 2 1 3 2 1 1 2 2 5 1 1 2 5 1 5 2 2 2 5 2 1 2 5 5 5 2 5 5 2 2 5 5 5 2 1 1
[889] 5 2 2 5 2 5 1 2 5 2 1 5 2 2 1 2 5 2 2 2 2 5 2 5 1 5 2 5 2 1 1 1 1 5 1 5 2
[926] 5 2 5 2 5 5 2 3 2 1 2 5 5 5 3 2 5 5 5 5 5 2 1 1 2 1 5 5 5 2 1 5 3 2 2 5 5
[963] 2 1 5 5 2 2 5 5 2 5 2 1 2 1 1 2 2 2 5 2 3 5 2 5 2 5 5 2 2 2 5 5 5 5 1 5 2
[1000] 2 1 2 1 5 2 2 5 1 2 2 2 1 2 2 1 5 1 1 2 5 5 2 2 2 3 5 5 2 2 2 2 1 2 1 1 1
[1037] 1 2 1 2 5 2 1 2 1 2 2 1 2 1 1 2 1 1 5 2 2 5 3 2 5 5 5 2 1 1 1 2 1 2 2 3 1
[1074] 5 2 1 2 5 1 2 2 1 3 2 2 5 2 5 2 2 1 2 2 2 5 2 5 2 2 3 5 1 2 5 1 3 5 2 5 2
[1111] 5 2 2 1 2 2 2 2 2 2 5 1 1 5 2 5 2 2 2 5 2 1 1 1 2 5 2 2 2 5 5 2 3 1 1 1 5
[1148] 1 2 2 5 1 1 2 2 2 2 1 2 1 2 2 5 2 2 2 2 1 1 2 5 5 2 2 5 5 1 5 1 2 1 1 1 3
[1185] 1 2 2 2 2 5 2 1 1 2 2 2 3 1 2 5 2 2 5 1 2 2 1 1 1 5 2 2 2 2 3 2 2 5 2 5 5
[1222] 1 3 2 5 5 2 2 1 3 2 1 2 2 1 1 2 2 1 1 1 2 2 5 2 3 1 2 1 1

```

Within cluster sum of squares by cluster:

```

[1] 5815.796 4821.056 2521.809    0.000 6146.645
(between_SS / total_SS = 38.2 %)

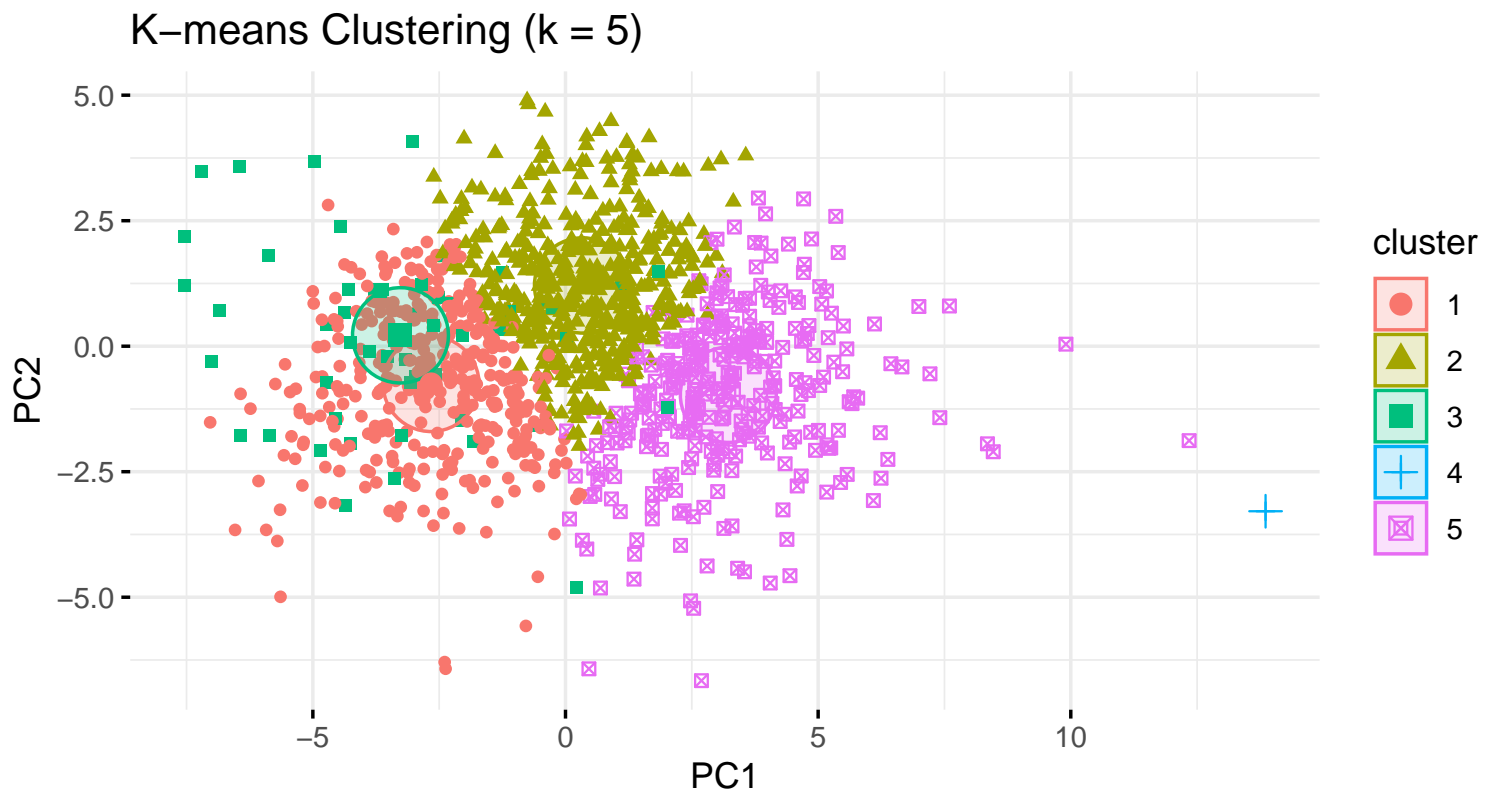
```

Available components:

```
[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"  
[6] "betweenss"    "size"         "iter"         "ifault"
```

```
# assign modeled clusters to each data point  
clustered_data <- data_imputed  
clustered_data$Cluster <- as.factor(kmeans_result$cluster)  
  
# visualize clusters  
fviz_cluster(kmeans_result,  
  data = clust_data_scaled,  
  ellipse.type = "euclid",  
  labelsize = 0,  
  show.clust.cent = TRUE,  
  ggtheme = theme_minimal()) +  
  labs(title = "K-means Clustering (k = 5)", x = "PC1", y = "PC2")
```

Too few points to calculate an ellipse



```
# run pca analysis  
pca_result <- prcomp(clust_data, scale. = TRUE)  
  
# calculate proportion of variance explained  
pve <- (pca_result$sdev)^2 / sum(pca_result$sdev^2)  
  
# plot proportion of variance for principal components  
plot(pve, type = "b", pch = 19, col = "steelblue", lwd = 2,
```

```

xlab = "Principal Component",
ylab = "Proportion of Variance Explained",
main = "PVE for Principal Components",
cex.main = 1.2, cex.lab = 1.1, cex.axis = 0.9)

```

```

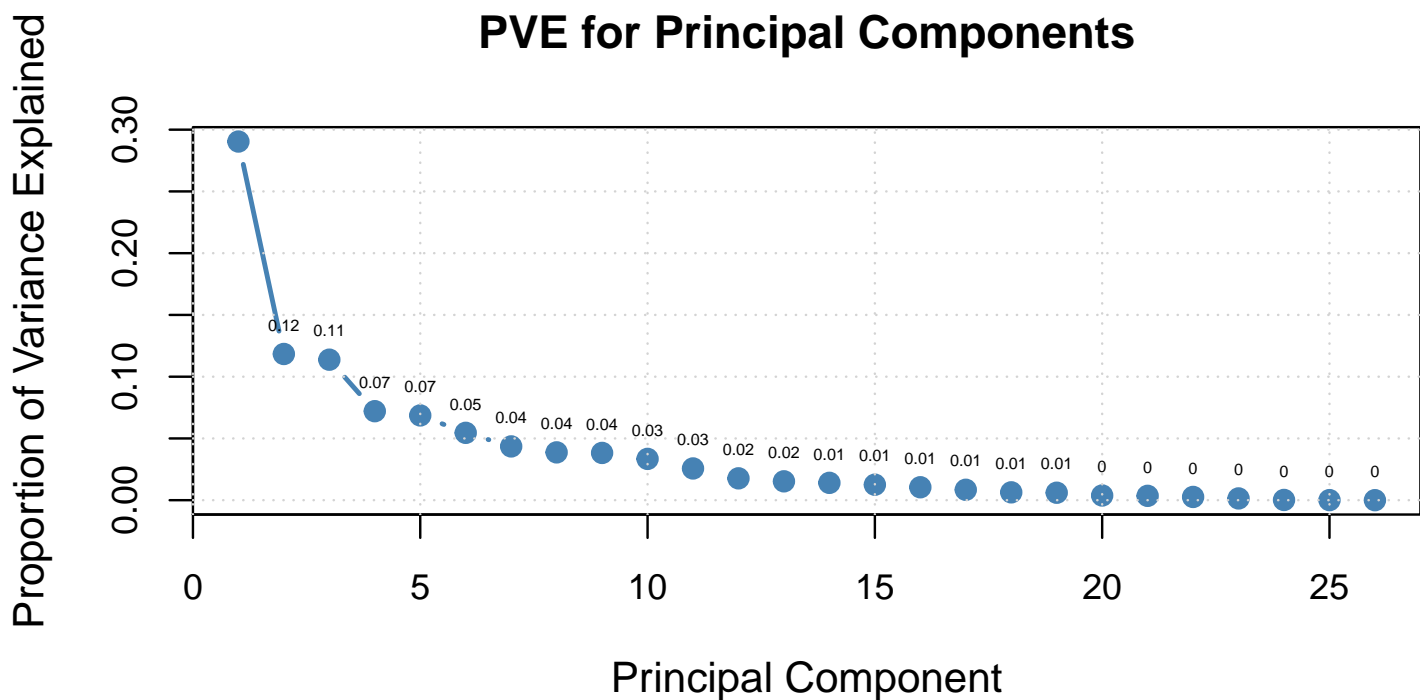
# add grid lines to graph
grid()

```

```

# label each point with exact variance value
text(x = 1:length(pve), y = pve,
     labels = round(pve, 2),
     pos = 3, cex = 0.4, col = "black")

```



```

# print proportion of variance for PC1 and PC2
pve[1:2]

```

```
[1] 0.2904021 0.1183942
```

```
pve[1]+pve[2]
```

```
[1] 0.4087963
```

```

# create a data frame with cluster assignments and true labels
df <- data.frame(Cluster = clustered_data$Cluster, CryType = data_imputed$Reason)

```

```

# generate a contingency table: distribution of true labels within each cluster

```



```
label_distribution <- table(df$Cluster, df$CryType)

# neat printed table
kable(label_distribution, caption = "Distribution of Cry Types Within Each Cluster")
```

Table 4: Distribution of Cry Types Within Each Cluster

Diaper-Change	Fussy	Hungry	Pain	Tired
88	112	65	52	71
85	91	98	98	117
13	10	8	9	13
1	0	0	0	0
63	37	79	91	49

```
# convert to proportions within each cluster
prop_distribution <- prop.table(label_distribution, margin = 1)
# for proportions
kable(round(prop_distribution, 2), caption = "Proportion of Cry Types Within Each Cluster")
```

Table 5: Proportion of Cry Types Within Each Cluster

Diaper-Change	Fussy	Hungry	Pain	Tired
0.23	0.29	0.17	0.13	0.18
0.17	0.19	0.20	0.20	0.24
0.25	0.19	0.15	0.17	0.25
1.00	0.00	0.00	0.00	0.00
0.20	0.12	0.25	0.29	0.15

```
# data frame with cluster assignments, reasons and frequency associated with each cluster/reason
↳ combo
cluster_counts <- df %>%
  group_by(Cluster, CryType) %>%
  summarise(Frequency = n(), .groups = 'drop')

# plot each reason against the cluster assignments
ggplot(cluster_counts, aes(x = CryType, y = Frequency, fill = CryType)) +
  geom_bar(stat = "identity", show.legend = FALSE) +
  facet_wrap(~ Cluster, ncol = 2) +
  labs(
    title = "Distribution of Cry Reasons Within Each Cluster",
    x = "Cry Reason",
    y = "Frequency"
  ) +
  theme_minimal(base_size = 12) +
  theme(
    axis.text.x = element_text(angle = 30, hjust = 1),
    strip.text = element_text(face = "bold")
  )
```

## Distribution of Cry Reasons Within Each Cluster



```
# dimensions
dim(clust_data)
```

```
[1] 1250  26
```

## Spectral Clustering

```
# generate random data for clustering
set.seed(605794011)
k <- 5

# extract the first two principal components
PC1 <- pca_result$x[, 1]
PC2 <- pca_result$x[, 2]

# compute the similarity matrix
similarity_matrix <- exp(-dist(clust_data)^2)

# perform spectral decomposition
eigen_result <- eigen(similarity_matrix)

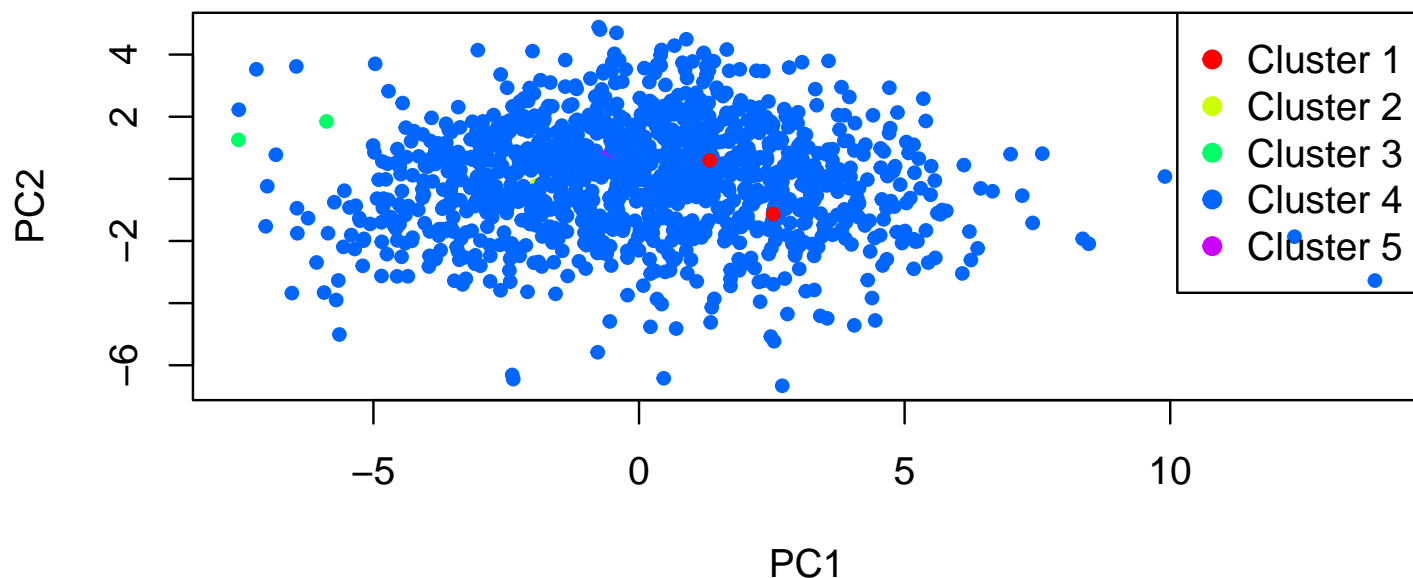
# extract the top-k eigenvectors
k_eigenvectors <- eigen_result$vectors[, 1:k]

# perform k-means clustering on the eigenvectors
cluster_assignments <- kmeans(k_eigenvectors, centers = k)$cluster

# visualize clusters
cluster_colors <- rainbow(k)
```

```
plot(PC1, PC2, col = cluster_colors[cluster_assignments], pch = 19, cex = 0.7,
     main = "Spectral Clustering with k-means", xlab = "PC1", ylab = "PC2")
legend("topright", legend = paste("Cluster", 1:k), col = cluster_colors, pch = 19)
```

## Spectral Clustering with k-means



## Gaussian Mixture Models

```
df <- read.csv("full_data_cleaned_without_nas.csv")

# Identify all numeric columns
numeric_cols <- sapply(df, is.numeric)
numeric_col_names <- names(df)[numeric_cols]

# Exclude the non-numeric/irrelevant columns
cols_to_exclude <- c("newID", "Age", "Date", "Sample")
numeric_data <- df[, setdiff(numeric_col_names, cols_to_exclude)]

# Perform GMM
gmm <- Mclust(numeric_data)

# Get the cluster assignments
cluster_assignments <- gmm$classification

# Perform PCA on the data used for GMM
pca_res <- prcomp(numeric_data, scale. = TRUE) # scale.=TRUE is important for PCA

# Create a data frame for plotting PCA results with cluster assignments
pca_data <- as.data.frame(pca_res$x)
```

```
pca_data$cluster <- as.factor(cluster_assignments)
```

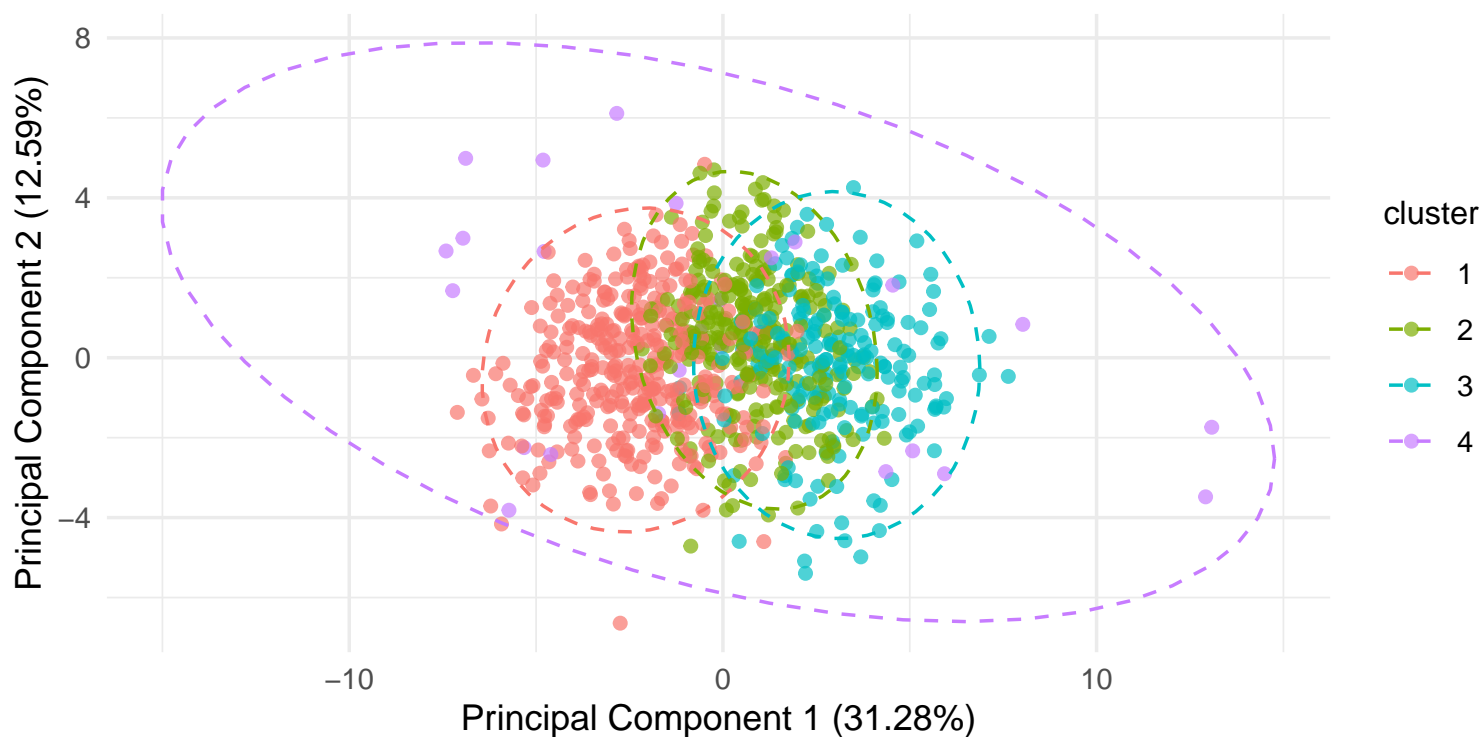
```
# Plot the first two principal components, colored by cluster  
table(cluster_assignments)
```

```
cluster_assignments
```

```
  1    2    3    4  
356 291 194  27
```

```
ggplot(pca_data, aes(x = PC1, y = PC2, color = cluster)) +  
  geom_point(alpha = 0.7) +  
  stat_ellipse(aes(group = cluster), type = "norm", linetype = 2) +  
  labs(title = "GMM Clusters Visualized with PCA",  
       x = paste0("Principal Component 1 (", round(summary(pca_res)$importance[2,1]*100, 2), "%)"),  
       y = paste0("Principal Component 2 (", round(summary(pca_res)$importance[2,2]*100, 2), "%)"))  
  ↪ +  
  theme_minimal() +  
  theme(legend.title = element_text(size = 10))
```

## GMM Clusters Visualized with PCA



## Question 3: Supervised Learning

### Regression Models

```

data2$Reason <- as.factor(data$Reason) # factor data

set.seed(333) # set up training data
trainIndex <- createDataPartition(data2$Reason, p = 0.8, list = FALSE)
trainData <- data2[trainIndex, ]
testData <- data2[-trainIndex, ]

ctrl <- trainControl(method = "cv", number = 10, verboseIter = FALSE)

set.seed(333) # logistic model, just a test!
invisible(capture.output({
  suppressMessages({
    suppressWarnings({
      model_logit <- train(
        Reason ~ . - ID,
        data = trainData,
        method = "multinom",
        trControl = ctrl
      )
    })
  })
}))

model_logit$results

```

	decay	Accuracy	Kappa	AccuracySD	KappaSD
1	0e+00	0.9914268	0.9892831	0.01531699	0.01914626
2	1e-04	1.0000000	1.0000000	0.00000000	0.00000000
3	1e-01	0.9942437	0.9928026	0.01002952	0.01253884

```
head(data)
```

	newID	ID	Reason	Age	Gender	Date
1	1 bfb4662ea7ea4b8468d74c7ad1909ef1	Diaper-Change	49	female	181002	
2	4 3b09f1cad01fe3972282858c331f52d5	Diaper-Change	23	female	210717	
3	5 e8f2d8b96f020af62e904e8e49445ce3	Diaper-Change	60	male	190606	
4	6 6a82f817144649d0b8ff551570c6824e	Diaper-Change	74	male	180711	
5	9 8222356f4d4be372fb94488cdaabb075	Diaper-Change	8	male	180705	
6	10 5ec09ae3e9fd6fb143bf92b431e182f1	Diaper-Change	81	female	190212	
	Sample	ParentFile	shimmerLocaldB_sma3nz_stddevNorm			
1	340074	diaper	0.7027443			
2	1079369	diaper	0.6111611			
3	526227	diaper	1.3477150			
4	224920	diaper	0.5269586			
5	201998	diaper	1.1081220			
6	458364	diaper	0.8726283			
	loudness_sma3_percentile20.0	F3amplitudeLogRelF0_sma3nz_amean				
1		0.11481330	-147.90350			
2		0.07673505	-74.69855			
3		0.49998700	-53.44516			
4		0.40500970	-108.06370			
5		0.28399970	-69.01035			
6		0.43889410	-49.47916			

	loudness_sma3_percentile50.0	loudness_sma3_amean
1	0.1428274	0.4213910
2	0.4041929	0.4412344
3	1.6900650	1.6746600
4	0.6827049	0.7537612
5	2.6455030	2.2942330
6	1.4687040	1.3787450

	F2amplitudeLogRelF0_sma3nz_amean	F3amplitudeLogRelF0_sma3nz_stddevNorm
1	-146.46640	-0.5471651
2	-72.39424	-1.3117100
3	-47.35921	-1.4569950
4	-111.10530	-0.9248785
5	-66.83566	-1.2720410
6	-48.83880	-1.7023990

	MeanUnvoicedSegmentLength	F2amplitudeLogRelF0_sma3nz_stddevNorm
1	0.2428571	-0.5677297
2	0.3620000	-1.3779880
3	0.1700000	-1.7414370
4	0.2141667	-0.8698995
5	0.1577778	-1.3362150
6	0.1614286	-1.7253130

	F0semitoneFrom27.5Hz_sma3nz_percentile80.0	F1amplitudeLogRelF0_sma3nz_amean
1	46.81261	-152.73810
2	46.94024	-76.52715
3	50.69794	-50.17403
4	44.43988	-131.68280
5	47.34345	-73.17527
6	48.19924	-51.49702

	F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	alphaRatioV_sma3nz_stddevNorm
1	5.167824	-2.190032
2	6.519093	1.314629
3	4.542534	-3.228497
4	1.203712	7.815800
5	6.009083	1.168851
6	3.712673	2.269837

	StddevUnvoicedSegmentLength	loudness_sma3_stddevNorm
1	0.25220260	1.2175340
2	0.30472280	0.8059498
3	0.10832050	0.6468157
4	0.19750350	0.5271363
5	0.12335840	0.5847681
6	0.08407965	0.5834538

	loudness_sma3_percentile80.0	shimmerLocaldB_sma3nz_amean
1	0.9868522	1.0691180
2	0.8503428	1.0793920
3	2.5423420	0.5166118
4	1.0504700	1.0174220
5	3.5476430	0.7986757
6	1.9161340	0.8547453

	F0semitoneFrom27.5Hz_sma3nz_stddevNorm
1	0.06150837
2	0.09242810
3	0.09557015
4	0.09890169
5	0.12676860

6	0.06160650	
	F0semitoneFrom27.5Hz_sma3nz_percentile50.0	HNRdBACF_sma3nz_amean
1	44.66841	7.481863
2	44.59288	7.745597
3	47.33990	13.455450
4	43.78660	5.959348
5	44.88856	8.342858
6	46.69179	8.056822
	slopeV500.1500_sma3nz_amean	loudness_sma3_meanRisingSlope
1	0.008295592	8.998878
2	0.021390640	2.926372
3	0.004193363	18.998730
4	0.005033952	4.795324
5	0.012155850	23.805280
6	0.012637170	9.674027
	alphaRatioV_sma3nz_amean	F0semitoneFrom27.5Hz_sma3nz_percentile20.0
1	-3.4233770	41.64479
2	5.9832670	40.42115
3	-3.3107370	46.15540
4	0.8115537	43.23617
5	4.8444340	41.33437
6	3.6916260	44.48657
	FlamplitudeLogRelF0_sma3nz_stddevNorm	
1	-0.5381386	
2	-1.3479890	
3	-1.9113570	
4	-0.7263191	
5	-1.3526220	
6	-1.7327520	

## Logistic Regression

```
# preferred model
data$Reason <- as.factor(data$Reason)
data$Gender <- as.factor(data$Gender)

data_clean <- data %>%
  select(-newID, -ID, -Date, -Sample) # remove categorical data

acoustic_features <- data_clean %>%
  select_if(is.numeric) %>%
  scale() %>%
  as.data.frame() # get the acoustic features

data_model <- bind_cols(acoustic_features, data %>% select(Reason, Gender, Age))
```

New names:

```
* `Age` -> `Age...1`
* `Age` -> `Age...29`
```

```
set.seed(123)
logit_model <- multinom(Reason ~ ., data = data_model) # logistic model creation
```

```
# weights: 150 (116 variable)
initial value 1396.992108
iter 10 value 1341.955910
iter 20 value 1320.397761
iter 30 value 1307.343988
iter 40 value 1303.640738
iter 50 value 1301.603012
iter 60 value 1300.152200
iter 70 value 1299.670833
iter 80 value 1299.431509
iter 90 value 1299.130402
iter 100 value 1298.864561
final value 1298.864561
stopped after 100 iterations
```

```
preds <- predict(logit_model, newdata = data_model)

conf_mat <- confusionMatrix(preds, data_model$Reason) # produce confusion matrix

print(conf_mat$overall['Accuracy'])
```

```
Accuracy
0.3306452
```

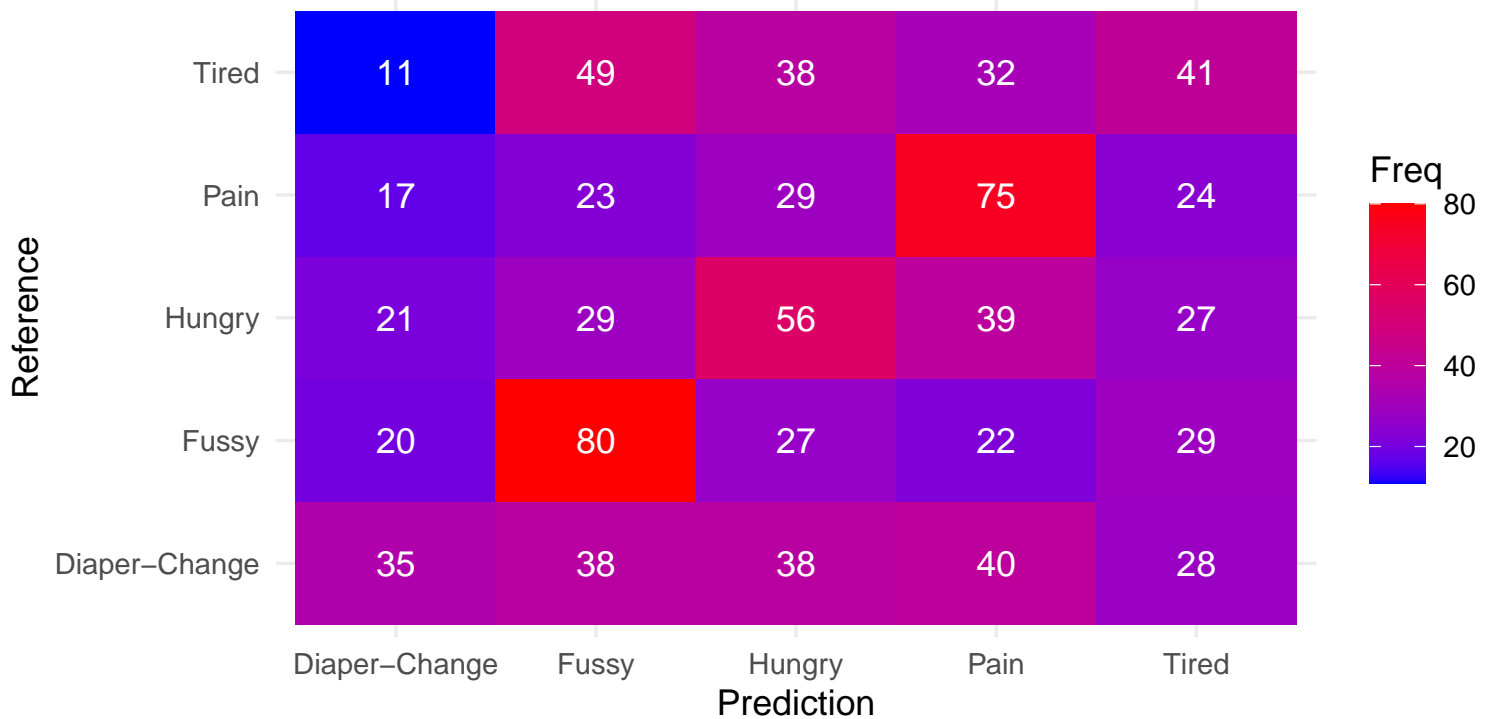
```
print(conf_mat$table)
```

	Reference				
Prediction	Diaper-Change	Fussy	Hungry	Pain	Tired
Diaper-Change	35	20	21	17	11
Fussy	38	80	29	23	49
Hungry	38	27	56	29	38
Pain	40	22	39	75	32
Tired	28	29	27	24	41

```
conf_df <- as.data.frame(conf_mat$table) # print the matrix
ggplot(conf_df, aes(Prediction, Reference, fill = Freq)) +
  geom_tile() +
  geom_text(aes(label = Freq), color = "white", size = 4) +
  scale_fill_gradient(low = "blue", high = "red") +
  theme_minimal() +
  labs(title = "Confusion Matrix")
```



## Confusion Matrix



## Linear Regression

```
data_lm <- data %>% # linear model data
  select(loudness_sma3_amean, Age, Gender,
    starts_with("shimmer"),
    starts_with("F0"),
    starts_with("alpha"),
    starts_with("F1"),
    starts_with("F2"))

data_lm$Gender <- as.factor(data_lm$Gender)

lm_model <- lm(loudness_sma3_amean ~ ., data = data_lm) # set up model

summary(lm_model) # summarize
```

Call:

```
lm(formula = loudness_sma3_amean ~ ., data = data_lm)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.29770	-0.24596	-0.05427	0.20554	1.62916

Coefficients: (1 not defined because of singularities)

	Estimate	Std. Error	t value
(Intercept)	1.110e+00	2.369e-01	4.687
Age	1.682e-06	1.950e-05	0.086
Gendermale	-1.511e-03	2.695e-02	-0.056

shimmerLocaldB_sma3nz_stddevNorm	3.014e-01	6.790e-02	4.438
shimmerLocaldB_sma3nz_amean	7.408e-02	4.955e-02	1.495
F0semitoneFrom27.5Hz_sma3nz_percentile80.0	-3.633e-03	5.909e-03	-0.615
F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	4.401e-03	3.952e-03	1.114
F0semitoneFrom27.5Hz_sma3nz_stddevNorm	9.466e-02	3.060e-01	0.309
F0semitoneFrom27.5Hz_sma3nz_percentile50.0	2.422e-03	5.418e-03	0.447
F0semitoneFrom27.5Hz_sma3nz_percentile20.0	NA	NA	NA
alphaRatioV_sma3nz_stddevNorm	7.477e-05	1.670e-04	0.448
alphaRatioV_sma3nz_amean	2.075e-02	2.115e-03	9.814
F1amplitudeLogRelF0_sma3nz_amean	-3.856e-04	1.561e-03	-0.247
F1amplitudeLogRelF0_sma3nz_stddevNorm	-1.124e-01	6.117e-02	-1.838
F2amplitudeLogRelF0_sma3nz_amean	5.896e-03	1.350e-03	4.368
F2amplitudeLogRelF0_sma3nz_stddevNorm	1.380e-02	4.413e-03	3.128

Pr(>|t|)

(Intercept)	3.23e-06 ***
Age	0.93127
Gendermale	0.95530
shimmerLocaldB_sma3nz_stddevNorm	1.03e-05 ***
shimmerLocaldB_sma3nz_amean	0.13526
F0semitoneFrom27.5Hz_sma3nz_percentile80.0	0.53884
F0semitoneFrom27.5Hz_sma3nz_pctlrange0.2	0.26570
F0semitoneFrom27.5Hz_sma3nz_stddevNorm	0.75713
F0semitoneFrom27.5Hz_sma3nz_percentile50.0	0.65499
F0semitoneFrom27.5Hz_sma3nz_percentile20.0	NA
alphaRatioV_sma3nz_stddevNorm	0.65444
alphaRatioV_sma3nz_amean	< 2e-16 ***
F1amplitudeLogRelF0_sma3nz_amean	0.80494
F1amplitudeLogRelF0_sma3nz_stddevNorm	0.06646 .
F2amplitudeLogRelF0_sma3nz_amean	1.41e-05 ***
F2amplitudeLogRelF0_sma3nz_stddevNorm	0.00182 **

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

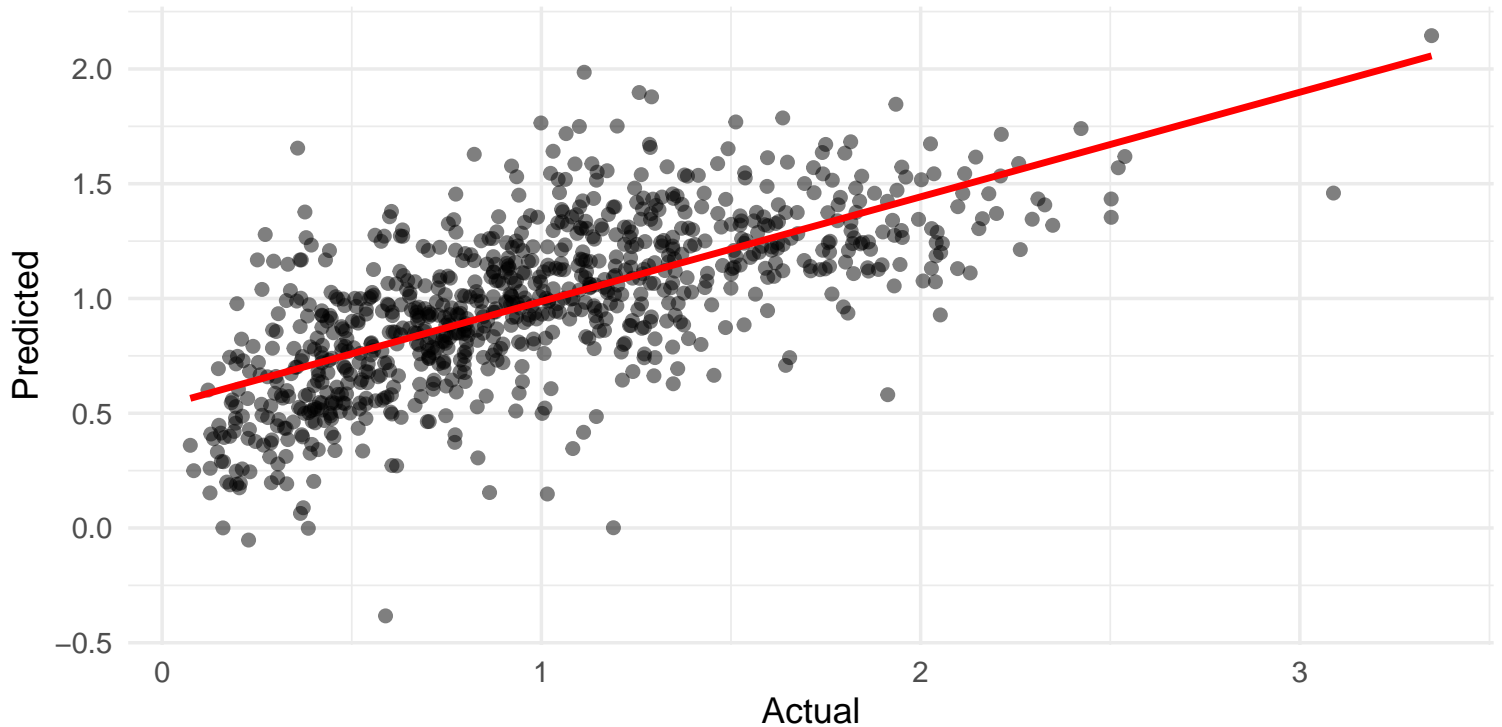
Residual standard error: 0.393 on 853 degrees of freedom  
Multiple R-squared: 0.4559, Adjusted R-squared: 0.447  
F-statistic: 51.05 on 14 and 853 DF, p-value: < 2.2e-16

```
data_lm$Predicted <- predict(lm_model, newdata = data_lm)

# plot the model
ggplot(data_lm, aes(x = loudness_sma3_amean, y = Predicted)) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  theme_minimal() +
  labs(title = "Predicted vs Actual Cry Loudness",
       x = "Actual",
       y = "Predicted")
```

`geom\_smooth()` using formula = 'y ~ x'

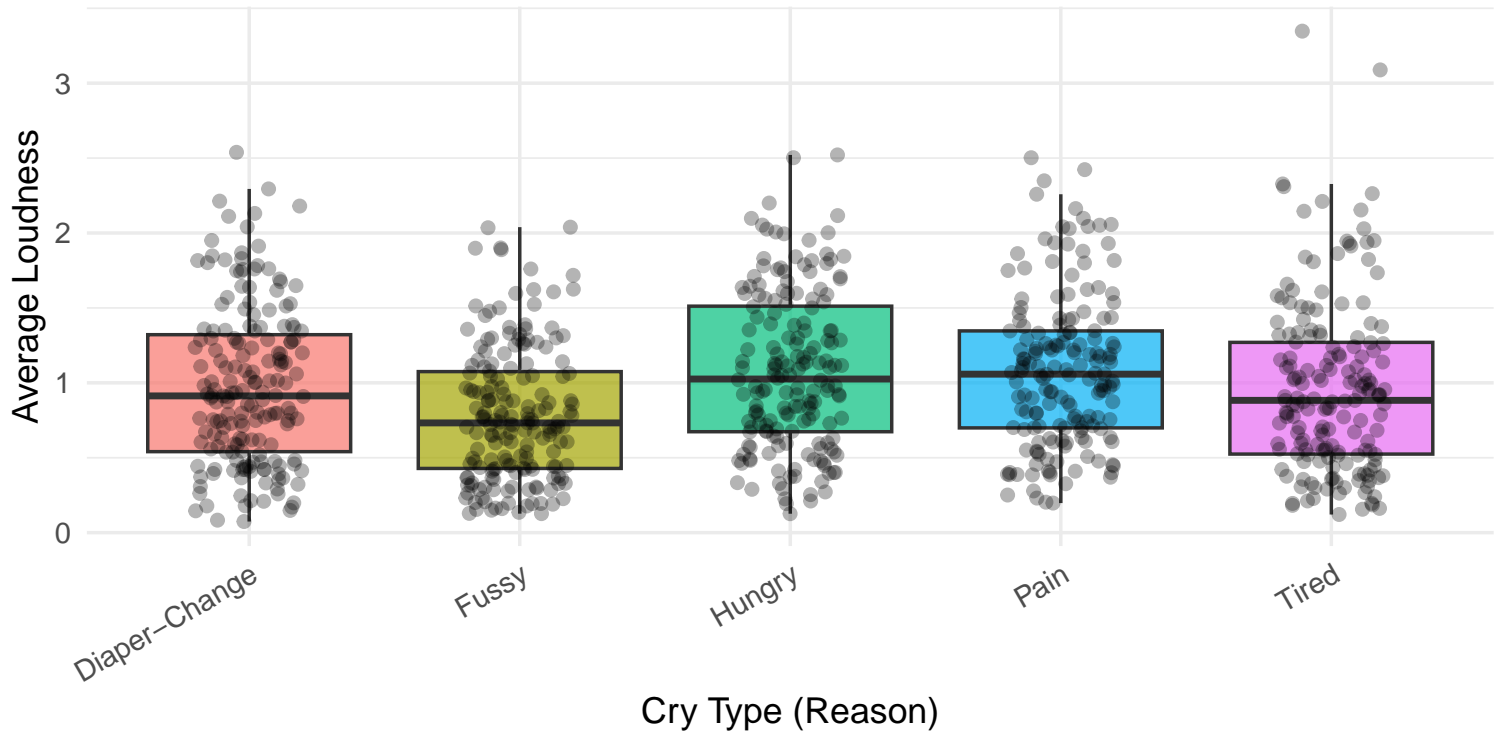
## Predicted vs Actual Cry Loudness



```
# just a simple plot for more linear regression showcase
ggplot(data, aes(x = Reason, y = loudness_sma3_amean, fill = Reason)) +
  geom_boxplot(alpha = 0.7, outlier.shape = NA) +
  geom_jitter(width = 0.2, alpha = 0.3, color = "black") +
  theme_minimal() +
  labs(
    title = "Cry Loudness by Parent-Labeled Reason",
    x = "Cry Type (Reason)",
    y = "Average Loudness"
  ) +
  theme(axis.text.x = element_text(angle = 30, hjust = 1)) +
  guides(fill = FALSE)
```

Warning: The ``<scale>`` argument of ``guides()`` cannot be ``FALSE``. Use "none" instead as of ggplot2 3.3.4.

## Cry Loudness by Parent-Labeled Reason



## Non-Linear Supervised Learning Models

```
# loading incomplete and complete data into R
data_with_nas <- read.csv("full_data_cleaned_include_nas.csv")
data_complete <- read.csv("full_data_cleaned_without_nas.csv")

# removing columns (newID, ID, Date, Sample, ParentFile)
rf_with_nas <- read.csv("full_data_cleaned_include_nas.csv")[, -c(1, 2, 6:8)]
rf_complete <- read.csv("full_data_cleaned_without_nas.csv")[, -c(1, 2, 4:8)]
rf_with_nas$Reason <- as.factor(rf_with_nas$Reason)
rf_complete$Reason <- as.factor(rf_complete$Reason)
```

## Random Forest

```
# set seed for reproducibility
set.seed(605794011)

# train/test split
train_index <- createDataPartition(rf_complete$Reason, p = 0.8, list = FALSE)
train_complete <- rf_complete[train_index, ]
test_complete <- rf_complete[-train_index, ]

# fit random forest model
randomforest_complete <- randomForest(Reason ~ ., data = train_complete, importance = TRUE)

# predictions and evaluation of accuracy
preds_complete <- predict(randomforest_complete, test_complete)
```

```
conf_matrix_complete <- confusionMatrix(preds_complete, test_complete$Reason)
accuracy_complete <- conf_matrix_complete$overall['Accuracy']

# show results
print(conf_matrix_complete)
```

Confusion Matrix and Statistics

Prediction	Reference				
	Diaper-Change	Fussy	Hungry	Pain	Tired
Diaper-Change	10	3	6	5	5
Fussy	6	15	9	5	8
Hungry	5	6	10	8	8
Pain	11	3	5	12	8
Tired	3	8	4	3	5

Overall Statistics

Accuracy : 0.3041  
95% CI : (0.2362, 0.3789)  
No Information Rate : 0.2047  
P-Value [Acc > NIR] : 0.001373  
  
Kappa : 0.1302  
  
McNemar's Test P-Value : 0.509556

Statistics by Class:

	Class: Diaper-Change	Class: Fussy	Class: Hungry
Sensitivity	0.28571	0.42857	0.29412
Specificity	0.86029	0.79412	0.80292
Pos Pred Value	0.34483	0.34884	0.27027
Neg Pred Value	0.82394	0.84375	0.82090
Prevalence	0.20468	0.20468	0.19883
Detection Rate	0.05848	0.08772	0.05848
Detection Prevalence	0.16959	0.25146	0.21637
Balanced Accuracy	0.57300	0.61134	0.54852

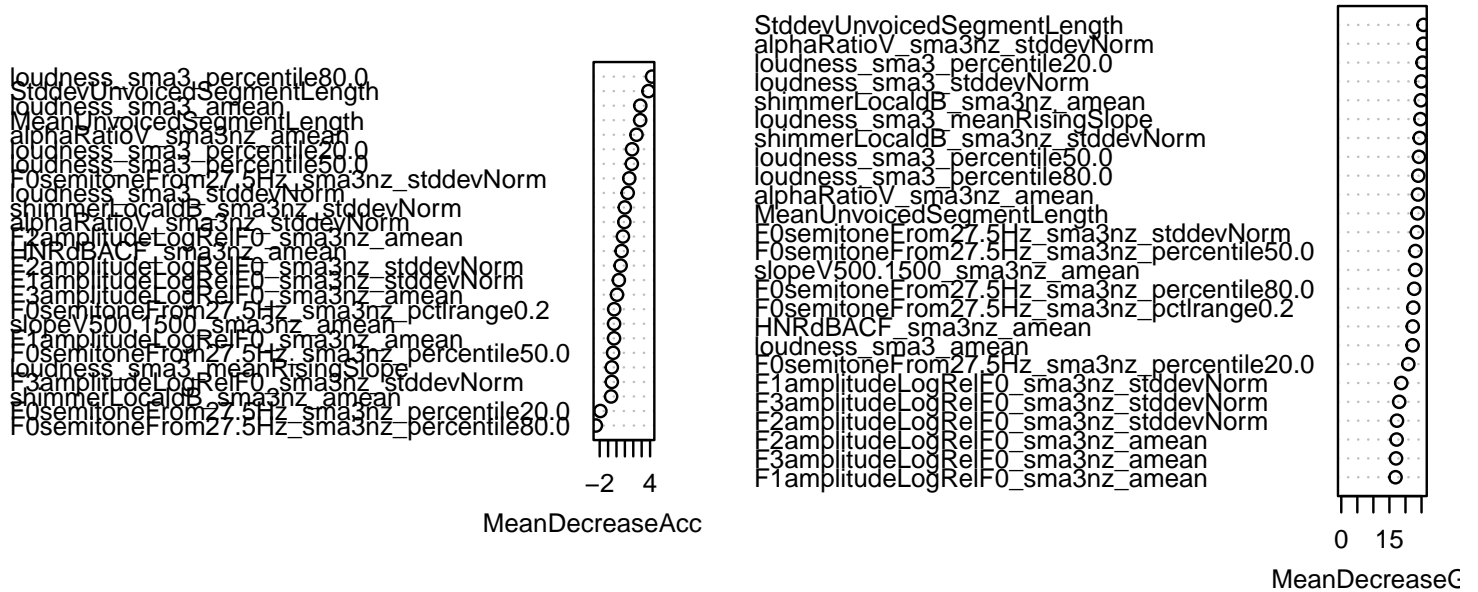
	Class: Pain	Class: Tired
Sensitivity	0.36364	0.14706
Specificity	0.80435	0.86861
Pos Pred Value	0.30769	0.21739
Neg Pred Value	0.84091	0.80405
Prevalence	0.19298	0.19883
Detection Rate	0.07018	0.02924
Detection Prevalence	0.22807	0.13450
Balanced Accuracy	0.58399	0.50784

```
print(accuracy_complete)
```

Accuracy  
0.3040936

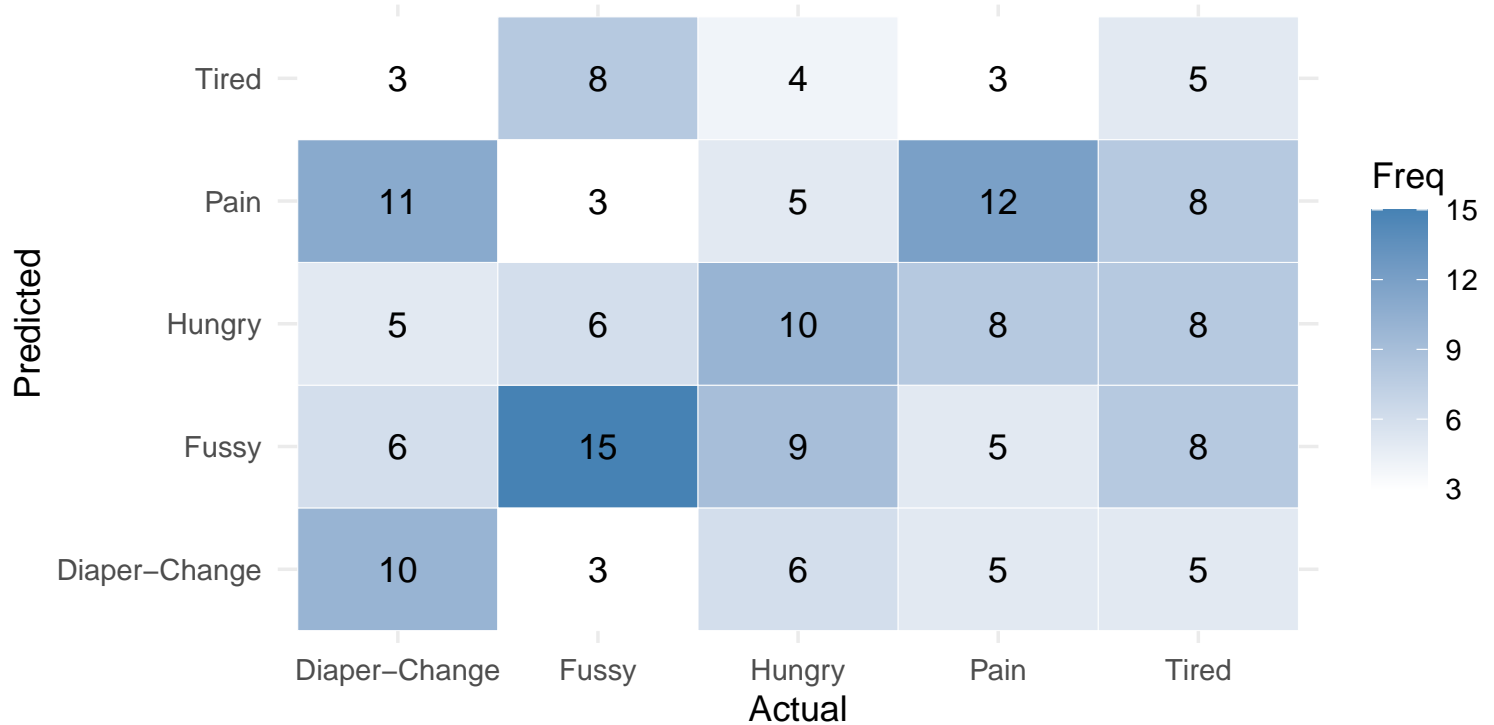
```
varImpPlot(randomforest_complete, main = "Variable Importance (Complete Data)", cex = 0.7)
```

## Variable Importance (Complete Data)



```
# creating a confusion matrix heatmap (pretty)
cm_df <- as.data.frame(conf_matrix_complete$table)
ggplot(cm_df, aes(x = Reference, y = Prediction)) +
  geom_tile(aes(fill = Freq), color = "white") +
  geom_text(aes(label = Freq), size = 4) +
  scale_fill_gradient(low = "white", high = "steelblue") +
  theme_minimal() +
  labs(title = "Confusion Matrix Heatmap", x = "Actual", y = "Predicted")
```

## Confusion Matrix Heatmap



## Random Forest w/ mice imputation

```
# create method vector for mice
methods <- make.method(rf_with_nas)
rf_with_nas$Gender[rf_with_nas$Gender == "MULT-REDCAP-GENDER"] <- NA
rf_with_nas$Gender <- as.factor(rf_with_nas$Gender)
init <- mice(rf_with_nas, maxit = 0)
methods <- init$method
methods["Reason"] <- ""
methods["Gender"] <- "logreg" # or "polyreg" if >2 levels

# impute missing values using mice
imputed_data <- mice(rf_with_nas, m = 1, method = methods, seed = 605794011)
```

```
iter imp variable
1 1 Age Gender
2 1 Age Gender
3 1 Age Gender
4 1 Age Gender
5 1 Age Gender
```

Warning: Number of logged events: 10

```
data_imputed <- complete(imputed_data, action = 1)

# ensure target and gender are factors
data_imputed$Reason <- as.factor(data_imputed$Reason)
```

```
data_imputed$Gender <- as.factor(data_imputed$Gender)

# set seed for reproducibility
set.seed(605794011)

# train/test split
train_index2 <- createDataPartition(data_imputed$Reason, p = 0.8, list = FALSE)
train_imputed <- data_imputed[train_index2, ]
test_imputed <- data_imputed[-train_index2, ]

# fit random forest model
rf_imputed <- randomForest(Reason ~ ., data = train_imputed, importance = TRUE)

# predictions and evaluations of accuracy
preds_imputed <- predict(rf_imputed, test_imputed)
conf_matrix_imputed <- confusionMatrix(preds_imputed, test_imputed$Reason)
accuracy_imputed <- conf_matrix_imputed$overall['Accuracy']

# show results
print(conf_matrix_imputed)
```

Confusion Matrix and Statistics

Prediction	Reference				
	Diaper-Change	Fussy	Hungry	Pain	Tired
Diaper-Change	10	8	5	11	8
Fussy	15	12	11	6	10
Hungry	8	13	12	12	7
Pain	7	6	12	14	9
Tired	10	11	10	7	16

Overall Statistics

Accuracy : 0.256  
95% CI : (0.2031, 0.3148)  
No Information Rate : 0.2  
P-Value [Acc > NIR] : 0.01852

Kappa : 0.07

Mcnemar's Test P-Value : 0.89596

Statistics by Class:

	Class: Diaper-Change	Class: Fussy	Class: Hungry
Sensitivity	0.2000	0.2400	0.2400
Specificity	0.8400	0.7900	0.8000
Pos Pred Value	0.2381	0.2222	0.2308
Neg Pred Value	0.8077	0.8061	0.8081
Prevalence	0.2000	0.2000	0.2000
Detection Rate	0.0400	0.0480	0.0480
Detection Prevalence	0.1680	0.2160	0.2080
Balanced Accuracy	0.5200	0.5150	0.5200
	Class: Pain	Class: Tired	



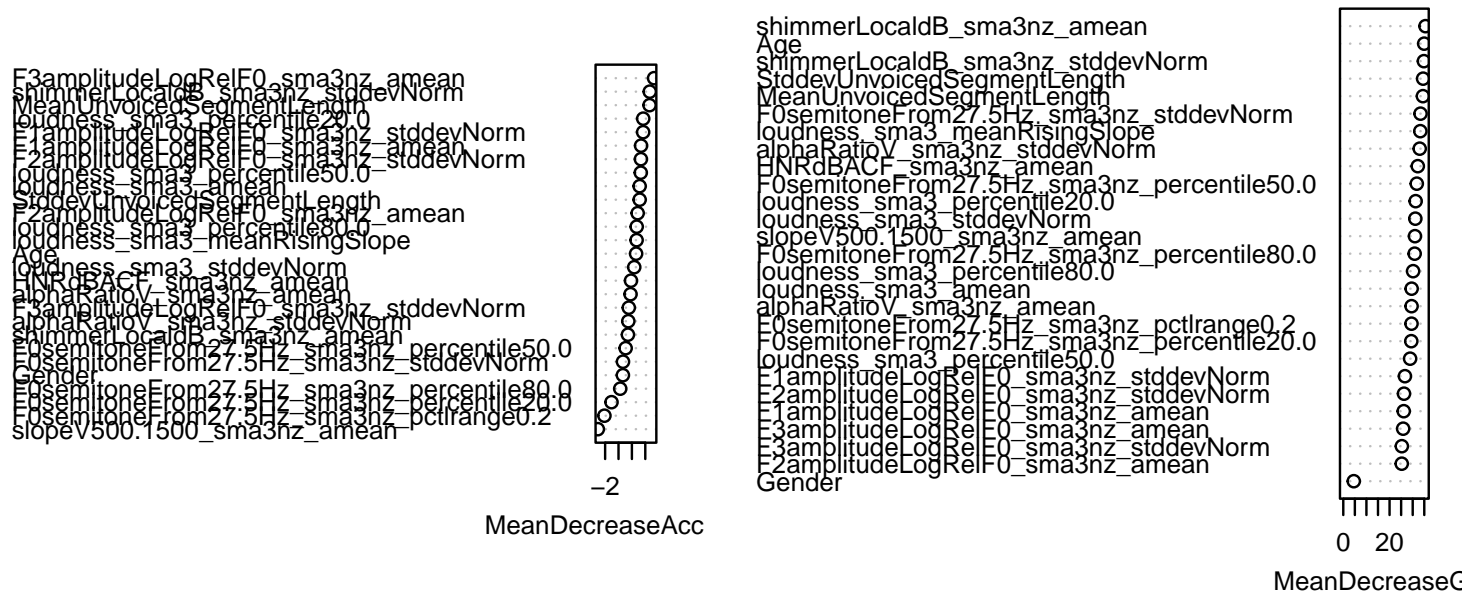
Sensitivity	0.2800	0.3200
Specificity	0.8300	0.8100
Pos Pred Value	0.2917	0.2963
Neg Pred Value	0.8218	0.8265
Prevalence	0.2000	0.2000
Detection Rate	0.0560	0.0640
Detection Prevalence	0.1920	0.2160
Balanced Accuracy	0.5550	0.5650

```
print(accuracy_imputed)
```

Accuracy  
0.256

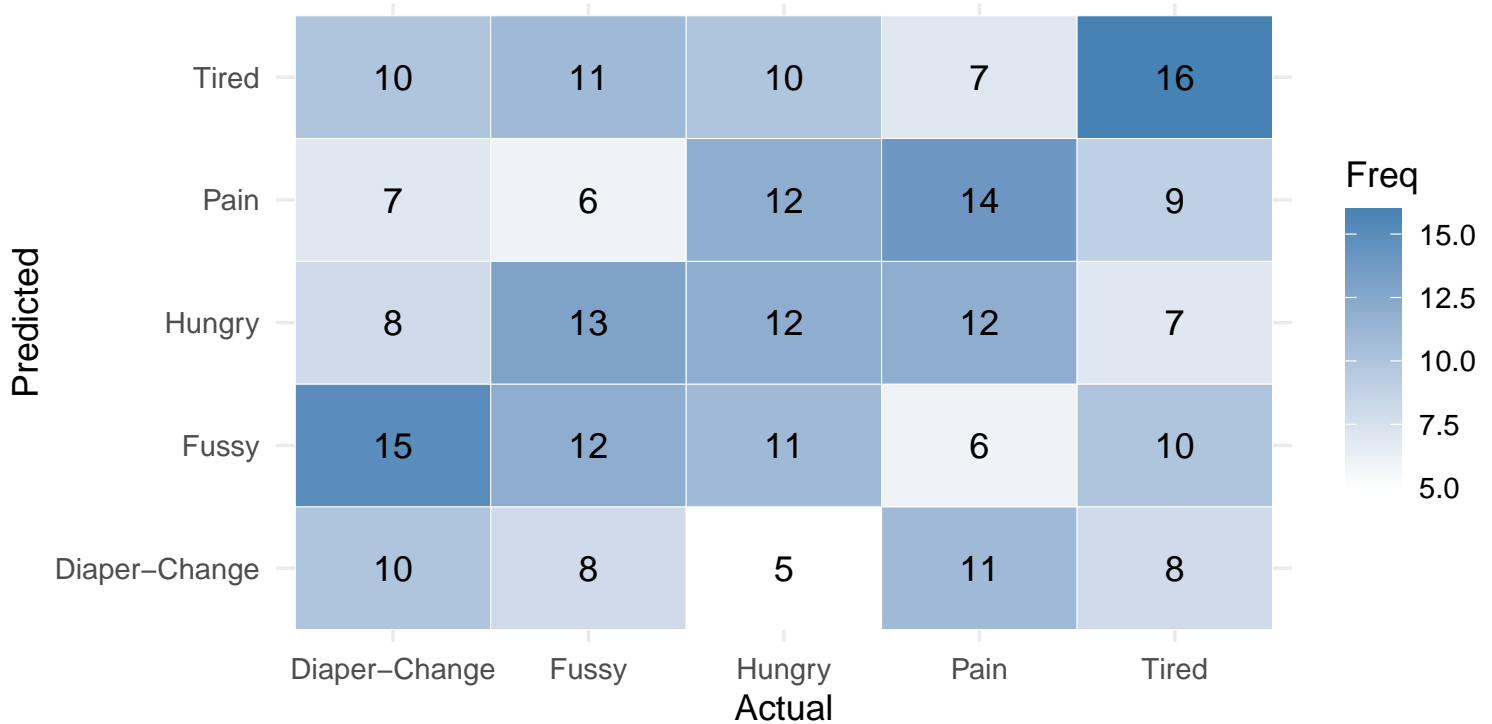
```
varImpPlot(rf_imputed, main = "Variable Importance (MICE Imputed Data)", cex = 0.7)
```

Variable Importance (MICE Imputed Data)



```
# creating a confusion matrix heatmap (pretty)
cm_df <- as.data.frame(conf_matrix_imputed$table)
ggplot(cm_df, aes(x = Reference, y = Prediction)) +
  geom_tile(aes(fill = Freq, color = "white")) +
  geom_text(aes(label = Freq), size = 4) +
  scale_fill_gradient(low = "white", high = "steelblue") +
  theme_minimal() +
  labs(title = "Confusion Matrix Heatmap (Imputed Data)", x = "Actual", y = "Predicted")
```

# Confusion Matrix Heatmap (Imputed Data)



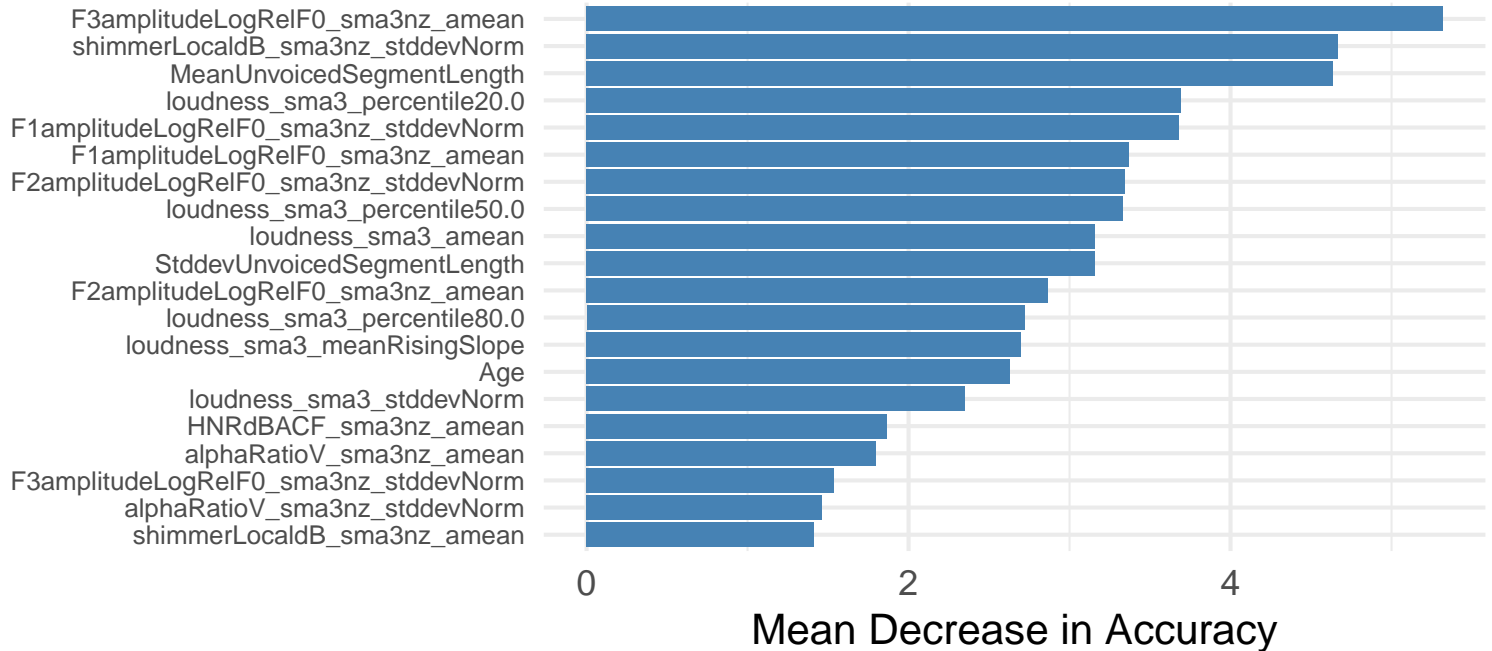
```
# extract variable importance
var_imp <- importance(rf_imputed, type = 1) # MeanDecreaseAccuracy
var_imp_df <- as.data.frame(var_imp)
colnames(var_imp_df) <- make.names(colnames(var_imp_df)) # Ensure clean column names
var_imp_df$Variable <- rownames(var_imp_df)

# select top 20 variables
top_n <- 20
var_imp_df <- as_tibble(var_imp_df) %>%
  arrange(desc(MeanDecreaseAccuracy)) %>%
  dplyr::slice(1:top_n)

# create pretty plot for variable importance
ggplot(var_imp_df, aes(x = reorder(Variable, MeanDecreaseAccuracy),
                        y = MeanDecreaseAccuracy)) +
  geom_col(fill = "#4682B4") +
  coord_flip() +
  theme_minimal(base_size = 13) +
  labs(title = "Top 20 Most Important Variables",
       subtitle = "Measured by Mean Decrease in Accuracy (Imputed Data)",
       x = NULL,
       y = "Mean Decrease in Accuracy") +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", size = 15),
    plot.subtitle = element_text(hjust = 0.5, size = 12),
    axis.text.y = element_text(size = 8),
    axis.text.x = element_text(size = 11)
  )
)
```

## Top 20 Most Important Variables

Measured by Mean Decrease in Accuracy (Imputed Data)



### Random Forest w/ subset of features

```
# subset of variables from variable importance
rf_with_nas <- rf_with_nas[, c("Reason", "loudness_sma3_percentile50.0",
  ↳ "loudness_sma3_stddevNorm", "F2amplitudeLogRelF0_sma3nz_stddevNorm",
  ↳ "StddevUnvoicedSegmentLength", "loudness_sma3_percentile20.0",
  ↳ "F2amplitudeLogRelF0_sma3nz_amean", "MeanUnvoicedSegmentLength", "loudness_sma3_amean",
  ↳ "loudness_sma3_percentile80.0", "F1amplitudeLogRelF0_sma3nz_stddevNorm")]

# impute missing values using mice
imputed_data <- mice(rf_with_nas, m = 1, method = "pmm", seed = 605794011)
```

```
iter imp variable
1 1
2 1
3 1
4 1
5 1
```

```
data_imputed <- complete(imputed_data, action = 1)

# ensure target and gender are factors
data_imputed$Reason <- as.factor(data_imputed$Reason)

# set seed for reproducibility
set.seed(605794011)
```

```
# train/test split
train_index2 <- createDataPartition(data_imputed$Reason, p = 0.8, list = FALSE)
train_imputed <- data_imputed[train_index2, ]
test_imputed <- data_imputed[-train_index2, ]

# fit random forest model with selected variables
rf_imputed <- randomForest(Reason ~ ., data = train_imputed, importance = TRUE)

# predictions and evaluations of accuracy
preds_imputed <- predict(rf_imputed, test_imputed)
conf_matrix_imputed <- confusionMatrix(preds_imputed, test_imputed$Reason)
accuracy_imputed <- conf_matrix_imputed$overall['Accuracy']

# show results
print(conf_matrix_imputed)
```

## Confusion Matrix and Statistics

Prediction	Reference				
	Diaper-Change	Fussy	Hungry	Pain	Tired
Diaper-Change	11	8	10	10	7
Fussy	17	10	11	8	11
Hungry	12	11	10	9	14
Pain	6	10	13	19	6
Tired	4	11	6	4	12

## Overall Statistics

Accuracy : 0.248  
 95% CI : (0.1957, 0.3063)  
 No Information Rate : 0.2  
 P-Value [Acc > NIR] : 0.03705

Kappa : 0.06

Mcnemar's Test P-Value : 0.45915

## Statistics by Class:

	Class: Diaper-Change	Class: Fussy	Class: Hungry
Sensitivity	0.2200	0.2000	0.2000
Specificity	0.8250	0.7650	0.7700
Pos Pred Value	0.2391	0.1754	0.1786
Neg Pred Value	0.8088	0.7927	0.7938
Prevalence	0.2000	0.2000	0.2000
Detection Rate	0.0440	0.0400	0.0400
Detection Prevalence	0.1840	0.2280	0.2240
Balanced Accuracy	0.5225	0.4825	0.4850
	Class: Pain	Class: Tired	
Sensitivity	0.3800	0.2400	
Specificity	0.8250	0.8750	
Pos Pred Value	0.3519	0.3243	
Neg Pred Value	0.8418	0.8216	
Prevalence	0.2000	0.2000	

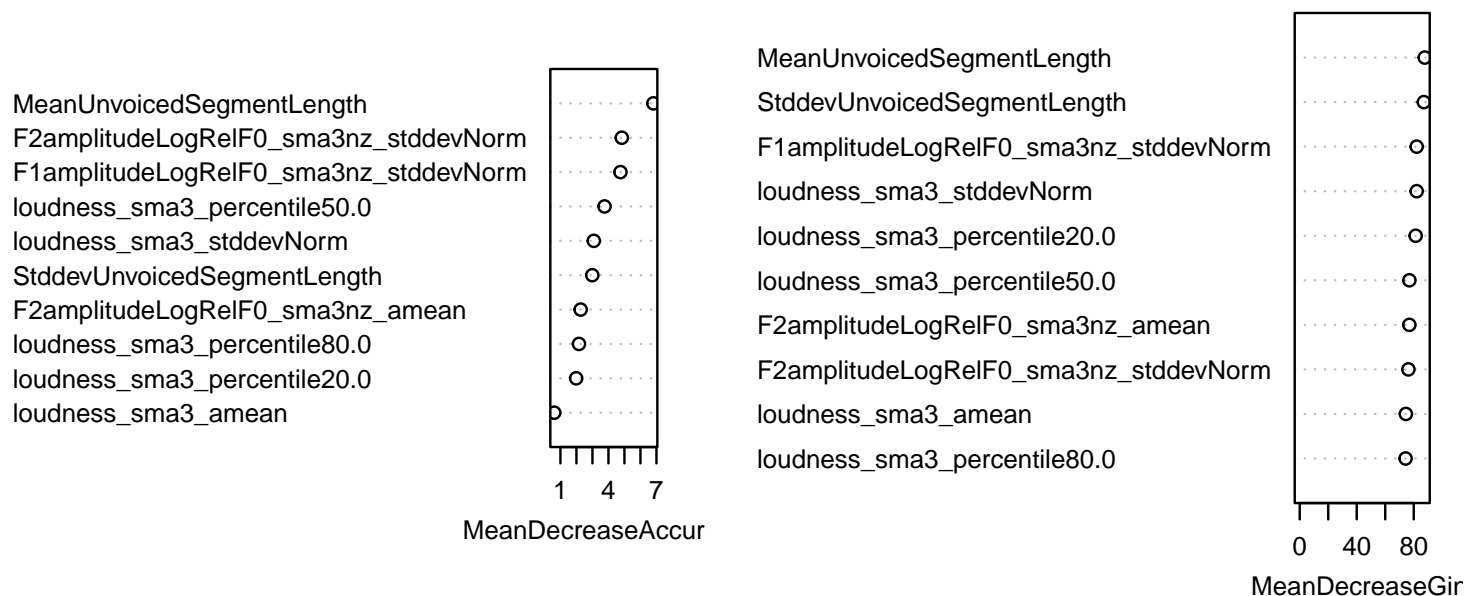
Detection Rate	0.0760	0.0480
Detection Prevalence	0.2160	0.1480
Balanced Accuracy	0.6025	0.5575

```
print(accuracy_imputed)
```

```
Accuracy
0.248
```

```
varImpPlot(rf_imputed, main = "Variable Importance (MICE Imputed Data)", cex = 0.7)
```

## Variable Importance (MICE Imputed Data)



## XGBoost

```
# ensure Reason is a factor
data_imputed$Reason <- as.factor(data_imputed$Reason)

# clean up class levels to be valid R variable names
levels(data_imputed$Reason) <- make.names(levels(data_imputed$Reason))

# train/test split (optional if using cross-validation)
set.seed(605794011)
train_index <- createDataPartition(data_imputed$Reason, p = 0.8, list = FALSE)
train_data <- data_imputed[train_index, ]
test_data <- data_imputed[-train_index, ]

# cross-validation setup
```

```

ctrl <- trainControl(
  method = "cv",          # 10 fold cross-validaton
  number = 10,
  classProbs = TRUE,      # needed for multiclass AUC etc.
  summaryFunction = multiClassSummary,
  verboseIter = FALSE
)

# train XGBoost model
set.seed(605794011)
invisible(capture.output({
  suppressMessages({
    suppressWarnings({
      xgb_model <- train(
        Reason ~ .,
        data = train_data,
        method = "xgbTree",
        trControl = ctrl,
        tuneLength = 5,      # tries 5 different combinations of params, trains 10 models per set
                             ↳ of params, 10 x 5 = 50 models total
        metric = "Accuracy"
      )
    })
  })
}))

# print model summary and best tuning parameters
print(xgb_model)

```

## eXtreme Gradient Boosting

1000 samples  
 10 predictor  
 5 classes: 'Diaper.Change', 'Fussy', 'Hungry', 'Pain', 'Tired'

No pre-processing

Resampling: Cross-Validated (10 fold)

Summary of sample sizes: 900, 900, 900, 900, 900, 900, ...

Resampling results across tuning parameters:

eta	max_depth	colsample_bytree	subsample	nrounds	logLoss	AUC
0.3	1	0.6	0.500	50	1.622083	0.5531000
0.3	1	0.6	0.500	100	1.653972	0.5460375
0.3	1	0.6	0.500	150	1.682211	0.5389875
0.3	1	0.6	0.500	200	1.712036	0.5370000
0.3	1	0.6	0.500	250	1.733616	0.5343375
0.3	1	0.6	0.625	50	1.610880	0.5623375
0.3	1	0.6	0.625	100	1.641706	0.5511875
0.3	1	0.6	0.625	150	1.674356	0.5439000
0.3	1	0.6	0.625	200	1.699994	0.5379500
0.3	1	0.6	0.625	250	1.722548	0.5365250
0.3	1	0.6	0.750	50	1.609826	0.5589875
0.3	1	0.6	0.750	100	1.644689	0.5479625
0.3	1	0.6	0.750	150	1.674628	0.5410000

0.3	1	0.6	0.750	200	1.707059	0.5311125
0.3	1	0.6	0.750	250	1.725706	0.5300625
0.3	1	0.6	0.875	50	1.612310	0.5558000
0.3	1	0.6	0.875	100	1.646947	0.5443875
0.3	1	0.6	0.875	150	1.676778	0.5359875
0.3	1	0.6	0.875	200	1.701503	0.5300750
0.3	1	0.6	0.875	250	1.727169	0.5256750
0.3	1	0.6	1.000	50	1.609522	0.5518000
0.3	1	0.6	1.000	100	1.634070	0.5442250
0.3	1	0.6	1.000	150	1.656421	0.5391750
0.3	1	0.6	1.000	200	1.677213	0.5340250
0.3	1	0.6	1.000	250	1.693684	0.5302250
0.3	1	0.8	0.500	50	1.623325	0.5506375
0.3	1	0.8	0.500	100	1.652338	0.5476375
0.3	1	0.8	0.500	150	1.685991	0.5424750
0.3	1	0.8	0.500	200	1.714671	0.5339875
0.3	1	0.8	0.500	250	1.749256	0.5252500
0.3	1	0.8	0.625	50	1.616717	0.5538000
0.3	1	0.8	0.625	100	1.647852	0.5503875
0.3	1	0.8	0.625	150	1.677386	0.5422375
0.3	1	0.8	0.625	200	1.705661	0.5381250
0.3	1	0.8	0.625	250	1.732034	0.5314875
0.3	1	0.8	0.750	50	1.614770	0.5543250
0.3	1	0.8	0.750	100	1.646151	0.5489375
0.3	1	0.8	0.750	150	1.678405	0.5402250
0.3	1	0.8	0.750	200	1.703874	0.5342375
0.3	1	0.8	0.750	250	1.729168	0.5291000
0.3	1	0.8	0.875	50	1.614045	0.5527625
0.3	1	0.8	0.875	100	1.646158	0.5443625
0.3	1	0.8	0.875	150	1.673664	0.5387625
0.3	1	0.8	0.875	200	1.699860	0.5343625
0.3	1	0.8	0.875	250	1.720030	0.5328000
0.3	1	0.8	1.000	50	1.610616	0.5508750
0.3	1	0.8	1.000	100	1.633327	0.5454375
0.3	1	0.8	1.000	150	1.654971	0.5398125
0.3	1	0.8	1.000	200	1.676281	0.5343000
0.3	1	0.8	1.000	250	1.694432	0.5293250
0.3	2	0.6	0.500	50	1.704025	0.5313750
0.3	2	0.6	0.500	100	1.804554	0.5254625
0.3	2	0.6	0.500	150	1.894354	0.5186875
0.3	2	0.6	0.500	200	1.975006	0.5105125
0.3	2	0.6	0.500	250	2.053404	0.5076500
0.3	2	0.6	0.625	50	1.697298	0.5338750
0.3	2	0.6	0.625	100	1.785582	0.5315125
0.3	2	0.6	0.625	150	1.867173	0.5186625
0.3	2	0.6	0.625	200	1.954038	0.5105000
0.3	2	0.6	0.625	250	2.016966	0.5113875
0.3	2	0.6	0.750	50	1.678522	0.5425125
0.3	2	0.6	0.750	100	1.782315	0.5242375
0.3	2	0.6	0.750	150	1.870244	0.5184750
0.3	2	0.6	0.750	200	1.957353	0.5090625
0.3	2	0.6	0.750	250	2.031823	0.5071750
0.3	2	0.6	0.875	50	1.685350	0.5354250
0.3	2	0.6	0.875	100	1.777469	0.5237000
0.3	2	0.6	0.875	150	1.851991	0.5201625

0.3	2	0.6	0.875	200	1.934409	0.5140500
0.3	2	0.6	0.875	250	2.006926	0.5141250
0.3	2	0.6	1.000	50	1.683403	0.5242750
0.3	2	0.6	1.000	100	1.778992	0.5113500
0.3	2	0.6	1.000	150	1.856043	0.5074875
0.3	2	0.6	1.000	200	1.927269	0.5054000
0.3	2	0.6	1.000	250	2.002188	0.5035625
0.3	2	0.8	0.500	50	1.697815	0.5441125
0.3	2	0.8	0.500	100	1.797511	0.5314875
0.3	2	0.8	0.500	150	1.879019	0.5285250
0.3	2	0.8	0.500	200	1.946467	0.5261625
0.3	2	0.8	0.500	250	2.001980	0.5264000
0.3	2	0.8	0.625	50	1.683613	0.5455250
0.3	2	0.8	0.625	100	1.790812	0.5298000
0.3	2	0.8	0.625	150	1.885236	0.5205000
0.3	2	0.8	0.625	200	1.970900	0.5143375
0.3	2	0.8	0.625	250	2.035335	0.5159250
0.3	2	0.8	0.750	50	1.700770	0.5265000
0.3	2	0.8	0.750	100	1.803632	0.5161625
0.3	2	0.8	0.750	150	1.898353	0.5085750
0.3	2	0.8	0.750	200	1.981210	0.5048125
0.3	2	0.8	0.750	250	2.048161	0.5063875
0.3	2	0.8	0.875	50	1.693418	0.5291500
0.3	2	0.8	0.875	100	1.793934	0.5173250
0.3	2	0.8	0.875	150	1.882952	0.5095875
0.3	2	0.8	0.875	200	1.961864	0.5086125
0.3	2	0.8	0.875	250	2.036155	0.5064250
0.3	2	0.8	1.000	50	1.686902	0.5210250
0.3	2	0.8	1.000	100	1.791116	0.5078875
0.3	2	0.8	1.000	150	1.875663	0.5056875
0.3	2	0.8	1.000	200	1.956712	0.5027125
0.3	2	0.8	1.000	250	2.034742	0.5024375
0.3	3	0.6	0.500	50	1.785456	0.5325375
0.3	3	0.6	0.500	100	1.937698	0.5262000
0.3	3	0.6	0.500	150	2.076342	0.5198875
0.3	3	0.6	0.500	200	2.191872	0.5184500
0.3	3	0.6	0.500	250	2.285524	0.5190500
0.3	3	0.6	0.625	50	1.766163	0.5327750
0.3	3	0.6	0.625	100	1.907255	0.5275875
0.3	3	0.6	0.625	150	2.056634	0.5201875
0.3	3	0.6	0.625	200	2.188347	0.5183625
0.3	3	0.6	0.625	250	2.297910	0.5166000
0.3	3	0.6	0.750	50	1.752932	0.5331375
0.3	3	0.6	0.750	100	1.905769	0.5225250
0.3	3	0.6	0.750	150	2.037538	0.5202375
0.3	3	0.6	0.750	200	2.160441	0.5172125
0.3	3	0.6	0.750	250	2.263703	0.5187250
0.3	3	0.6	0.875	50	1.743639	0.5310250
0.3	3	0.6	0.875	100	1.881258	0.5236125
0.3	3	0.6	0.875	150	2.015180	0.5182875
0.3	3	0.6	0.875	200	2.135446	0.5133750
0.3	3	0.6	0.875	250	2.250090	0.5141875
0.3	3	0.6	1.000	50	1.756958	0.5141625
0.3	3	0.6	1.000	100	1.898359	0.5073125
0.3	3	0.6	1.000	150	2.020832	0.5079500



0.3	3	0.6	1.000	200	2.128670	0.5130000
0.3	3	0.6	1.000	250	2.235146	0.5121375
0.3	3	0.8	0.500	50	1.804273	0.5245375
0.3	3	0.8	0.500	100	1.965675	0.5199500
0.3	3	0.8	0.500	150	2.104190	0.5196375
0.3	3	0.8	0.500	200	2.236054	0.5159125
0.3	3	0.8	0.500	250	2.348667	0.5157500
0.3	3	0.8	0.625	50	1.787780	0.5268375
0.3	3	0.8	0.625	100	1.965410	0.5167375
0.3	3	0.8	0.625	150	2.101618	0.5142875
0.3	3	0.8	0.625	200	2.224935	0.5131375
0.3	3	0.8	0.625	250	2.339229	0.5133000
0.3	3	0.8	0.750	50	1.787846	0.5220000
0.3	3	0.8	0.750	100	1.929335	0.5160375
0.3	3	0.8	0.750	150	2.070357	0.5119125
0.3	3	0.8	0.750	200	2.205844	0.5091875
0.3	3	0.8	0.750	250	2.335594	0.5085875
0.3	3	0.8	0.875	50	1.763780	0.5233000
0.3	3	0.8	0.875	100	1.902349	0.5219500
0.3	3	0.8	0.875	150	2.031215	0.5231375
0.3	3	0.8	0.875	200	2.155945	0.5196625
0.3	3	0.8	0.875	250	2.262672	0.5210750
0.3	3	0.8	1.000	50	1.764181	0.5151125
0.3	3	0.8	1.000	100	1.914320	0.5079625
0.3	3	0.8	1.000	150	2.044156	0.5090250
0.3	3	0.8	1.000	200	2.182249	0.5042875
0.3	3	0.8	1.000	250	2.294187	0.5053875
0.3	4	0.6	0.500	50	1.846647	0.5417250
0.3	4	0.6	0.500	100	2.058554	0.5334500
0.3	4	0.6	0.500	150	2.225476	0.5284375
0.3	4	0.6	0.500	200	2.349253	0.5287000
0.3	4	0.6	0.500	250	2.458246	0.5272750
0.3	4	0.6	0.625	50	1.872512	0.5190125
0.3	4	0.6	0.625	100	2.063698	0.5179375
0.3	4	0.6	0.625	150	2.239773	0.5155000
0.3	4	0.6	0.625	200	2.391921	0.5138500
0.3	4	0.6	0.625	250	2.500370	0.5159750
0.3	4	0.6	0.750	50	1.846563	0.5200750
0.3	4	0.6	0.750	100	2.064267	0.5131000
0.3	4	0.6	0.750	150	2.238595	0.5126625
0.3	4	0.6	0.750	200	2.399115	0.5096250
0.3	4	0.6	0.750	250	2.519784	0.5103875
0.3	4	0.6	0.875	50	1.838767	0.5173000
0.3	4	0.6	0.875	100	2.037352	0.5118250
0.3	4	0.6	0.875	150	2.205579	0.5104125
0.3	4	0.6	0.875	200	2.361102	0.5090000
0.3	4	0.6	0.875	250	2.493581	0.5089250
0.3	4	0.6	1.000	50	1.801902	0.5259375
0.3	4	0.6	1.000	100	2.007103	0.5122625
0.3	4	0.6	1.000	150	2.172361	0.5111000
0.3	4	0.6	1.000	200	2.317634	0.5092625
0.3	4	0.6	1.000	250	2.455366	0.5063250
0.3	4	0.8	0.500	50	1.894025	0.5297875
0.3	4	0.8	0.500	100	2.136454	0.5231750
0.3	4	0.8	0.500	150	2.296164	0.5221625

0.3	4	0.8	0.500	200	2.413732	0.5231500
0.3	4	0.8	0.500	250	2.534928	0.5230875
0.3	4	0.8	0.625	50	1.899705	0.5185875
0.3	4	0.8	0.625	100	2.112119	0.5224875
0.3	4	0.8	0.625	150	2.300240	0.5182750
0.3	4	0.8	0.625	200	2.455384	0.5153125
0.3	4	0.8	0.625	250	2.574158	0.5143500
0.3	4	0.8	0.750	50	1.858542	0.5245750
0.3	4	0.8	0.750	100	2.075272	0.5170875
0.3	4	0.8	0.750	150	2.252813	0.5182375
0.3	4	0.8	0.750	200	2.414003	0.5149500
0.3	4	0.8	0.750	250	2.547417	0.5126125
0.3	4	0.8	0.875	50	1.861176	0.5176625
0.3	4	0.8	0.875	100	2.066304	0.5148375
0.3	4	0.8	0.875	150	2.250467	0.5115875
0.3	4	0.8	0.875	200	2.408329	0.5119250
0.3	4	0.8	0.875	250	2.541988	0.5102750
0.3	4	0.8	1.000	50	1.834338	0.5153625
0.3	4	0.8	1.000	100	2.030163	0.5145500
0.3	4	0.8	1.000	150	2.209464	0.5121125
0.3	4	0.8	1.000	200	2.365060	0.5103625
0.3	4	0.8	1.000	250	2.493914	0.5105500
0.3	5	0.6	0.500	50	1.956974	0.5228625
0.3	5	0.6	0.500	100	2.203522	0.5223875
0.3	5	0.6	0.500	150	2.380039	0.5204375
0.3	5	0.6	0.500	200	2.486656	0.5232125
0.3	5	0.6	0.500	250	2.581081	0.5211500
0.3	5	0.6	0.625	50	1.948299	0.5263500
0.3	5	0.6	0.625	100	2.180571	0.5237250
0.3	5	0.6	0.625	150	2.371336	0.5208000
0.3	5	0.6	0.625	200	2.491180	0.5209500
0.3	5	0.6	0.625	250	2.582363	0.5207125
0.3	5	0.6	0.750	50	1.950875	0.5143000
0.3	5	0.6	0.750	100	2.213657	0.5108750
0.3	5	0.6	0.750	150	2.396411	0.5128500
0.3	5	0.6	0.750	200	2.533701	0.5117250
0.3	5	0.6	0.750	250	2.631277	0.5122625
0.3	5	0.6	0.875	50	1.893787	0.5228875
0.3	5	0.6	0.875	100	2.127066	0.5171250
0.3	5	0.6	0.875	150	2.320250	0.5148500
0.3	5	0.6	0.875	200	2.469419	0.5142500
0.3	5	0.6	0.875	250	2.589145	0.5124375
0.3	5	0.6	1.000	50	1.870577	0.5220250
0.3	5	0.6	1.000	100	2.112933	0.5091375
0.3	5	0.6	1.000	150	2.297277	0.5066625
0.3	5	0.6	1.000	200	2.436720	0.5074875
0.3	5	0.6	1.000	250	2.549722	0.5079125
0.3	5	0.8	0.500	50	1.974677	0.5306000
0.3	5	0.8	0.500	100	2.223919	0.5315250
0.3	5	0.8	0.500	150	2.404203	0.5277125
0.3	5	0.8	0.500	200	2.522440	0.5275750
0.3	5	0.8	0.500	250	2.612327	0.5251250
0.3	5	0.8	0.625	50	1.927424	0.5422125
0.3	5	0.8	0.625	100	2.192999	0.5355062
0.3	5	0.8	0.625	150	2.370406	0.5312750

0.3	5	0.8	0.625	200	2.500201	0.5286375
0.3	5	0.8	0.625	250	2.592108	0.5264750
0.3	5	0.8	0.750	50	1.939876	0.5271125
0.3	5	0.8	0.750	100	2.206185	0.5260625
0.3	5	0.8	0.750	150	2.402630	0.5216875
0.3	5	0.8	0.750	200	2.543338	0.5188875
0.3	5	0.8	0.750	250	2.639612	0.5184500
0.3	5	0.8	0.875	50	1.910769	0.5244500
0.3	5	0.8	0.875	100	2.167223	0.5169125
0.3	5	0.8	0.875	150	2.374245	0.5139500
0.3	5	0.8	0.875	200	2.522419	0.5133375
0.3	5	0.8	0.875	250	2.637521	0.5112125
0.3	5	0.8	1.000	50	1.888179	0.5233750
0.3	5	0.8	1.000	100	2.130499	0.5148875
0.3	5	0.8	1.000	150	2.336260	0.5105000
0.3	5	0.8	1.000	200	2.481311	0.5099625
0.3	5	0.8	1.000	250	2.593438	0.5104500
0.4	1	0.6	0.500	50	1.632317	0.5546062
0.4	1	0.6	0.500	100	1.682137	0.5397250
0.4	1	0.6	0.500	150	1.721360	0.5330875
0.4	1	0.6	0.500	200	1.748899	0.5319125
0.4	1	0.6	0.500	250	1.783398	0.5261875
0.4	1	0.6	0.625	50	1.629020	0.5525500
0.4	1	0.6	0.625	100	1.674983	0.5404250
0.4	1	0.6	0.625	150	1.712610	0.5360500
0.4	1	0.6	0.625	200	1.748655	0.5276875
0.4	1	0.6	0.625	250	1.786947	0.5202500
0.4	1	0.6	0.750	50	1.629429	0.5513875
0.4	1	0.6	0.750	100	1.668785	0.5405875
0.4	1	0.6	0.750	150	1.708984	0.5325250
0.4	1	0.6	0.750	200	1.745277	0.5255000
0.4	1	0.6	0.750	250	1.776291	0.5212875
0.4	1	0.6	0.875	50	1.626931	0.5514875
0.4	1	0.6	0.875	100	1.666880	0.5416125
0.4	1	0.6	0.875	150	1.702917	0.5346000
0.4	1	0.6	0.875	200	1.733429	0.5288250
0.4	1	0.6	0.875	250	1.765518	0.5205500
0.4	1	0.6	1.000	50	1.619198	0.5508625
0.4	1	0.6	1.000	100	1.649340	0.5411625
0.4	1	0.6	1.000	150	1.676589	0.5343250
0.4	1	0.6	1.000	200	1.701308	0.5290500
0.4	1	0.6	1.000	250	1.719932	0.5261625
0.4	1	0.8	0.500	50	1.633057	0.5526000
0.4	1	0.8	0.500	100	1.685640	0.5395000
0.4	1	0.8	0.500	150	1.721810	0.5328125
0.4	1	0.8	0.500	200	1.760350	0.5245250
0.4	1	0.8	0.500	250	1.798366	0.5194625
0.4	1	0.8	0.625	50	1.640257	0.5462250
0.4	1	0.8	0.625	100	1.677580	0.5445250
0.4	1	0.8	0.625	150	1.717510	0.5343625
0.4	1	0.8	0.625	200	1.764565	0.5277250
0.4	1	0.8	0.625	250	1.789885	0.5209875
0.4	1	0.8	0.750	50	1.623250	0.5575000
0.4	1	0.8	0.750	100	1.667837	0.5440375
0.4	1	0.8	0.750	150	1.703143	0.5382500

0.4	1	0.8	0.750	200	1.740830	0.5313125
0.4	1	0.8	0.750	250	1.773578	0.5252250
0.4	1	0.8	0.875	50	1.628184	0.5485250
0.4	1	0.8	0.875	100	1.666179	0.5410125
0.4	1	0.8	0.875	150	1.704857	0.5333000
0.4	1	0.8	0.875	200	1.741617	0.5263250
0.4	1	0.8	0.875	250	1.771211	0.5208125
0.4	1	0.8	1.000	50	1.618461	0.5506375
0.4	1	0.8	1.000	100	1.650245	0.5408625
0.4	1	0.8	1.000	150	1.677539	0.5345500
0.4	1	0.8	1.000	200	1.700703	0.5289375
0.4	1	0.8	1.000	250	1.721144	0.5250625
0.4	2	0.6	0.500	50	1.765501	0.5217000
0.4	2	0.6	0.500	100	1.909731	0.5069625
0.4	2	0.6	0.500	150	2.013817	0.5066750
0.4	2	0.6	0.500	200	2.102888	0.5081375
0.4	2	0.6	0.500	250	2.192846	0.5098500
0.4	2	0.6	0.625	50	1.740726	0.5334000
0.4	2	0.6	0.625	100	1.871112	0.5192000
0.4	2	0.6	0.625	150	1.987919	0.5166875
0.4	2	0.6	0.625	200	2.081047	0.5145500
0.4	2	0.6	0.625	250	2.162637	0.5131875
0.4	2	0.6	0.750	50	1.738168	0.5249500
0.4	2	0.6	0.750	100	1.846239	0.5162000
0.4	2	0.6	0.750	150	1.950031	0.5154125
0.4	2	0.6	0.750	200	2.035452	0.5152250
0.4	2	0.6	0.750	250	2.124255	0.5148625
0.4	2	0.6	0.875	50	1.729665	0.5293125
0.4	2	0.6	0.875	100	1.863797	0.5133375
0.4	2	0.6	0.875	150	1.969232	0.5099375
0.4	2	0.6	0.875	200	2.078498	0.5060750
0.4	2	0.6	0.875	250	2.170221	0.5061125
0.4	2	0.6	1.000	50	1.722131	0.5196875
0.4	2	0.6	1.000	100	1.832714	0.5135500
0.4	2	0.6	1.000	150	1.939370	0.5083750
0.4	2	0.6	1.000	200	2.037825	0.5065875
0.4	2	0.6	1.000	250	2.134664	0.5061750
0.4	2	0.8	0.500	50	1.761315	0.5349250
0.4	2	0.8	0.500	100	1.867661	0.5355750
0.4	2	0.8	0.500	150	1.988282	0.5236375
0.4	2	0.8	0.500	200	2.089383	0.5209875
0.4	2	0.8	0.500	250	2.155299	0.5247750
0.4	2	0.8	0.625	50	1.750705	0.5307250
0.4	2	0.8	0.625	100	1.895448	0.5173250
0.4	2	0.8	0.625	150	2.013512	0.5094250
0.4	2	0.8	0.625	200	2.107394	0.5131750
0.4	2	0.8	0.625	250	2.204735	0.5094625
0.4	2	0.8	0.750	50	1.744933	0.5213500
0.4	2	0.8	0.750	100	1.876671	0.5110875
0.4	2	0.8	0.750	150	1.990412	0.5071125
0.4	2	0.8	0.750	200	2.087944	0.5076500
0.4	2	0.8	0.750	250	2.196062	0.5023875
0.4	2	0.8	0.875	50	1.741763	0.5211875
0.4	2	0.8	0.875	100	1.864845	0.5162875
0.4	2	0.8	0.875	150	1.970035	0.5155000

0.4	2	0.8	0.875	200	2.076957	0.5099375
0.4	2	0.8	0.875	250	2.168041	0.5096875
0.4	2	0.8	1.000	50	1.717290	0.5238625
0.4	2	0.8	1.000	100	1.837392	0.5139875
0.4	2	0.8	1.000	150	1.952682	0.5091625
0.4	2	0.8	1.000	200	2.047707	0.5069375
0.4	2	0.8	1.000	250	2.147941	0.5063250
0.4	3	0.6	0.500	50	1.878745	0.5308000
0.4	3	0.6	0.500	100	2.084280	0.5213250
0.4	3	0.6	0.500	150	2.261435	0.5139250
0.4	3	0.6	0.500	200	2.409308	0.5149875
0.4	3	0.6	0.500	250	2.534038	0.5106500
0.4	3	0.6	0.625	50	1.852744	0.5258750
0.4	3	0.6	0.625	100	2.061435	0.5172125
0.4	3	0.6	0.625	150	2.259549	0.5128500
0.4	3	0.6	0.625	200	2.413165	0.5118625
0.4	3	0.6	0.625	250	2.539079	0.5109500
0.4	3	0.6	0.750	50	1.823096	0.5271875
0.4	3	0.6	0.750	100	2.020498	0.5195500
0.4	3	0.6	0.750	150	2.200892	0.5166250
0.4	3	0.6	0.750	200	2.363433	0.5153625
0.4	3	0.6	0.750	250	2.493720	0.5147625
0.4	3	0.6	0.875	50	1.819953	0.5251625
0.4	3	0.6	0.875	100	2.005132	0.5180750
0.4	3	0.6	0.875	150	2.152457	0.5207375
0.4	3	0.6	0.875	200	2.295760	0.5214250
0.4	3	0.6	0.875	250	2.428434	0.5221125
0.4	3	0.6	1.000	50	1.811074	0.5162000
0.4	3	0.6	1.000	100	1.979506	0.5134375
0.4	3	0.6	1.000	150	2.143206	0.5107125
0.4	3	0.6	1.000	200	2.275218	0.5129500
0.4	3	0.6	1.000	250	2.410403	0.5110750
0.4	3	0.8	0.500	50	1.887573	0.5282750
0.4	3	0.8	0.500	100	2.100579	0.5227250
0.4	3	0.8	0.500	150	2.273973	0.5227125
0.4	3	0.8	0.500	200	2.428786	0.5175125
0.4	3	0.8	0.500	250	2.563832	0.5163875
0.4	3	0.8	0.625	50	1.860841	0.5292875
0.4	3	0.8	0.625	100	2.094780	0.5126125
0.4	3	0.8	0.625	150	2.268076	0.5126750
0.4	3	0.8	0.625	200	2.424759	0.5109375
0.4	3	0.8	0.625	250	2.552819	0.5115000
0.4	3	0.8	0.750	50	1.836440	0.5297875
0.4	3	0.8	0.750	100	2.035441	0.5221375
0.4	3	0.8	0.750	150	2.208698	0.5215250
0.4	3	0.8	0.750	200	2.364617	0.5198875
0.4	3	0.8	0.750	250	2.515558	0.5165500
0.4	3	0.8	0.875	50	1.813931	0.5342875
0.4	3	0.8	0.875	100	2.025420	0.5195000
0.4	3	0.8	0.875	150	2.193708	0.5193250
0.4	3	0.8	0.875	200	2.352313	0.5181625
0.4	3	0.8	0.875	250	2.491643	0.5177250
0.4	3	0.8	1.000	50	1.827960	0.5131000
0.4	3	0.8	1.000	100	2.022742	0.5077250
0.4	3	0.8	1.000	150	2.180338	0.5076125

0.4	3	0.8	1.000	200	2.333556	0.5062500
0.4	3	0.8	1.000	250	2.489699	0.5051375
0.4	4	0.6	0.500	50	2.004810	0.5196875
0.4	4	0.6	0.500	100	2.276647	0.5114375
0.4	4	0.6	0.500	150	2.483665	0.5093875
0.4	4	0.6	0.500	200	2.635350	0.5090250
0.4	4	0.6	0.500	250	2.749064	0.5054250
0.4	4	0.6	0.625	50	1.975794	0.5216500
0.4	4	0.6	0.625	100	2.227814	0.5235625
0.4	4	0.6	0.625	150	2.429752	0.5240750
0.4	4	0.6	0.625	200	2.562406	0.5223625
0.4	4	0.6	0.625	250	2.681322	0.5213000
0.4	4	0.6	0.750	50	1.996209	0.5090750
0.4	4	0.6	0.750	100	2.238932	0.5149250
0.4	4	0.6	0.750	150	2.417397	0.5177625
0.4	4	0.6	0.750	200	2.560308	0.5192625
0.4	4	0.6	0.750	250	2.682177	0.5187625
0.4	4	0.6	0.875	50	1.919118	0.5225500
0.4	4	0.6	0.875	100	2.156219	0.5216500
0.4	4	0.6	0.875	150	2.359137	0.5210000
0.4	4	0.6	0.875	200	2.533044	0.5192250
0.4	4	0.6	0.875	250	2.655566	0.5190000
0.4	4	0.6	1.000	50	1.889881	0.5210375
0.4	4	0.6	1.000	100	2.126331	0.5134375
0.4	4	0.6	1.000	150	2.333438	0.5095125
0.4	4	0.6	1.000	200	2.495440	0.5077250
0.4	4	0.6	1.000	250	2.625655	0.5059875
0.4	4	0.8	0.500	50	2.007596	0.5248625
0.4	4	0.8	0.500	100	2.278026	0.5195000
0.4	4	0.8	0.500	150	2.458493	0.5201500
0.4	4	0.8	0.500	200	2.600591	0.5185375
0.4	4	0.8	0.500	250	2.708361	0.5160500
0.4	4	0.8	0.625	50	2.035149	0.5069500
0.4	4	0.8	0.625	100	2.305754	0.5055375
0.4	4	0.8	0.625	150	2.502881	0.5081000
0.4	4	0.8	0.625	200	2.671480	0.5041500
0.4	4	0.8	0.625	250	2.779576	0.5049750
0.4	4	0.8	0.750	50	1.954644	0.5236625
0.4	4	0.8	0.750	100	2.240623	0.5171125
0.4	4	0.8	0.750	150	2.453239	0.5159750
0.4	4	0.8	0.750	200	2.603189	0.5160250
0.4	4	0.8	0.750	250	2.712333	0.5163500
0.4	4	0.8	0.875	50	1.932006	0.5265625
0.4	4	0.8	0.875	100	2.194969	0.5206000
0.4	4	0.8	0.875	150	2.404689	0.5185000
0.4	4	0.8	0.875	200	2.563578	0.5184750
0.4	4	0.8	0.875	250	2.688240	0.5165625
0.4	4	0.8	1.000	50	1.911366	0.5161125
0.4	4	0.8	1.000	100	2.158304	0.5126625
0.4	4	0.8	1.000	150	2.370105	0.5124875
0.4	4	0.8	1.000	200	2.532255	0.5125000
0.4	4	0.8	1.000	250	2.656985	0.5135500
0.4	5	0.6	0.500	50	2.119384	0.5226750
0.4	5	0.6	0.500	100	2.417031	0.5163000
0.4	5	0.6	0.500	150	2.581004	0.5145875

0.4	5	0.6	0.500	200	2.687803	0.5130000
0.4	5	0.6	0.500	250	2.766937	0.5126125
0.4	5	0.6	0.625	50	2.053051	0.5301875
0.4	5	0.6	0.625	100	2.348487	0.5236125
0.4	5	0.6	0.625	150	2.539558	0.5229875
0.4	5	0.6	0.625	200	2.640786	0.5235250
0.4	5	0.6	0.625	250	2.719239	0.5227750
0.4	5	0.6	0.750	50	2.041403	0.5297375
0.4	5	0.6	0.750	100	2.336032	0.5279250
0.4	5	0.6	0.750	150	2.527214	0.5234750
0.4	5	0.6	0.750	200	2.647308	0.5234750
0.4	5	0.6	0.750	250	2.731680	0.5224750
0.4	5	0.6	0.875	50	1.996648	0.5267125
0.4	5	0.6	0.875	100	2.276300	0.5274000
0.4	5	0.6	0.875	150	2.500888	0.5196000
0.4	5	0.6	0.875	200	2.643933	0.5163125
0.4	5	0.6	0.875	250	2.737430	0.5160500
0.4	5	0.6	1.000	50	1.984762	0.5155875
0.4	5	0.6	1.000	100	2.252942	0.5113250
0.4	5	0.6	1.000	150	2.442682	0.5109000
0.4	5	0.6	1.000	200	2.591718	0.5108125
0.4	5	0.6	1.000	250	2.693523	0.5112375
0.4	5	0.8	0.500	50	2.138886	0.5192250
0.4	5	0.8	0.500	100	2.440891	0.5140125
0.4	5	0.8	0.500	150	2.626910	0.5113625
0.4	5	0.8	0.500	200	2.754321	0.5088375
0.4	5	0.8	0.500	250	2.812949	0.5095250
0.4	5	0.8	0.625	50	2.109922	0.5263375
0.4	5	0.8	0.625	100	2.423349	0.5220375
0.4	5	0.8	0.625	150	2.597857	0.5185625
0.4	5	0.8	0.625	200	2.712671	0.5162000
0.4	5	0.8	0.625	250	2.794734	0.5146625
0.4	5	0.8	0.750	50	2.086250	0.5218375
0.4	5	0.8	0.750	100	2.402814	0.5174750
0.4	5	0.8	0.750	150	2.574556	0.5188875
0.4	5	0.8	0.750	200	2.692567	0.5165875
0.4	5	0.8	0.750	250	2.774315	0.5154000
0.4	5	0.8	0.875	50	2.052983	0.5158125
0.4	5	0.8	0.875	100	2.355130	0.5118875
0.4	5	0.8	0.875	150	2.560160	0.5124875
0.4	5	0.8	0.875	200	2.690163	0.5126875
0.4	5	0.8	0.875	250	2.774833	0.5128750
0.4	5	0.8	1.000	50	2.017544	0.5135875
0.4	5	0.8	1.000	100	2.313075	0.5094625
0.4	5	0.8	1.000	150	2.522506	0.5092125
0.4	5	0.8	1.000	200	2.673726	0.5094750
0.4	5	0.8	1.000	250	2.782299	0.5089000

prAUC	Accuracy	Kappa	Mean_F1	Mean_Sensitivity
0.2409999	0.247	5.875000e-02	0.2345539	0.247
0.2347799	0.233	4.125000e-02	0.2322273	0.233
0.2317203	0.228	3.500000e-02	0.2233178	0.228
0.2316555	0.225	3.125000e-02	0.2235788	0.225
0.2314141	0.231	3.875000e-02	0.2301568	0.231
0.2448351	0.255	6.875000e-02	0.2502481	0.255
0.2419446	0.246	5.750000e-02	0.2467271	0.246

0.2360568	0.227	3.375000e-02	0.2297852	0.227
0.2331528	0.210	1.250000e-02	0.2238900	0.210
0.2310396	0.203	3.750000e-03	0.2156322	0.203
0.2479057	0.272	9.000000e-02	0.2623901	0.272
0.2350077	0.242	5.250000e-02	0.2451579	0.242
0.2320909	0.222	2.750000e-02	0.2191149	0.222
0.2263472	0.212	1.500000e-02	0.2173695	0.212
0.2271454	0.204	5.000000e-03	0.2140044	0.204
0.2408065	0.257	7.125000e-02	0.2434317	0.257
0.2331056	0.240	5.000000e-02	0.2416736	0.240
0.2300423	0.230	3.750000e-02	0.2345899	0.230
0.2268929	0.212	1.500000e-02	0.2245720	0.212
0.2248866	0.204	5.000000e-03	0.1987182	0.204
0.2390402	0.272	9.000000e-02	0.2668467	0.272
0.2340166	0.247	5.875000e-02	0.2368959	0.247
0.2318819	0.241	5.125000e-02	0.2358329	0.241
0.2290295	0.226	3.250000e-02	0.2252870	0.226
0.2258954	0.227	3.375000e-02	0.2265921	0.227
0.2430118	0.248	6.000000e-02	0.2423893	0.248
0.2382267	0.232	4.000000e-02	0.2299045	0.232
0.2332135	0.223	2.875000e-02	0.2242644	0.223
0.2284968	0.211	1.375000e-02	0.2112733	0.211
0.2273446	0.225	3.125000e-02	0.2263265	0.225
0.2411929	0.254	6.750000e-02	0.2542639	0.254
0.2397291	0.244	5.500000e-02	0.2558097	0.244
0.2323955	0.223	2.875000e-02	0.2343192	0.223
0.2311884	0.218	2.250000e-02	0.2277165	0.218
0.2271412	0.219	2.375000e-02	0.2269628	0.219
0.2428945	0.263	7.875000e-02	0.2522821	0.263
0.2321509	0.234	4.250000e-02	0.2323638	0.234
0.2294227	0.226	3.250000e-02	0.2319939	0.226
0.2281486	0.223	2.875000e-02	0.2238630	0.223
0.2273702	0.217	2.125000e-02	0.2199336	0.217
0.2395192	0.261	7.625000e-02	0.2538851	0.261
0.2363835	0.237	4.625000e-02	0.2309410	0.237
0.2300172	0.228	3.500000e-02	0.2267693	0.228
0.2289620	0.205	6.250000e-03	0.2078806	0.205
0.2280531	0.211	1.375000e-02	0.2148572	0.211
0.2370578	0.270	8.750000e-02	0.2597719	0.270
0.2338413	0.247	5.875000e-02	0.2368319	0.247
0.2320999	0.236	4.500000e-02	0.2325500	0.236
0.2290467	0.228	3.500000e-02	0.2268140	0.228
0.2257330	0.218	2.250000e-02	0.2185306	0.218
0.2264010	0.211	1.375000e-02	0.2132341	0.211
0.2233933	0.210	1.250000e-02	0.2123071	0.210
0.2230237	0.212	1.500000e-02	0.2158151	0.212
0.2192765	0.205	6.250000e-03	0.2092237	0.205
0.2160506	0.209	1.125000e-02	0.2117212	0.209
0.2309321	0.234	4.250000e-02	0.2287816	0.234
0.2281354	0.225	3.125000e-02	0.2290207	0.225
0.2231926	0.225	3.125000e-02	0.2215484	0.225
0.2172180	0.214	1.750000e-02	0.2117696	0.214
0.2171076	0.210	1.250000e-02	0.2078450	0.210
0.2322075	0.227	3.375000e-02	0.2278490	0.227
0.2242312	0.196	-5.000000e-03	0.1986030	0.196



0.2152748	0.191	-1.125000e-02	0.1887355	0.191
0.2134469	0.188	-1.500000e-02	0.1854663	0.188
0.2118808	0.189	-1.375000e-02	0.1874732	0.189
0.2277894	0.217	2.125000e-02	0.2112236	0.217
0.2229202	0.205	6.250000e-03	0.2063301	0.205
0.2202569	0.210	1.250000e-02	0.2078773	0.210
0.2185088	0.195	-6.250000e-03	0.1942899	0.195
0.2177217	0.204	5.000000e-03	0.2068482	0.204
0.2264963	0.229	3.625000e-02	0.2279212	0.229
0.2155296	0.201	1.250000e-03	0.2048074	0.201
0.2146717	0.194	-7.500000e-03	0.1922373	0.194
0.2112501	0.208	1.000000e-02	0.2101337	0.208
0.2102697	0.203	3.750000e-03	0.1990501	0.203
0.2353534	0.238	4.750000e-02	0.2432074	0.238
0.2281197	0.242	5.250000e-02	0.2394429	0.242
0.2238184	0.221	2.625000e-02	0.2197166	0.221
0.2237588	0.210	1.250000e-02	0.2070927	0.210
0.2219595	0.211	1.375000e-02	0.2104611	0.211
0.2284403	0.216	2.000000e-02	0.2104717	0.216
0.2256250	0.204	5.000000e-03	0.2000876	0.204
0.2198980	0.209	1.125000e-02	0.2067102	0.209
0.2182240	0.209	1.125000e-02	0.2081292	0.209
0.2182189	0.209	1.125000e-02	0.2111807	0.209
0.2239029	0.202	2.500000e-03	0.2094683	0.202
0.2176049	0.203	3.750000e-03	0.2013041	0.203
0.2134180	0.193	-8.750000e-03	0.1901633	0.193
0.2129760	0.204	5.000000e-03	0.2009315	0.204
0.2098715	0.189	-1.375000e-02	0.1865899	0.189
0.2292437	0.227	3.375000e-02	0.2350691	0.227
0.2199296	0.201	1.250000e-03	0.2124127	0.201
0.2168152	0.195	-6.250000e-03	0.2135832	0.195
0.2152661	0.196	-5.000000e-03	0.2026198	0.196
0.2155137	0.191	-1.125000e-02	0.1913954	0.191
0.2233461	0.218	2.250000e-02	0.2225963	0.218
0.2130304	0.202	2.500000e-03	0.1995190	0.202
0.2120732	0.196	-5.000000e-03	0.1956527	0.196
0.2122928	0.195	-6.250000e-03	0.1941984	0.195
0.2102378	0.191	-1.125000e-02	0.1925338	0.191
0.2243871	0.218	2.250000e-02	0.2187763	0.218
0.2243036	0.223	2.875000e-02	0.2184594	0.223
0.2198020	0.222	2.750000e-02	0.2188925	0.222
0.2203050	0.211	1.375000e-02	0.2071638	0.211
0.2167840	0.219	2.375000e-02	0.2147121	0.219
0.2250515	0.227	3.375000e-02	0.2310645	0.227
0.2285194	0.217	2.125000e-02	0.2235287	0.217
0.2234450	0.224	3.000000e-02	0.2308258	0.224
0.2227441	0.225	3.125000e-02	0.2242466	0.225
0.2193273	0.213	1.625000e-02	0.2103140	0.213
0.2283092	0.218	2.250000e-02	0.2246244	0.218
0.2245363	0.222	2.750000e-02	0.2170807	0.222
0.2220229	0.210	1.250000e-02	0.2045292	0.210
0.2193838	0.213	1.625000e-02	0.2100425	0.213
0.2185168	0.211	1.375000e-02	0.2121598	0.211
0.2254597	0.209	1.125000e-02	0.2072258	0.209
0.2206421	0.220	2.500000e-02	0.2169906	0.220

0.2165215	0.216	2.000000e-02	0.2209890	0.216
0.2147679	0.203	3.750000e-03	0.1994127	0.203
0.2156936	0.200	-6.938894e-18	0.1965944	0.200
0.2200766	0.216	2.000000e-02	0.2212949	0.216
0.2137747	0.212	1.500000e-02	0.2146908	0.212
0.2111204	0.205	6.250000e-03	0.2005575	0.205
0.2135535	0.201	1.250000e-03	0.1990031	0.201
0.2151709	0.204	5.000000e-03	0.2012590	0.204
0.2186153	0.232	4.000000e-02	0.2287386	0.232
0.2238087	0.209	1.125000e-02	0.2104064	0.209
0.2234543	0.230	3.750000e-02	0.2258133	0.230
0.2214059	0.210	1.250000e-02	0.2084192	0.210
0.2235399	0.201	1.250000e-03	0.1990640	0.201
0.2253018	0.208	1.000000e-02	0.2103702	0.208
0.2190482	0.211	1.375000e-02	0.2093877	0.211
0.2172883	0.211	1.375000e-02	0.2075475	0.211
0.2154009	0.203	3.750000e-03	0.2016788	0.203
0.2138527	0.194	-7.500000e-03	0.1898500	0.194
0.2187046	0.204	5.000000e-03	0.2083207	0.204
0.2178481	0.211	1.375000e-02	0.2062808	0.211
0.2160489	0.192	-1.000000e-02	0.1879366	0.192
0.2141158	0.201	1.250000e-03	0.1975849	0.201
0.2135488	0.201	1.250000e-03	0.1991497	0.201
0.2210938	0.226	3.250000e-02	0.2283350	0.226
0.2222101	0.214	1.750000e-02	0.2116639	0.214
0.2231894	0.212	1.500000e-02	0.2077410	0.212
0.2201541	0.212	1.500000e-02	0.2074974	0.212
0.2216445	0.213	1.625000e-02	0.2091134	0.213
0.2161614	0.217	2.125000e-02	0.2134198	0.217
0.2128443	0.197	-3.750000e-03	0.1940553	0.197
0.2121343	0.206	7.500000e-03	0.2016762	0.206
0.2101652	0.198	-2.500000e-03	0.1938532	0.198
0.2117544	0.196	-5.000000e-03	0.1916503	0.196
0.2283416	0.225	3.125000e-02	0.2275391	0.225
0.2268189	0.215	1.875000e-02	0.2126025	0.215
0.2230606	0.205	6.250000e-03	0.2034793	0.205
0.2220488	0.215	1.875000e-02	0.2133003	0.215
0.2218928	0.210	1.250000e-02	0.2064827	0.210
0.2195069	0.205	6.250000e-03	0.2029074	0.205
0.2191273	0.211	1.375000e-02	0.2091661	0.211
0.2200214	0.212	1.500000e-02	0.2104695	0.212
0.2189714	0.206	7.500000e-03	0.2058200	0.206
0.2194734	0.205	6.250000e-03	0.2009062	0.205
0.2180124	0.209	1.125000e-02	0.2051706	0.209
0.2160251	0.207	8.750000e-03	0.2004331	0.207
0.2169255	0.200	-1.387779e-17	0.1981978	0.200
0.2146731	0.206	7.500000e-03	0.2038978	0.206
0.2141647	0.206	7.500000e-03	0.2022514	0.206
0.2158417	0.210	1.250000e-02	0.2103950	0.210
0.2138753	0.188	-1.500000e-02	0.1865900	0.188
0.2131287	0.190	-1.250000e-02	0.1910533	0.190
0.2128228	0.189	-1.375000e-02	0.1868380	0.189
0.2129802	0.193	-8.750000e-03	0.1886261	0.193
0.2262997	0.226	3.250000e-02	0.2255397	0.226
0.2190181	0.188	-1.500000e-02	0.1832013	0.188

0.2174408	0.193	-8.750000e-03	0.1869588	0.193
0.2181677	0.190	-1.250000e-02	0.1836790	0.190
0.2156553	0.192	-1.000000e-02	0.1864809	0.192
0.2255228	0.215	1.875000e-02	0.2112336	0.215
0.2201006	0.214	1.750000e-02	0.2113237	0.214
0.2210079	0.213	1.625000e-02	0.2079000	0.213
0.2198716	0.217	2.125000e-02	0.2113761	0.217
0.2210269	0.209	1.125000e-02	0.2054713	0.209
0.2217720	0.202	2.500000e-03	0.2003184	0.202
0.2225565	0.202	2.500000e-03	0.2003637	0.202
0.2214077	0.197	-3.750000e-03	0.1931507	0.197
0.2189570	0.199	-1.250000e-03	0.1954007	0.199
0.2173664	0.196	-5.000000e-03	0.1920709	0.196
0.2248324	0.214	1.750000e-02	0.2124932	0.214
0.2201629	0.215	1.875000e-02	0.2118150	0.215
0.2172056	0.207	8.750000e-03	0.2044335	0.207
0.2165323	0.206	7.500000e-03	0.2035580	0.206
0.2147429	0.193	-8.750000e-03	0.1900371	0.193
0.2150034	0.207	8.750000e-03	0.2074214	0.207
0.2175540	0.202	2.500000e-03	0.1993145	0.202
0.2152609	0.202	2.500000e-03	0.1985456	0.202
0.2155368	0.203	3.750000e-03	0.1990381	0.203
0.2148830	0.203	3.750000e-03	0.1999330	0.203
0.2182655	0.213	1.625000e-02	0.2161286	0.213
0.2169196	0.198	-2.500000e-03	0.1931317	0.198
0.2153041	0.195	-6.250000e-03	0.1871579	0.195
0.2145709	0.184	-2.000000e-02	0.1843865	0.184
0.2155953	0.182	-2.250000e-02	0.1765333	0.182
0.2192705	0.194	-7.500000e-03	0.1907551	0.194
0.2206791	0.202	2.500000e-03	0.2001344	0.202
0.2210108	0.212	1.500000e-02	0.2091837	0.212
0.2226803	0.212	1.500000e-02	0.2102390	0.212
0.2229813	0.213	1.625000e-02	0.2109878	0.213
0.2199584	0.210	1.250000e-02	0.2060965	0.210
0.2186813	0.209	1.125000e-02	0.2065464	0.209
0.2165868	0.200	-6.245005e-18	0.1978508	0.200
0.2158218	0.200	-9.714451e-18	0.1982908	0.200
0.2157674	0.210	1.250000e-02	0.2084522	0.210
0.2219977	0.212	1.500000e-02	0.2114828	0.212
0.2168732	0.185	-1.875000e-02	0.1815553	0.185
0.2173513	0.185	-1.875000e-02	0.1794157	0.185
0.2166802	0.193	-8.750000e-03	0.1871277	0.193
0.2164864	0.192	-1.000000e-02	0.1878552	0.192
0.2213153	0.200	-9.714451e-18	0.1977400	0.200
0.2189335	0.201	1.250000e-03	0.1993089	0.201
0.2172693	0.196	-5.000000e-03	0.1969627	0.196
0.2168061	0.190	-1.250000e-02	0.1865150	0.190
0.2161111	0.200	-1.595946e-17	0.1971155	0.200
0.2195626	0.202	2.500000e-03	0.2092047	0.202
0.2130053	0.195	-6.250000e-03	0.1922614	0.195
0.2133217	0.200	-6.938894e-18	0.1979112	0.200
0.2137489	0.188	-1.500000e-02	0.1816979	0.188
0.2150876	0.196	-5.000000e-03	0.1906667	0.196
0.2264020	0.233	4.125000e-02	0.2306810	0.233
0.2247049	0.224	3.000000e-02	0.2203098	0.224

0.2228017	0.224	3.000000e-02	0.2201473	0.224
0.2204899	0.220	2.500000e-02	0.2163414	0.220
0.2205387	0.212	1.500000e-02	0.2087822	0.212
0.2330138	0.221	2.625000e-02	0.2176180	0.221
0.2272738	0.215	1.875000e-02	0.2122686	0.215
0.2278419	0.214	1.750000e-02	0.2133356	0.214
0.2239820	0.219	2.375000e-02	0.2199197	0.219
0.2229884	0.212	1.500000e-02	0.2130478	0.212
0.2256930	0.217	2.125000e-02	0.2163465	0.217
0.2217226	0.202	2.500000e-03	0.2033738	0.202
0.2193078	0.196	-5.000000e-03	0.1924584	0.196
0.2197346	0.201	1.250000e-03	0.1988611	0.201
0.2192944	0.200	-9.714451e-18	0.1974393	0.200
0.2247208	0.202	2.500000e-03	0.2001283	0.202
0.2207738	0.212	1.500000e-02	0.2085562	0.212
0.2188889	0.202	2.500000e-03	0.1993652	0.202
0.2193692	0.206	7.500000e-03	0.2046190	0.206
0.2167942	0.205	6.250000e-03	0.2046628	0.205
0.2211577	0.206	7.500000e-03	0.2009796	0.206
0.2173476	0.199	-1.250000e-03	0.1984272	0.199
0.2139910	0.195	-6.250000e-03	0.1937316	0.195
0.2151695	0.198	-2.500000e-03	0.1986158	0.198
0.2154852	0.191	-1.125000e-02	0.1925975	0.191
0.2446248	0.244	5.500000e-02	0.2374985	0.244
0.2310221	0.227	3.375000e-02	0.2250719	0.227
0.2232945	0.218	2.250000e-02	0.2202560	0.218
0.2230581	0.223	2.875000e-02	0.2263714	0.223
0.2218094	0.211	1.375000e-02	0.2208103	0.211
0.2367505	0.249	6.125000e-02	0.2392071	0.249
0.2307242	0.238	4.750000e-02	0.2368110	0.238
0.2273906	0.220	2.500000e-02	0.2256341	0.220
0.2232768	0.200	-5.551115e-18	0.2046158	0.200
0.2174263	0.203	3.750000e-03	0.2114551	0.203
0.2384554	0.251	6.375000e-02	0.2470744	0.251
0.2337062	0.234	4.250000e-02	0.2439665	0.234
0.2283931	0.213	1.625000e-02	0.2266363	0.213
0.2229745	0.205	6.250000e-03	0.2173705	0.205
0.2218470	0.207	8.750000e-03	0.2057156	0.207
0.2359819	0.254	6.750000e-02	0.2423574	0.254
0.2313894	0.227	3.375000e-02	0.2240722	0.227
0.2284365	0.219	2.375000e-02	0.2292567	0.219
0.2238023	0.216	2.000000e-02	0.2287367	0.216
0.2204791	0.202	2.500000e-03	0.2146497	0.202
0.2371424	0.261	7.625000e-02	0.2497876	0.261
0.2328174	0.242	5.250000e-02	0.2380853	0.242
0.2279170	0.221	2.625000e-02	0.2214009	0.221
0.2259457	0.220	2.500000e-02	0.2258791	0.220
0.2232385	0.214	1.750000e-02	0.2155556	0.214
0.2391148	0.248	6.000000e-02	0.2504459	0.248
0.2325913	0.224	3.000000e-02	0.2262325	0.224
0.2278632	0.217	2.125000e-02	0.2152290	0.217
0.2227093	0.223	2.875000e-02	0.2251228	0.223
0.2194538	0.210	1.250000e-02	0.2170307	0.210
0.2371204	0.244	5.500000e-02	0.2422181	0.244
0.2366632	0.252	6.500000e-02	0.2542352	0.252

0.2281821	0.226	3.250000e-02	0.2243088	0.226
0.2228921	0.217	2.125000e-02	0.2204697	0.217
0.2197377	0.208	1.000000e-02	0.2129353	0.208
0.2406016	0.232	4.000000e-02	0.2276057	0.232
0.2311009	0.220	2.500000e-02	0.2205026	0.220
0.2296527	0.208	1.000000e-02	0.2182622	0.208
0.2253093	0.205	6.250000e-03	0.2112149	0.205
0.2216556	0.209	1.125000e-02	0.2266954	0.209
0.2365327	0.253	6.625000e-02	0.2484185	0.253
0.2336041	0.236	4.500000e-02	0.2360631	0.236
0.2295860	0.215	1.875000e-02	0.2157095	0.215
0.2251515	0.207	8.750000e-03	0.2100142	0.207
0.2218728	0.200	-1.040834e-17	0.2060838	0.200
0.2372082	0.259	7.375000e-02	0.2500688	0.259
0.2319068	0.247	5.875000e-02	0.2387550	0.247
0.2281607	0.226	3.250000e-02	0.2241062	0.226
0.2253912	0.217	2.125000e-02	0.2171624	0.217
0.2223995	0.209	1.125000e-02	0.2071955	0.209
0.2186408	0.212	1.500000e-02	0.2074039	0.212
0.2086883	0.216	2.000000e-02	0.2140937	0.216
0.2132115	0.214	1.750000e-02	0.2130461	0.214
0.2123606	0.206	7.500000e-03	0.2034550	0.206
0.2124575	0.199	-1.250000e-03	0.1963723	0.199
0.2292357	0.215	1.875000e-02	0.2209095	0.215
0.2186876	0.211	1.375000e-02	0.2176474	0.211
0.2172458	0.217	2.125000e-02	0.2189947	0.217
0.2147783	0.220	2.500000e-02	0.2238205	0.220
0.2131920	0.208	1.000000e-02	0.2065600	0.208
0.2224189	0.213	1.625000e-02	0.2079606	0.213
0.2193877	0.210	1.250000e-02	0.2130258	0.210
0.2192262	0.215	1.875000e-02	0.2217217	0.215
0.2191236	0.216	2.000000e-02	0.2217450	0.216
0.2182662	0.204	5.000000e-03	0.2078177	0.204
0.2258969	0.226	3.250000e-02	0.2268085	0.226
0.2169799	0.208	1.000000e-02	0.2094183	0.208
0.2126487	0.202	2.500000e-03	0.2095965	0.202
0.2115959	0.192	-1.000000e-02	0.1981254	0.192
0.2103810	0.197	-3.750000e-03	0.2039441	0.197
0.2212117	0.228	3.500000e-02	0.2243642	0.228
0.2149721	0.210	1.250000e-02	0.2123521	0.210
0.2136501	0.197	-3.750000e-03	0.2045317	0.197
0.2152349	0.195	-6.250000e-03	0.1979160	0.195
0.2140972	0.201	1.250000e-03	0.1991490	0.201
0.2295022	0.212	1.500000e-02	0.2243739	0.212
0.2298628	0.244	5.500000e-02	0.2494829	0.244
0.2254549	0.224	3.000000e-02	0.2231083	0.224
0.2208028	0.209	1.125000e-02	0.2077074	0.209
0.2197535	0.218	2.250000e-02	0.2228612	0.218
0.2279055	0.239	4.875000e-02	0.2363587	0.239
0.2181872	0.215	1.875000e-02	0.2108937	0.215
0.2139886	0.201	1.250000e-03	0.2035510	0.201
0.2161767	0.198	-2.500000e-03	0.2040678	0.198
0.2142438	0.198	-2.500000e-03	0.1993591	0.198
0.2218787	0.203	3.750000e-03	0.2020489	0.203
0.2155179	0.199	-1.250000e-03	0.1963275	0.199

0.2123557	0.193	-8.750000e-03	0.1915231	0.193
0.2119446	0.192	-1.000000e-02	0.1891060	0.192
0.2105250	0.184	-2.000000e-02	0.1817283	0.184
0.2222112	0.221	2.625000e-02	0.2181284	0.221
0.2183926	0.202	2.500000e-03	0.2014801	0.202
0.2202252	0.212	1.500000e-02	0.2144517	0.212
0.2154875	0.209	1.125000e-02	0.2108433	0.209
0.2169136	0.205	6.250000e-03	0.2061595	0.205
0.2250200	0.219	2.375000e-02	0.2265605	0.219
0.2179745	0.224	3.000000e-02	0.2225625	0.224
0.2133413	0.206	7.500000e-03	0.2087332	0.206
0.2130792	0.207	8.750000e-03	0.2021840	0.207
0.2123613	0.202	2.500000e-03	0.2050595	0.202
0.2261801	0.224	3.000000e-02	0.2201507	0.224
0.2213810	0.217	2.125000e-02	0.2153984	0.217
0.2152945	0.216	2.000000e-02	0.2127358	0.216
0.2150829	0.216	2.000000e-02	0.2139873	0.216
0.2127547	0.199	-1.250000e-03	0.2047225	0.199
0.2245282	0.223	2.875000e-02	0.2287103	0.223
0.2210522	0.212	1.500000e-02	0.2101384	0.212
0.2200900	0.212	1.500000e-02	0.2081659	0.212
0.2202847	0.216	2.000000e-02	0.2204222	0.216
0.2195648	0.217	2.125000e-02	0.2151252	0.217
0.2209510	0.206	7.500000e-03	0.2055992	0.206
0.2169283	0.201	1.250000e-03	0.1987623	0.201
0.2176653	0.200	-1.040834e-17	0.1969514	0.200
0.2172366	0.202	2.500000e-03	0.1985700	0.202
0.2161070	0.198	-2.500000e-03	0.1944916	0.198
0.2219180	0.210	1.250000e-02	0.2102115	0.210
0.2181596	0.202	2.500000e-03	0.2019572	0.202
0.2184596	0.200	-9.714451e-18	0.2052344	0.200
0.2189140	0.197	-3.750000e-03	0.1969988	0.197
0.2180063	0.199	-1.250000e-03	0.1973756	0.199
0.2185090	0.221	2.625000e-02	0.2154289	0.221
0.2151721	0.193	-8.750000e-03	0.2011837	0.193
0.2151609	0.195	-6.250000e-03	0.1987973	0.195
0.2162272	0.194	-7.500000e-03	0.1887614	0.194
0.2152142	0.190	-1.250000e-02	0.1903925	0.190
0.2253469	0.225	3.125000e-02	0.2215290	0.225
0.2251641	0.204	5.000000e-03	0.2028760	0.204
0.2243702	0.221	2.625000e-02	0.2186901	0.221
0.2234050	0.207	8.750000e-03	0.2044911	0.207
0.2239937	0.210	1.250000e-02	0.2081616	0.210
0.2242399	0.210	1.250000e-02	0.2072897	0.210
0.2153813	0.197	-3.750000e-03	0.2005146	0.197
0.2165037	0.194	-7.500000e-03	0.2047887	0.194
0.2169470	0.201	1.250000e-03	0.1948150	0.201
0.2151675	0.203	3.750000e-03	0.1960843	0.203
0.2251150	0.204	5.000000e-03	0.2079392	0.204
0.2218920	0.191	-1.125000e-02	0.1883791	0.191
0.2188379	0.207	8.750000e-03	0.2029903	0.207
0.2176785	0.201	1.250000e-03	0.1974980	0.201
0.2159262	0.196	-5.000000e-03	0.1926957	0.196
0.2241339	0.210	1.250000e-02	0.2081455	0.210
0.2162610	0.196	-5.000000e-03	0.1923196	0.196

0.2187034	0.191	-1.125000e-02	0.1866893	0.191
0.2191949	0.209	1.125000e-02	0.2034672	0.209
0.2197344	0.203	3.750000e-03	0.1986221	0.203
0.2142483	0.208	1.000000e-02	0.2039194	0.208
0.2115605	0.187	-1.625000e-02	0.1814111	0.187
0.2111677	0.189	-1.375000e-02	0.1894417	0.189
0.2110429	0.195	-6.250000e-03	0.1931651	0.195
0.2115844	0.191	-1.125000e-02	0.1940137	0.191
0.2194263	0.207	8.750000e-03	0.2044050	0.207
0.2149856	0.205	6.250000e-03	0.2013635	0.205
0.2130251	0.204	5.000000e-03	0.1999909	0.204
0.2122451	0.204	5.000000e-03	0.2032587	0.204
0.2122077	0.195	-6.250000e-03	0.1919931	0.195
0.2260346	0.224	3.000000e-02	0.2209833	0.224
0.2265256	0.211	1.375000e-02	0.2042835	0.211
0.2240080	0.219	2.375000e-02	0.2176605	0.219
0.2225465	0.218	2.250000e-02	0.2152623	0.218
0.2225644	0.218	2.250000e-02	0.2155637	0.218
0.2143111	0.189	-1.375000e-02	0.1865827	0.189
0.2178149	0.194	-7.500000e-03	0.1944325	0.194
0.2171269	0.197	-3.750000e-03	0.1944378	0.197
0.2186960	0.200	-6.938894e-18	0.1972468	0.200
0.2171114	0.197	-3.750000e-03	0.1951718	0.197
0.2197973	0.222	2.750000e-02	0.2198337	0.222
0.2198275	0.217	2.125000e-02	0.2140552	0.217
0.2196221	0.207	8.750000e-03	0.2033728	0.207
0.2194844	0.206	7.500000e-03	0.2015133	0.206
0.2190818	0.201	1.250000e-03	0.1966547	0.201
0.2234624	0.216	2.000000e-02	0.2150143	0.216
0.2166411	0.192	-1.000000e-02	0.1988550	0.192
0.2140047	0.194	-7.500000e-03	0.1952749	0.194
0.2124495	0.188	-1.500000e-02	0.1885648	0.188
0.2131811	0.194	-7.500000e-03	0.1918179	0.194
0.2231659	0.208	1.000000e-02	0.2077436	0.208
0.2172951	0.201	1.250000e-03	0.1996676	0.201
0.2159146	0.191	-1.125000e-02	0.1897235	0.191
0.2126446	0.193	-8.750000e-03	0.1896185	0.193
0.2112960	0.189	-1.375000e-02	0.1824039	0.189
0.2135652	0.199	-1.250000e-03	0.1980569	0.199
0.2093379	0.201	1.250000e-03	0.1960621	0.201
0.2112799	0.197	-3.750000e-03	0.1932999	0.197
0.2088879	0.192	-1.000000e-02	0.1950457	0.192
0.2109118	0.189	-1.375000e-02	0.1941749	0.189
0.2228670	0.205	6.250000e-03	0.2026023	0.205
0.2172037	0.210	1.250000e-02	0.2086998	0.210
0.2170285	0.202	2.500000e-03	0.1959678	0.202
0.2183179	0.204	5.000000e-03	0.2010574	0.204
0.2182418	0.205	6.250000e-03	0.2029892	0.205
0.2225763	0.213	1.625000e-02	0.2081793	0.213
0.2184617	0.213	1.625000e-02	0.2101055	0.213
0.2160817	0.207	8.750000e-03	0.2032567	0.207
0.2178479	0.207	8.750000e-03	0.2063948	0.207
0.2167988	0.208	1.000000e-02	0.2044854	0.208
0.2186005	0.216	2.000000e-02	0.2103699	0.216
0.2194525	0.197	-3.750000e-03	0.1945179	0.197

0.2164540	0.193	-8.750000e-03	0.1849824	0.193
0.2147081	0.187	-1.625000e-02	0.1808251	0.187
0.2154776	0.188	-1.500000e-02	0.1828215	0.188
0.2159999	0.219	2.375000e-02	0.2158098	0.219
0.2156625	0.207	8.750000e-03	0.2048638	0.207
0.2172117	0.212	1.500000e-02	0.2087230	0.212
0.2138104	0.208	1.000000e-02	0.2061858	0.208
0.2156620	0.207	8.750000e-03	0.2052188	0.207
0.2259850	0.215	1.875000e-02	0.2111993	0.215
0.2211819	0.217	2.125000e-02	0.2134049	0.217
0.2204743	0.218	2.250000e-02	0.2162388	0.218
0.2196458	0.220	2.500000e-02	0.2198954	0.220
0.2192947	0.218	2.250000e-02	0.2173364	0.218
0.2266130	0.212	1.500000e-02	0.2136050	0.212
0.2250844	0.205	6.250000e-03	0.2131583	0.205
0.2217841	0.197	-3.750000e-03	0.1966749	0.197
0.2214899	0.199	-1.250000e-03	0.1977709	0.199
0.2203802	0.204	5.000000e-03	0.2036024	0.204
0.2250234	0.210	1.250000e-02	0.2067367	0.210
0.2269014	0.206	7.500000e-03	0.2018968	0.206
0.2209999	0.199	-1.250000e-03	0.1941027	0.199
0.2207992	0.199	-1.250000e-03	0.1937113	0.199
0.2204015	0.198	-2.500000e-03	0.1933616	0.198
0.2152900	0.193	-8.750000e-03	0.1903016	0.193
0.2147347	0.205	6.250000e-03	0.2066431	0.205
0.2151158	0.201	1.250000e-03	0.1979902	0.201
0.2158473	0.200	-1.734723e-17	0.1960983	0.200
0.2154519	0.195	-6.250000e-03	0.1913092	0.195
0.2148758	0.189	-1.375000e-02	0.1849656	0.189
0.2120329	0.179	-2.625000e-02	0.1791084	0.179
0.2096373	0.183	-2.125000e-02	0.1789474	0.183
0.2100827	0.185	-1.875000e-02	0.1819778	0.185
0.2114167	0.191	-1.125000e-02	0.1880615	0.191
0.2210004	0.216	2.000000e-02	0.2131798	0.216
0.2187855	0.211	1.375000e-02	0.2068425	0.211
0.2163721	0.207	8.750000e-03	0.2031730	0.207
0.2159710	0.208	1.000000e-02	0.2046194	0.208
0.2149262	0.204	5.000000e-03	0.2002145	0.204
0.2228298	0.220	2.500000e-02	0.2175557	0.220
0.2189754	0.203	3.750000e-03	0.2004602	0.203
0.2183200	0.204	5.000000e-03	0.2198826	0.204
0.2183103	0.203	3.750000e-03	0.2074747	0.203
0.2162329	0.205	6.250000e-03	0.2101146	0.205
0.2140347	0.193	-8.750000e-03	0.1934401	0.193
0.2166241	0.202	2.500000e-03	0.2082615	0.202
0.2155014	0.197	-3.750000e-03	0.1948730	0.197
0.2156409	0.193	-8.750000e-03	0.1909040	0.193
0.2153983	0.197	-3.750000e-03	0.1954665	0.197
0.2159348	0.219	2.375000e-02	0.2153273	0.219
0.2196045	0.207	8.750000e-03	0.2024985	0.207
0.2189498	0.213	1.625000e-02	0.2094642	0.213
0.2198827	0.209	1.125000e-02	0.2060623	0.209
0.2190713	0.206	7.500000e-03	0.2032478	0.206
Mean_Specificity	Mean_Pos_Pred_Value	Mean_Neg_Pred_Value	Mean_Precision	
0.81175	0.2387100	0.8125563	0.2387100	



0.80825	0.2277826	0.8087348	0.2277826
0.80700	0.2274336	0.8072635	0.2274336
0.80625	0.2272636	0.8061586	0.2272636
0.80775	0.2344315	0.8075554	0.2344315
0.81375	0.2547062	0.8145977	0.2547062
0.81150	0.2471288	0.8118193	0.2471288
0.80675	0.2317502	0.8067141	0.2317502
0.80250	0.2129675	0.8023974	0.2129675
0.80075	0.2065979	0.8006093	0.2065979
0.81800	0.2702748	0.8191015	0.2702748
0.81050	0.2434176	0.8107652	0.2434176
0.80550	0.2239098	0.8056048	0.2239098
0.80300	0.2127425	0.8031006	0.2127425
0.80100	0.2036221	0.8010037	0.2036221
0.81425	0.2450211	0.8158562	0.2450211
0.81000	0.2353998	0.8105951	0.2353998
0.80750	0.2290304	0.8077133	0.2290304
0.80300	0.2158663	0.8028792	0.2158663
0.80100	0.2062737	0.8008900	0.2062737
0.81800	0.2599808	0.8198968	0.2599808
0.81175	0.2364930	0.8127194	0.2364930
0.81025	0.2350653	0.8109077	0.2350653
0.80650	0.2250258	0.8067583	0.2250258
0.80675	0.2244708	0.8070610	0.2244708
0.81200	0.2445431	0.8127708	0.2445431
0.80800	0.2273684	0.8084894	0.2273684
0.80575	0.2250239	0.8057350	0.2250239
0.80275	0.2124155	0.8027307	0.2124155
0.80625	0.2257345	0.8062403	0.2257345
0.81350	0.2504571	0.8144414	0.2504571
0.81100	0.2414672	0.8115765	0.2414672
0.80575	0.2259744	0.8058800	0.2259744
0.80450	0.2187552	0.8045875	0.2187552
0.80475	0.2169849	0.8049160	0.2169849
0.81575	0.2532008	0.8172456	0.2532008
0.80850	0.2310968	0.8088503	0.2310968
0.80650	0.2285519	0.8065660	0.2285519
0.80575	0.2234368	0.8058395	0.2234368
0.80425	0.2174510	0.8042141	0.2174510
0.81525	0.2447458	0.8168157	0.2447458
0.80925	0.2310332	0.8099655	0.2310332
0.80700	0.2308729	0.8071810	0.2308729
0.80125	0.2080264	0.8011453	0.2080264
0.80275	0.2161174	0.8025342	0.2161174
0.81750	0.2611239	0.8192486	0.2611239
0.81175	0.2388762	0.8127074	0.2388762
0.80900	0.2276320	0.8097410	0.2276320
0.80700	0.2237478	0.8073882	0.2237478
0.80450	0.2166812	0.8046411	0.2166812
0.80275	0.2092082	0.8029539	0.2092082
0.80250	0.2068238	0.8026757	0.2068238
0.80300	0.2112684	0.8031470	0.2112684
0.80125	0.2069395	0.8011537	0.2069395
0.80225	0.2105589	0.8022090	0.2105589
0.80850	0.2289481	0.8090359	0.2289481

0.80625	0.2243912	0.8064467	0.2243912
0.80625	0.2192976	0.8065970	0.2192976
0.80350	0.2138418	0.8035465	0.2138418
0.80250	0.2100606	0.8024839	0.2100606
0.80675	0.2243340	0.8070771	0.2243340
0.79900	0.1947020	0.7990322	0.1947020
0.79775	0.1899438	0.7977648	0.1899438
0.79700	0.1868559	0.7970566	0.1868559
0.79725	0.1921172	0.7970315	0.1921172
0.80425	0.2131074	0.8045899	0.2131074
0.80125	0.2060070	0.8012032	0.2060070
0.80250	0.2068819	0.8026488	0.2068819
0.79875	0.1923262	0.7988337	0.1923262
0.80100	0.2004306	0.8010797	0.2004306
0.80725	0.2224651	0.8077831	0.2224651
0.80025	0.1969166	0.8005536	0.1969166
0.79850	0.1884877	0.7987854	0.1884877
0.80200	0.2081212	0.8020813	0.2081212
0.80075	0.2011586	0.8009287	0.2011586
0.80950	0.2423063	0.8093992	0.2423063
0.81050	0.2417794	0.8106312	0.2417794
0.80525	0.2213049	0.8052680	0.2213049
0.80250	0.2081207	0.8025795	0.2081207
0.80275	0.2143827	0.8025630	0.2143827
0.80400	0.2121288	0.8042092	0.2121288
0.80100	0.2010369	0.8011169	0.2010369
0.80225	0.2078718	0.8022514	0.2078718
0.80225	0.2100274	0.8021854	0.2100274
0.80225	0.2099399	0.8020759	0.2099399
0.80050	0.1959303	0.8008585	0.1959303
0.80075	0.1986233	0.8010059	0.1986233
0.79825	0.1926383	0.7982583	0.1926383
0.80100	0.2013690	0.8011372	0.2013690
0.79725	0.1879794	0.7972950	0.1879794
0.80675	0.2227928	0.8071072	0.2227928
0.80025	0.2017094	0.8001806	0.2017094
0.79875	0.1949101	0.7986315	0.1949101
0.79900	0.1948755	0.7989787	0.1948755
0.79775	0.1890300	0.7977891	0.1890300
0.80450	0.2127755	0.8050487	0.2127755
0.80050	0.2022603	0.8005335	0.2022603
0.79900	0.1934694	0.7990940	0.1934694
0.79875	0.1876971	0.7990743	0.1876971
0.79775	0.1850642	0.7980155	0.1850642
0.80450	0.2142526	0.8047548	0.2142526
0.80575	0.2208271	0.8060322	0.2208271
0.80550	0.2234433	0.8056604	0.2234433
0.80275	0.2101893	0.8029843	0.2101893
0.80475	0.2175151	0.8049617	0.2175151
0.80675	0.2261021	0.8070021	0.2261021
0.80425	0.2170267	0.8042368	0.2170267
0.80600	0.2277559	0.8060594	0.2277559
0.80625	0.2294788	0.8061103	0.2294788
0.80325	0.2119057	0.8033552	0.2119057
0.80450	0.2174438	0.8046177	0.2174438

0.80550	0.2200584	0.8059094	0.2200584
0.80250	0.2051828	0.8028419	0.2051828
0.80325	0.2122018	0.8033994	0.2122018
0.80275	0.2094824	0.8029491	0.2094824
0.80225	0.2046806	0.8025681	0.2046806
0.80500	0.2234394	0.8050591	0.2234394
0.80400	0.2191004	0.8039626	0.2191004
0.80075	0.2015357	0.8008202	0.2015357
0.80000	0.1975719	0.8001902	0.1975719
0.80400	0.2131477	0.8043279	0.2131477
0.80300	0.2059048	0.8033649	0.2059048
0.80125	0.2015303	0.8015157	0.2015303
0.80025	0.1968208	0.8004621	0.1968208
0.80100	0.1991028	0.8013137	0.1991028
0.80800	0.2302841	0.8081913	0.2302841
0.80225	0.2076422	0.8023946	0.2076422
0.80750	0.2275005	0.8077689	0.2275005
0.80250	0.2115155	0.8024399	0.2115155
0.80025	0.2029439	0.8001705	0.2029439
0.80200	0.2096819	0.8018943	0.2096819
0.80275	0.2156627	0.8025893	0.2156627
0.80275	0.2105608	0.8027678	0.2105608
0.80075	0.1969226	0.8011078	0.1969226
0.79850	0.1903042	0.7986460	0.1903042
0.80100	0.2023569	0.8011394	0.2023569
0.80275	0.2087741	0.8030375	0.2087741
0.79800	0.1924299	0.7980653	0.1924299
0.80025	0.2040879	0.8000923	0.2040879
0.80025	0.2025135	0.8002279	0.2025135
0.80650	0.2263499	0.8066834	0.2263499
0.80350	0.2145576	0.8035762	0.2145576
0.80300	0.2106044	0.8031981	0.2106044
0.80300	0.2091909	0.8032430	0.2091909
0.80325	0.2115174	0.8034597	0.2115174
0.80425	0.2107681	0.8047088	0.2107681
0.79925	0.1963246	0.7993436	0.1963246
0.80150	0.2023925	0.8017774	0.2023925
0.79950	0.1957348	0.7997125	0.1957348
0.79900	0.1924378	0.7992962	0.1924378
0.80625	0.2268714	0.8061812	0.2268714
0.80375	0.2178438	0.8037326	0.2178438
0.80125	0.2073041	0.8010235	0.2073041
0.80375	0.2169144	0.8035890	0.2169144
0.80250	0.2082442	0.8025517	0.2082442
0.80125	0.2057614	0.8012070	0.2057614
0.80275	0.2120625	0.8027190	0.2120625
0.80300	0.2138444	0.8029433	0.2138444
0.80150	0.2043534	0.8016446	0.2043534
0.80125	0.2017597	0.8014796	0.2017597
0.80225	0.2057486	0.8025036	0.2057486
0.80175	0.2042652	0.8020519	0.2042652
0.80000	0.1984011	0.8000590	0.1984011
0.80150	0.2048472	0.8015232	0.2048472
0.80150	0.2044272	0.8015582	0.2044272
0.80250	0.2072296	0.8027580	0.2072296

0.79700	0.1828352	0.7972864	0.1828352
0.79750	0.1883132	0.7976196	0.1883132
0.79725	0.1877314	0.7973250	0.1877314
0.79825	0.1896445	0.7984271	0.1896445
0.80650	0.2267485	0.8067597	0.2267485
0.79700	0.1813489	0.7974196	0.1813489
0.79825	0.1869165	0.7987102	0.1869165
0.79750	0.1834014	0.7979845	0.1834014
0.79800	0.1870793	0.7983894	0.1870793
0.80375	0.2125852	0.8039037	0.2125852
0.80350	0.2136552	0.8035942	0.2136552
0.80325	0.2099421	0.8035649	0.2099421
0.80425	0.2126810	0.8046943	0.2126810
0.80225	0.2079611	0.8024175	0.2079611
0.80050	0.2031401	0.8004778	0.2031401
0.80050	0.2029536	0.8003503	0.2029536
0.79925	0.1947805	0.7993720	0.1947805
0.79975	0.1980046	0.7998358	0.1980046
0.79900	0.1933795	0.7991487	0.1933795
0.80350	0.2134372	0.8035633	0.2134372
0.80375	0.2145041	0.8038754	0.2145041
0.80175	0.2077410	0.8017510	0.2077410
0.80150	0.2075024	0.8014523	0.2075024
0.79825	0.1937067	0.7982581	0.1937067
0.80175	0.2040656	0.8020151	0.2040656
0.80050	0.1990169	0.8008132	0.1990169
0.80050	0.2006545	0.8006370	0.2006545
0.80075	0.2011951	0.8009344	0.2011951
0.80075	0.2024254	0.8008198	0.2024254
0.80325	0.2073781	0.8036202	0.2073781
0.79950	0.1924057	0.7998126	0.1924057
0.79875	0.1897747	0.7991166	0.1897747
0.79600	0.1777795	0.7963785	0.1777795
0.79550	0.1761868	0.7958464	0.1761868
0.79850	0.1923404	0.7986388	0.1923404
0.80050	0.2031482	0.8004612	0.2031482
0.80300	0.2127876	0.8030858	0.2127876
0.80300	0.2140073	0.8029806	0.2140073
0.80325	0.2139509	0.8032761	0.2139509
0.80250	0.2063886	0.8027130	0.2063886
0.80225	0.2090129	0.8021977	0.2090129
0.80000	0.2004375	0.7999931	0.2004375
0.80000	0.2007654	0.7999261	0.2007654
0.80250	0.2115819	0.8024148	0.2115819
0.80300	0.2145306	0.8028607	0.2145306
0.79625	0.1850089	0.7961563	0.1850089
0.79625	0.1831623	0.7963194	0.1831623
0.79825	0.1913625	0.7983197	0.1913625
0.79800	0.1891061	0.7980807	0.1891061
0.80000	0.1954275	0.8003010	0.1954275
0.80025	0.1975227	0.8005698	0.1975227
0.79900	0.1903261	0.7993596	0.1903261
0.79750	0.1882992	0.7976749	0.1882992
0.80000	0.1998245	0.8001148	0.1998245
0.80050	0.1983926	0.8006681	0.1983926

0.79875	0.1886903	0.7990578	0.1886903
0.80000	0.1942373	0.8003508	0.1942373
0.79700	0.1816409	0.7973566	0.1816409
0.79900	0.1907152	0.7993060	0.1907152
0.80825	0.2356087	0.8082552	0.2356087
0.80600	0.2197497	0.8064357	0.2197497
0.80600	0.2217984	0.8062492	0.2217984
0.80500	0.2177865	0.8052151	0.2177865
0.80300	0.2108887	0.8031174	0.2108887
0.80525	0.2205994	0.8054439	0.2205994
0.80375	0.2158062	0.8038048	0.2158062
0.80350	0.2186396	0.8033069	0.2186396
0.80475	0.2233485	0.8045117	0.2233485
0.80300	0.2153047	0.8028498	0.2153047
0.80425	0.2108999	0.8047113	0.2108999
0.80050	0.1987913	0.8007518	0.1987913
0.79900	0.1927744	0.7992638	0.1927744
0.80025	0.2006160	0.8003605	0.2006160
0.80000	0.1998998	0.8000943	0.1998998
0.80050	0.2040627	0.8004099	0.2040627
0.80300	0.2107641	0.8032100	0.2107641
0.80050	0.2028650	0.8005661	0.2028650
0.80150	0.2099444	0.8014279	0.2099444
0.80125	0.2095684	0.8010454	0.2095684
0.80150	0.2008492	0.8018523	0.2008492
0.79975	0.1951727	0.8000546	0.1951727
0.79875	0.1899588	0.7991397	0.1899588
0.79950	0.1970206	0.7996972	0.1970206
0.79775	0.1907561	0.7978376	0.1907561
0.81100	0.2404968	0.8114279	0.2404968
0.80675	0.2287161	0.8067390	0.2287161
0.80450	0.2166250	0.8046147	0.2166250
0.80575	0.2214970	0.8059152	0.2214970
0.80275	0.2120033	0.8027080	0.2120033
0.81225	0.2458704	0.8128852	0.2458704
0.80950	0.2424083	0.8094229	0.2424083
0.80500	0.2261000	0.8047279	0.2261000
0.80000	0.2018111	0.7998550	0.2018111
0.80075	0.2073102	0.8004782	0.2073102
0.81275	0.2537117	0.8131527	0.2537117
0.80850	0.2344325	0.8087572	0.2344325
0.80325	0.2165277	0.8031283	0.2165277
0.80125	0.2065099	0.8011288	0.2065099
0.80175	0.2089016	0.8017155	0.2089016
0.81350	0.2467125	0.8144949	0.2467125
0.80675	0.2235374	0.8070519	0.2235374
0.80475	0.2221393	0.8046741	0.2221393
0.80400	0.2197113	0.8038527	0.2197113
0.80050	0.2046946	0.8002368	0.2046946
0.81525	0.2560049	0.8166473	0.2560049
0.81050	0.2331799	0.8113729	0.2331799
0.80525	0.2188578	0.8055129	0.2188578
0.80500	0.2150637	0.8054320	0.2150637
0.80350	0.2129328	0.8036836	0.2129328
0.81200	0.2410868	0.8126837	0.2410868

0.80600	0.2245258	0.8060574	0.2245258
0.80425	0.2169263	0.8042864	0.2169263
0.80575	0.2217451	0.8059398	0.2217451
0.80250	0.2139228	0.8023491	0.2139228
0.81100	0.2428757	0.8114319	0.2428757
0.81300	0.2592378	0.8129290	0.2592378
0.80650	0.2308153	0.8063137	0.2308153
0.80425	0.2234824	0.8039622	0.2234824
0.80200	0.2156592	0.8015945	0.2156592
0.80800	0.2252149	0.8088223	0.2252149
0.80500	0.2196658	0.8050998	0.2196658
0.80200	0.2036365	0.8021916	0.2036365
0.80125	0.2051684	0.8012264	0.2051684
0.80225	0.2123333	0.8020529	0.2123333
0.81325	0.2464065	0.8142327	0.2464065
0.80900	0.2332725	0.8093493	0.2332725
0.80375	0.2190022	0.8036209	0.2190022
0.80175	0.2113770	0.8016493	0.2113770
0.80000	0.2044051	0.7997590	0.2044051
0.81475	0.2522162	0.8160796	0.2522162
0.81175	0.2387898	0.8126378	0.2387898
0.80650	0.2221525	0.8068910	0.2221525
0.80425	0.2115302	0.8046443	0.2115302
0.80225	0.2084643	0.8023488	0.2084643
0.80300	0.2074860	0.8032100	0.2074860
0.80400	0.2166113	0.8039738	0.2166113
0.80350	0.2162384	0.8033813	0.2162384
0.80150	0.2065191	0.8014569	0.2065191
0.79975	0.1984253	0.7998085	0.1984253
0.80375	0.2151396	0.8037763	0.2151396
0.80275	0.2107525	0.8028832	0.2107525
0.80425	0.2187102	0.8041982	0.2187102
0.80500	0.2216735	0.8049972	0.2216735
0.80200	0.2109470	0.8017775	0.2109470
0.80325	0.2099882	0.8034503	0.2099882
0.80250	0.2100275	0.8024801	0.2100275
0.80375	0.2199565	0.8034856	0.2199565
0.80400	0.2188168	0.8038700	0.2188168
0.80100	0.2067626	0.8008255	0.2067626
0.80650	0.2236166	0.8067007	0.2236166
0.80200	0.2035061	0.8021973	0.2035061
0.80050	0.1965299	0.8007501	0.1965299
0.79800	0.1875818	0.7982020	0.1875818
0.79925	0.1922924	0.7994830	0.1922924
0.80700	0.2192951	0.8074594	0.2192951
0.80250	0.2060895	0.8027022	0.2060895
0.79925	0.1969697	0.7992244	0.1969697
0.79875	0.1928646	0.7988664	0.1928646
0.80025	0.2019167	0.8001954	0.2019167
0.80300	0.2139214	0.8028988	0.2139214
0.81100	0.2454842	0.8109832	0.2454842
0.80600	0.2260029	0.8059125	0.2260029
0.80225	0.2112835	0.8020588	0.2112835
0.80450	0.2205461	0.8043438	0.2205461
0.80975	0.2385771	0.8098938	0.2385771

0.80375	0.2125254	0.8039658	0.2125254
0.80025	0.2002425	0.8001643	0.2002425
0.79950	0.1997066	0.7992497	0.1997066
0.79950	0.1955709	0.7995059	0.1955709
0.80075	0.2012251	0.8009772	0.2012251
0.79975	0.1978398	0.7998208	0.1978398
0.79825	0.1946672	0.7982068	0.1946672
0.79800	0.1906639	0.7980754	0.1906639
0.79600	0.1826529	0.7959957	0.1826529
0.80525	0.2199970	0.8053626	0.2199970
0.80050	0.2032750	0.8003611	0.2032750
0.80300	0.2122199	0.8029833	0.2122199
0.80225	0.2087902	0.8022313	0.2087902
0.80125	0.2054861	0.8011268	0.2054861
0.80475	0.2135072	0.8050766	0.2135072
0.80600	0.2186440	0.8064158	0.2186440
0.80150	0.1986654	0.8019066	0.1986654
0.80175	0.2043678	0.8019270	0.2043678
0.80050	0.1997755	0.8005784	0.1997755
0.80600	0.2211172	0.8062750	0.2211172
0.80425	0.2172097	0.8042030	0.2172097
0.80400	0.2132512	0.8042390	0.2132512
0.80400	0.2160124	0.8040467	0.2160124
0.79975	0.1971599	0.7997695	0.1971599
0.80575	0.2268897	0.8056084	0.2268897
0.80300	0.2130208	0.8029570	0.2130208
0.80300	0.2099212	0.8032411	0.2099212
0.80400	0.2187974	0.8038596	0.2187974
0.80425	0.2182562	0.8042347	0.2182562
0.80150	0.2018639	0.8017051	0.2018639
0.80025	0.1935786	0.8006052	0.1935786
0.80000	0.1979967	0.8001123	0.1979967
0.80050	0.1984127	0.8006504	0.1984127
0.79950	0.1944621	0.7996335	0.1944621
0.80250	0.2078827	0.8026619	0.2078827
0.80050	0.1986780	0.8007556	0.1986780
0.80000	0.1967896	0.8002102	0.1967896
0.79925	0.1948108	0.7993491	0.1948108
0.79975	0.1972009	0.7998368	0.1972009
0.80525	0.2182227	0.8055505	0.2182227
0.79825	0.1927455	0.7982896	0.1927455
0.79875	0.1935760	0.7988580	0.1935760
0.79850	0.1940957	0.7985412	0.1940957
0.79750	0.1855694	0.7977162	0.1855694
0.80625	0.2209014	0.8065116	0.2209014
0.80100	0.2061133	0.8008826	0.2061133
0.80525	0.2205519	0.8052848	0.2205519
0.80175	0.2063842	0.8017885	0.2063842
0.80250	0.2105890	0.8024587	0.2105890
0.80250	0.2110967	0.8025491	0.2110967
0.79925	0.1942358	0.7993410	0.1942358
0.79850	0.1904493	0.7985960	0.1904493
0.80025	0.1969826	0.8004909	0.1969826
0.80075	0.1997345	0.8009045	0.1997345
0.80100	0.2002613	0.8012155	0.2002613

0.79775	0.1906311	0.7977856	0.1906311
0.80175	0.2051958	0.8019322	0.2051958
0.80025	0.2005886	0.8003682	0.2005886
0.79900	0.1961871	0.7990901	0.1961871
0.80250	0.2108069	0.8024131	0.2108069
0.79900	0.1942690	0.7991137	0.1942690
0.79775	0.1871791	0.7980050	0.1871791
0.80225	0.2067128	0.8023348	0.2067128
0.80075	0.2005186	0.8008751	0.2005186
0.80200	0.2029529	0.8022660	0.2029529
0.79675	0.1810979	0.7971266	0.1810979
0.79725	0.1808097	0.7977237	0.1808097
0.79875	0.1893763	0.7992008	0.1893763
0.79775	0.1855571	0.7981271	0.1855571
0.80175	0.2075770	0.8018167	0.2075770
0.80125	0.2034414	0.8013878	0.2034414
0.80100	0.2012047	0.8011544	0.2012047
0.80100	0.2014319	0.8011326	0.2014319
0.79875	0.1928395	0.7988803	0.1928395
0.80600	0.2227126	0.8061307	0.2227126
0.80275	0.2090600	0.8029217	0.2090600
0.80475	0.2212368	0.8047172	0.2212368
0.80450	0.2172714	0.8046354	0.2172714
0.80450	0.2170786	0.8046226	0.2170786
0.79725	0.1861474	0.7974389	0.1861474
0.79850	0.1898907	0.7987459	0.1898907
0.79925	0.1956148	0.7993683	0.1956148
0.80000	0.1989549	0.8001431	0.1989549
0.79925	0.1982180	0.7992774	0.1982180
0.80550	0.2234004	0.8054431	0.2234004
0.80425	0.2139375	0.8046276	0.2139375
0.80175	0.2053091	0.8020138	0.2053091
0.80150	0.2032155	0.8017566	0.2032155
0.80025	0.1983303	0.8004765	0.1983303
0.80400	0.2131310	0.8041875	0.2131310
0.79800	0.1861547	0.7984222	0.1861547
0.79850	0.1903499	0.7987513	0.1903499
0.79700	0.1853013	0.7971338	0.1853013
0.79850	0.1926161	0.7986293	0.1926161
0.80200	0.2110931	0.8018296	0.2110931
0.80025	0.2034917	0.8001255	0.2034917
0.79775	0.1917295	0.7976662	0.1917295
0.79825	0.1944307	0.7981966	0.1944307
0.79725	0.1875066	0.7972830	0.1875066
0.79975	0.2006782	0.7996689	0.2006782
0.80025	0.1962190	0.8005601	0.1962190
0.79925	0.1948391	0.7994126	0.1948391
0.79800	0.1890228	0.7981646	0.1890228
0.79725	0.1888184	0.7972295	0.1888184
0.80125	0.2049213	0.8012647	0.2049213
0.80250	0.2075838	0.8026347	0.2075838
0.80050	0.1998816	0.8006604	0.1998816
0.80100	0.2040305	0.8010681	0.2040305
0.80125	0.2066349	0.8012108	0.2066349
0.80325	0.2076287	0.8035982	0.2076287



0.80325	0.2125647	0.8033501	0.2125647
0.80175	0.2048130	0.8018306	0.2048130
0.80175	0.2070324	0.8018386	0.2070324
0.80200	0.2074726	0.8020668	0.2074726
0.80400	0.2106876	0.8046267	0.2106876
0.79925	0.1946348	0.7994467	0.1946348
0.79825	0.1861282	0.7986967	0.1861282
0.79675	0.1797886	0.7971305	0.1797886
0.79700	0.1825422	0.7973730	0.1825422
0.80475	0.2179404	0.8049524	0.2179404
0.80175	0.2073670	0.8017849	0.2073670
0.80300	0.2106544	0.8031256	0.2106544
0.80200	0.2090975	0.8019858	0.2090975
0.80175	0.2077645	0.8016994	0.2077645
0.80375	0.2126954	0.8037940	0.2126954
0.80425	0.2150751	0.8043694	0.2150751
0.80450	0.2199560	0.8042893	0.2199560
0.80500	0.2235626	0.8047246	0.2235626
0.80450	0.2211307	0.8042498	0.2211307
0.80300	0.2090913	0.8031552	0.2090913
0.80125	0.2064991	0.8011145	0.2064991
0.79925	0.2013708	0.7989771	0.2013708
0.79975	0.2019737	0.7995112	0.2019737
0.80100	0.2083279	0.8006931	0.2083279
0.80250	0.2089059	0.8025416	0.2089059
0.80150	0.2030607	0.8017320	0.2030607
0.79975	0.1944015	0.8000057	0.1944015
0.79975	0.1937536	0.8001011	0.1937536
0.79950	0.1938267	0.7997679	0.1938267
0.79825	0.1870730	0.7986547	0.1870730
0.80125	0.2002003	0.8015673	0.2002003
0.80025	0.1992661	0.8004046	0.1992661
0.80000	0.1969368	0.8002321	0.1969368
0.79875	0.1921970	0.7989784	0.1921970
0.79725	0.1852887	0.7973483	0.1852887
0.79475	0.1736462	0.7950844	0.1736462
0.79575	0.1809618	0.7959439	0.1809618
0.79625	0.1842140	0.7963011	0.1842140
0.79775	0.1909880	0.7978489	0.1909880
0.80400	0.2146217	0.8041080	0.2146217
0.80275	0.2093104	0.8029608	0.2093104
0.80175	0.2059094	0.8019379	0.2059094
0.80200	0.2079617	0.8020757	0.2079617
0.80100	0.2025256	0.8011323	0.2025256
0.80500	0.2220155	0.8049103	0.2220155
0.80075	0.2032174	0.8007491	0.2032174
0.80100	0.2005513	0.8012023	0.2005513
0.80075	0.2006688	0.8009013	0.2006688
0.80125	0.2006254	0.8015053	0.2006254
0.79825	0.1921766	0.7982565	0.1921766
0.80050	0.2015947	0.8006207	0.2015947
0.79925	0.1983312	0.7993189	0.1983312
0.79825	0.1942053	0.7982732	0.1942053
0.79925	0.1983458	0.7992333	0.1983458
0.80475	0.2170939	0.8048562	0.2170939

0.80175	0.2059614	0.8020013	0.2059614
0.80325	0.2142148	0.8034165	0.2142148
0.80225	0.2121441	0.8023410	0.2121441
0.80150	0.2099171	0.8015537	0.2099171
Mean_Recall	Mean_Detection_Rate	Mean_Balanced_Accuracy	
0.247	0.0494	0.529375	
0.233	0.0466	0.520625	
0.228	0.0456	0.517500	
0.225	0.0450	0.515625	
0.231	0.0462	0.519375	
0.255	0.0510	0.534375	
0.246	0.0492	0.528750	
0.227	0.0454	0.516875	
0.210	0.0420	0.506250	
0.203	0.0406	0.501875	
0.272	0.0544	0.545000	
0.242	0.0484	0.526250	
0.222	0.0444	0.513750	
0.212	0.0424	0.507500	
0.204	0.0408	0.502500	
0.257	0.0514	0.535625	
0.240	0.0480	0.525000	
0.230	0.0460	0.518750	
0.212	0.0424	0.507500	
0.204	0.0408	0.502500	
0.272	0.0544	0.545000	
0.247	0.0494	0.529375	
0.241	0.0482	0.525625	
0.226	0.0452	0.516250	
0.227	0.0454	0.516875	
0.248	0.0496	0.530000	
0.232	0.0464	0.520000	
0.223	0.0446	0.514375	
0.211	0.0422	0.506875	
0.225	0.0450	0.515625	
0.254	0.0508	0.533750	
0.244	0.0488	0.527500	
0.223	0.0446	0.514375	
0.218	0.0436	0.511250	
0.219	0.0438	0.511875	
0.263	0.0526	0.539375	
0.234	0.0468	0.521250	
0.226	0.0452	0.516250	
0.223	0.0446	0.514375	
0.217	0.0434	0.510625	
0.261	0.0522	0.538125	
0.237	0.0474	0.523125	
0.228	0.0456	0.517500	
0.205	0.0410	0.503125	
0.211	0.0422	0.506875	
0.270	0.0540	0.543750	
0.247	0.0494	0.529375	
0.236	0.0472	0.522500	
0.228	0.0456	0.517500	
0.218	0.0436	0.511250	

0.211	0.0422	0.506875
0.210	0.0420	0.506250
0.212	0.0424	0.507500
0.205	0.0410	0.503125
0.209	0.0418	0.505625
0.234	0.0468	0.521250
0.225	0.0450	0.515625
0.225	0.0450	0.515625
0.214	0.0428	0.508750
0.210	0.0420	0.506250
0.227	0.0454	0.516875
0.196	0.0392	0.497500
0.191	0.0382	0.494375
0.188	0.0376	0.492500
0.189	0.0378	0.493125
0.217	0.0434	0.510625
0.205	0.0410	0.503125
0.210	0.0420	0.506250
0.195	0.0390	0.496875
0.204	0.0408	0.502500
0.229	0.0458	0.518125
0.201	0.0402	0.500625
0.194	0.0388	0.496250
0.208	0.0416	0.505000
0.203	0.0406	0.501875
0.238	0.0476	0.523750
0.242	0.0484	0.526250
0.221	0.0442	0.513125
0.210	0.0420	0.506250
0.211	0.0422	0.506875
0.216	0.0432	0.510000
0.204	0.0408	0.502500
0.209	0.0418	0.505625
0.209	0.0418	0.505625
0.209	0.0418	0.505625
0.202	0.0404	0.501250
0.203	0.0406	0.501875
0.193	0.0386	0.495625
0.204	0.0408	0.502500
0.189	0.0378	0.493125
0.227	0.0454	0.516875
0.201	0.0402	0.500625
0.195	0.0390	0.496875
0.196	0.0392	0.497500
0.191	0.0382	0.494375
0.218	0.0436	0.511250
0.202	0.0404	0.501250
0.196	0.0392	0.497500
0.195	0.0390	0.496875
0.191	0.0382	0.494375
0.218	0.0436	0.511250
0.223	0.0446	0.514375
0.222	0.0444	0.513750
0.211	0.0422	0.506875
0.219	0.0438	0.511875

0.227	0.0454	0.516875
0.217	0.0434	0.510625
0.224	0.0448	0.515000
0.225	0.0450	0.515625
0.213	0.0426	0.508125
0.218	0.0436	0.511250
0.222	0.0444	0.513750
0.210	0.0420	0.506250
0.213	0.0426	0.508125
0.211	0.0422	0.506875
0.209	0.0418	0.505625
0.220	0.0440	0.512500
0.216	0.0432	0.510000
0.203	0.0406	0.501875
0.200	0.0400	0.500000
0.216	0.0432	0.510000
0.212	0.0424	0.507500
0.205	0.0410	0.503125
0.201	0.0402	0.500625
0.204	0.0408	0.502500
0.232	0.0464	0.520000
0.209	0.0418	0.505625
0.230	0.0460	0.518750
0.210	0.0420	0.506250
0.201	0.0402	0.500625
0.208	0.0416	0.505000
0.211	0.0422	0.506875
0.211	0.0422	0.506875
0.203	0.0406	0.501875
0.194	0.0388	0.496250
0.204	0.0408	0.502500
0.211	0.0422	0.506875
0.192	0.0384	0.495000
0.201	0.0402	0.500625
0.201	0.0402	0.500625
0.226	0.0452	0.516250
0.214	0.0428	0.508750
0.212	0.0424	0.507500
0.212	0.0424	0.507500
0.213	0.0426	0.508125
0.217	0.0434	0.510625
0.197	0.0394	0.498125
0.206	0.0412	0.503750
0.198	0.0396	0.498750
0.196	0.0392	0.497500
0.225	0.0450	0.515625
0.215	0.0430	0.509375
0.205	0.0410	0.503125
0.215	0.0430	0.509375
0.210	0.0420	0.506250
0.205	0.0410	0.503125
0.211	0.0422	0.506875
0.212	0.0424	0.507500
0.206	0.0412	0.503750
0.205	0.0410	0.503125

0.209	0.0418	0.505625
0.207	0.0414	0.504375
0.200	0.0400	0.500000
0.206	0.0412	0.503750
0.206	0.0412	0.503750
0.210	0.0420	0.506250
0.188	0.0376	0.492500
0.190	0.0380	0.493750
0.189	0.0378	0.493125
0.193	0.0386	0.495625
0.226	0.0452	0.516250
0.188	0.0376	0.492500
0.193	0.0386	0.495625
0.190	0.0380	0.493750
0.192	0.0384	0.495000
0.215	0.0430	0.509375
0.214	0.0428	0.508750
0.213	0.0426	0.508125
0.217	0.0434	0.510625
0.209	0.0418	0.505625
0.202	0.0404	0.501250
0.202	0.0404	0.501250
0.197	0.0394	0.498125
0.199	0.0398	0.499375
0.196	0.0392	0.497500
0.214	0.0428	0.508750
0.215	0.0430	0.509375
0.207	0.0414	0.504375
0.206	0.0412	0.503750
0.193	0.0386	0.495625
0.207	0.0414	0.504375
0.202	0.0404	0.501250
0.202	0.0404	0.501250
0.203	0.0406	0.501875
0.203	0.0406	0.501875
0.213	0.0426	0.508125
0.198	0.0396	0.498750
0.195	0.0390	0.496875
0.184	0.0368	0.490000
0.182	0.0364	0.488750
0.194	0.0388	0.496250
0.202	0.0404	0.501250
0.212	0.0424	0.507500
0.212	0.0424	0.507500
0.213	0.0426	0.508125
0.210	0.0420	0.506250
0.209	0.0418	0.505625
0.200	0.0400	0.500000
0.200	0.0400	0.500000
0.210	0.0420	0.506250
0.212	0.0424	0.507500
0.185	0.0370	0.490625
0.185	0.0370	0.490625
0.193	0.0386	0.495625
0.192	0.0384	0.495000

0.200	0.0400	0.500000
0.201	0.0402	0.500625
0.196	0.0392	0.497500
0.190	0.0380	0.493750
0.200	0.0400	0.500000
0.202	0.0404	0.501250
0.195	0.0390	0.496875
0.200	0.0400	0.500000
0.188	0.0376	0.492500
0.196	0.0392	0.497500
0.233	0.0466	0.520625
0.224	0.0448	0.515000
0.224	0.0448	0.515000
0.220	0.0440	0.512500
0.212	0.0424	0.507500
0.221	0.0442	0.513125
0.215	0.0430	0.509375
0.214	0.0428	0.508750
0.219	0.0438	0.511875
0.212	0.0424	0.507500
0.217	0.0434	0.510625
0.202	0.0404	0.501250
0.196	0.0392	0.497500
0.201	0.0402	0.500625
0.200	0.0400	0.500000
0.202	0.0404	0.501250
0.212	0.0424	0.507500
0.202	0.0404	0.501250
0.206	0.0412	0.503750
0.205	0.0410	0.503125
0.206	0.0412	0.503750
0.199	0.0398	0.499375
0.195	0.0390	0.496875
0.198	0.0396	0.498750
0.191	0.0382	0.494375
0.244	0.0488	0.527500
0.227	0.0454	0.516875
0.218	0.0436	0.511250
0.223	0.0446	0.514375
0.211	0.0422	0.506875
0.249	0.0498	0.530625
0.238	0.0476	0.523750
0.220	0.0440	0.512500
0.200	0.0400	0.500000
0.203	0.0406	0.501875
0.251	0.0502	0.531875
0.234	0.0468	0.521250
0.213	0.0426	0.508125
0.205	0.0410	0.503125
0.207	0.0414	0.504375
0.254	0.0508	0.533750
0.227	0.0454	0.516875
0.219	0.0438	0.511875
0.216	0.0432	0.510000
0.202	0.0404	0.501250

0.261	0.0522	0.538125
0.242	0.0484	0.526250
0.221	0.0442	0.513125
0.220	0.0440	0.512500
0.214	0.0428	0.508750
0.248	0.0496	0.530000
0.224	0.0448	0.515000
0.217	0.0434	0.510625
0.223	0.0446	0.514375
0.210	0.0420	0.506250
0.244	0.0488	0.527500
0.252	0.0504	0.532500
0.226	0.0452	0.516250
0.217	0.0434	0.510625
0.208	0.0416	0.505000
0.232	0.0464	0.520000
0.220	0.0440	0.512500
0.208	0.0416	0.505000
0.205	0.0410	0.503125
0.209	0.0418	0.505625
0.253	0.0506	0.533125
0.236	0.0472	0.522500
0.215	0.0430	0.509375
0.207	0.0414	0.504375
0.200	0.0400	0.500000
0.259	0.0518	0.536875
0.247	0.0494	0.529375
0.226	0.0452	0.516250
0.217	0.0434	0.510625
0.209	0.0418	0.505625
0.212	0.0424	0.507500
0.216	0.0432	0.510000
0.214	0.0428	0.508750
0.206	0.0412	0.503750
0.199	0.0398	0.499375
0.215	0.0430	0.509375
0.211	0.0422	0.506875
0.217	0.0434	0.510625
0.220	0.0440	0.512500
0.208	0.0416	0.505000
0.213	0.0426	0.508125
0.210	0.0420	0.506250
0.215	0.0430	0.509375
0.216	0.0432	0.510000
0.204	0.0408	0.502500
0.226	0.0452	0.516250
0.208	0.0416	0.505000
0.202	0.0404	0.501250
0.192	0.0384	0.495000
0.197	0.0394	0.498125
0.228	0.0456	0.517500
0.210	0.0420	0.506250
0.197	0.0394	0.498125
0.195	0.0390	0.496875
0.201	0.0402	0.500625

0.212	0.0424	0.507500
0.244	0.0488	0.527500
0.224	0.0448	0.515000
0.209	0.0418	0.505625
0.218	0.0436	0.511250
0.239	0.0478	0.524375
0.215	0.0430	0.509375
0.201	0.0402	0.500625
0.198	0.0396	0.498750
0.198	0.0396	0.498750
0.203	0.0406	0.501875
0.199	0.0398	0.499375
0.193	0.0386	0.495625
0.192	0.0384	0.495000
0.184	0.0368	0.490000
0.221	0.0442	0.513125
0.202	0.0404	0.501250
0.212	0.0424	0.507500
0.209	0.0418	0.505625
0.205	0.0410	0.503125
0.219	0.0438	0.511875
0.224	0.0448	0.515000
0.206	0.0412	0.503750
0.207	0.0414	0.504375
0.202	0.0404	0.501250
0.224	0.0448	0.515000
0.217	0.0434	0.510625
0.216	0.0432	0.510000
0.216	0.0432	0.510000
0.199	0.0398	0.499375
0.223	0.0446	0.514375
0.212	0.0424	0.507500
0.212	0.0424	0.507500
0.216	0.0432	0.510000
0.217	0.0434	0.510625
0.206	0.0412	0.503750
0.201	0.0402	0.500625
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0.202	0.0404	0.501250
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0.210	0.0420	0.506250
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0.200	0.0400	0.500000
0.197	0.0394	0.498125
0.199	0.0398	0.499375
0.221	0.0442	0.513125
0.193	0.0386	0.495625
0.195	0.0390	0.496875
0.194	0.0388	0.496250
0.190	0.0380	0.493750
0.225	0.0450	0.515625
0.204	0.0408	0.502500
0.221	0.0442	0.513125
0.207	0.0414	0.504375
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0.197	0.0394	0.498125
0.194	0.0388	0.496250
0.201	0.0402	0.500625
0.203	0.0406	0.501875
0.204	0.0408	0.502500
0.191	0.0382	0.494375
0.207	0.0414	0.504375
0.201	0.0402	0.500625
0.196	0.0392	0.497500
0.210	0.0420	0.506250
0.196	0.0392	0.497500
0.191	0.0382	0.494375
0.209	0.0418	0.505625
0.203	0.0406	0.501875
0.208	0.0416	0.505000
0.187	0.0374	0.491875
0.189	0.0378	0.493125
0.195	0.0390	0.496875
0.191	0.0382	0.494375
0.207	0.0414	0.504375
0.205	0.0410	0.503125
0.204	0.0408	0.502500
0.204	0.0408	0.502500
0.195	0.0390	0.496875
0.224	0.0448	0.515000
0.211	0.0422	0.506875
0.219	0.0438	0.511875
0.218	0.0436	0.511250
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0.197	0.0394	0.498125
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0.216	0.0432	0.510000
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0.188	0.0376	0.492500
0.194	0.0388	0.496250
0.208	0.0416	0.505000
0.201	0.0402	0.500625
0.191	0.0382	0.494375
0.193	0.0386	0.495625
0.189	0.0378	0.493125
0.199	0.0398	0.499375
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0.213	0.0426	0.508125
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0.207	0.0414	0.504375
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0.208	0.0416	0.505000
0.216	0.0432	0.510000
0.197	0.0394	0.498125
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0.188	0.0376	0.492500
0.219	0.0438	0.511875
0.207	0.0414	0.504375
0.212	0.0424	0.507500
0.208	0.0416	0.505000
0.207	0.0414	0.504375
0.215	0.0430	0.509375
0.217	0.0434	0.510625
0.218	0.0436	0.511250
0.220	0.0440	0.512500
0.218	0.0436	0.511250
0.212	0.0424	0.507500
0.205	0.0410	0.503125
0.197	0.0394	0.498125
0.199	0.0398	0.499375
0.204	0.0408	0.502500
0.210	0.0420	0.506250
0.206	0.0412	0.503750
0.199	0.0398	0.499375
0.199	0.0398	0.499375
0.198	0.0396	0.498750
0.193	0.0386	0.495625
0.205	0.0410	0.503125
0.201	0.0402	0.500625
0.200	0.0400	0.500000
0.195	0.0390	0.496875
0.189	0.0378	0.493125
0.179	0.0358	0.486875
0.183	0.0366	0.489375
0.185	0.0370	0.490625
0.191	0.0382	0.494375
0.216	0.0432	0.510000
0.211	0.0422	0.506875
0.207	0.0414	0.504375
0.208	0.0416	0.505000
0.204	0.0408	0.502500
0.220	0.0440	0.512500
0.203	0.0406	0.501875
0.204	0.0408	0.502500
0.203	0.0406	0.501875
0.205	0.0410	0.503125

0.193	0.0386	0.495625
0.202	0.0404	0.501250
0.197	0.0394	0.498125
0.193	0.0386	0.495625
0.197	0.0394	0.498125
0.219	0.0438	0.511875
0.207	0.0414	0.504375
0.213	0.0426	0.508125
0.209	0.0418	0.505625
0.206	0.0412	0.503750

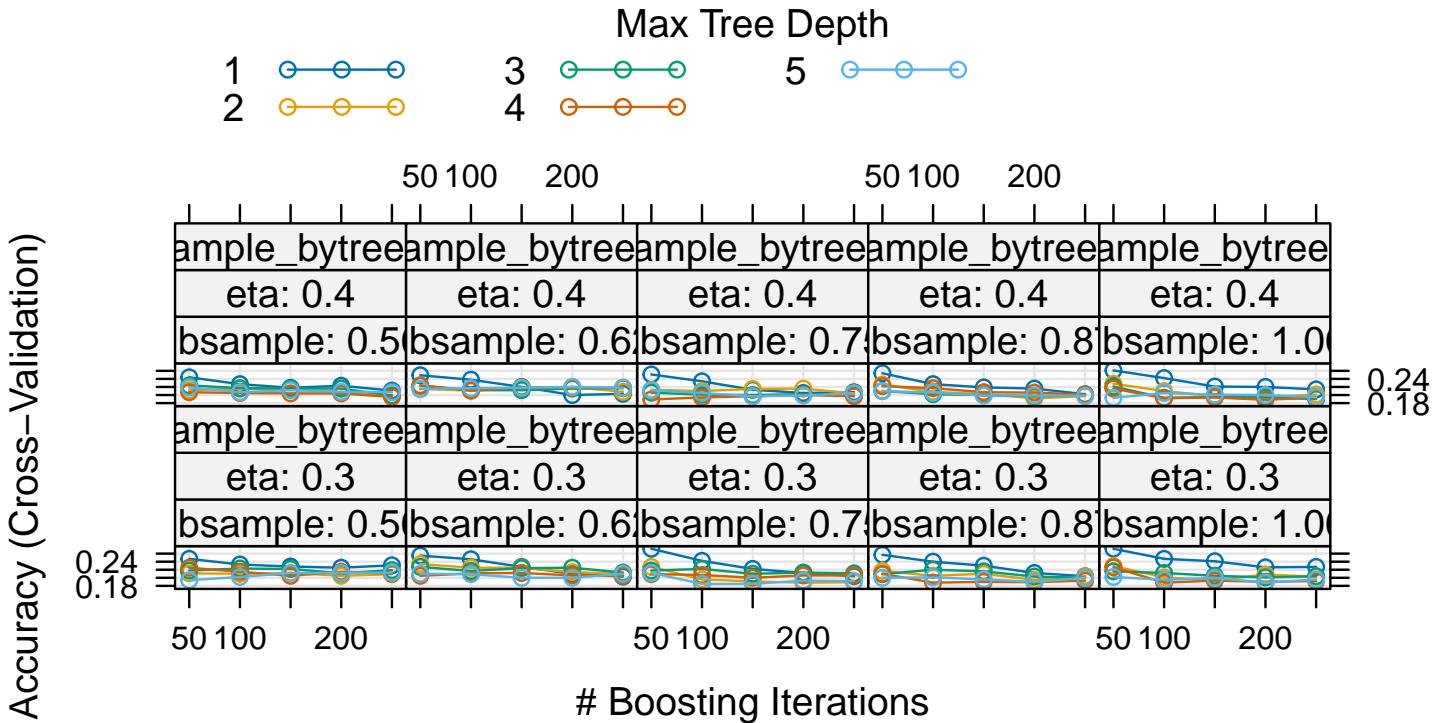
Tuning parameter 'gamma' was held constant at a value of 0

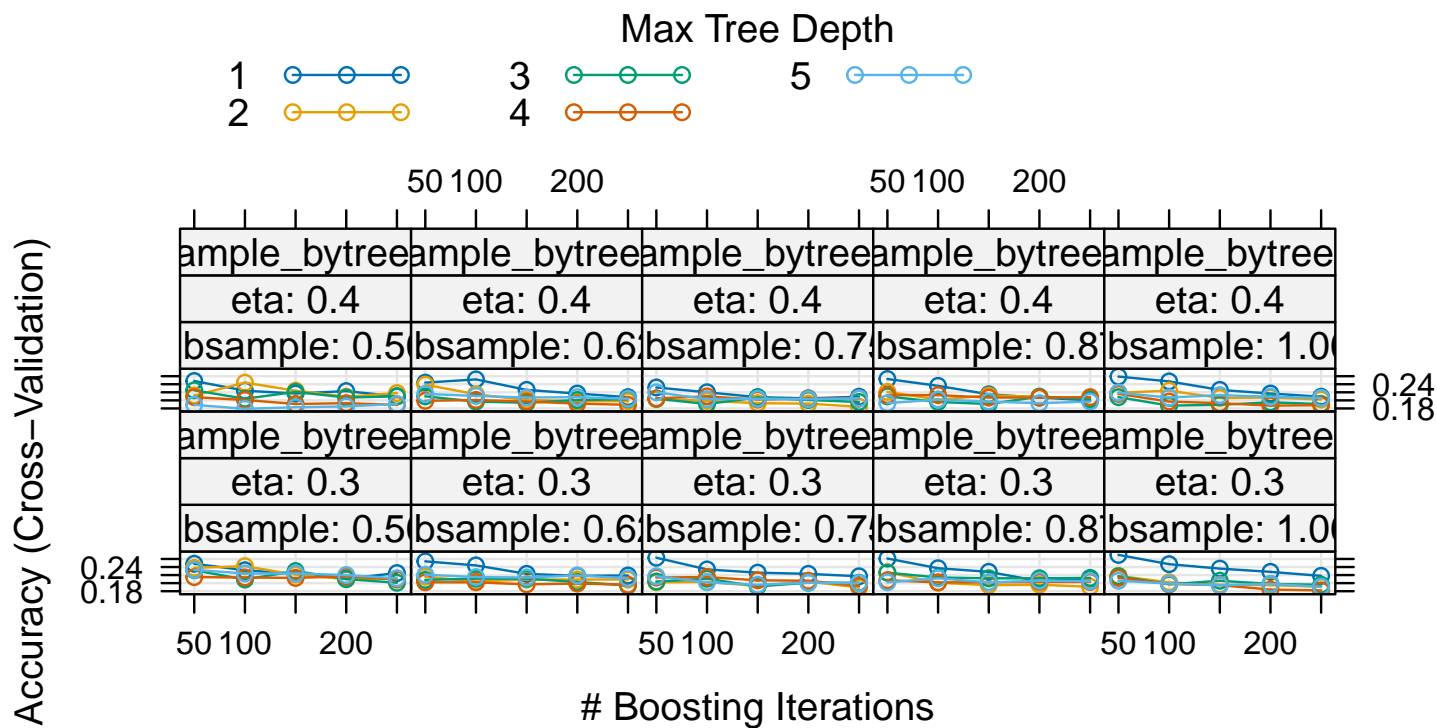
Tuning parameter 'min\_child\_weight' was held constant at a value of 1

Accuracy was used to select the optimal model using the largest value.

The final values used for the model were nrounds = 50, max\_depth = 1, eta = 0.3, gamma = 0, colsample\_bytree = 0.6, min\_child\_weight = 1 and subsample = 0.75.

```
plot(xgb_model)
```





```
# predict on test set
xgb_preds <- predict(xgb_model, newdata = test_data)

# confusion matrix and accuracy
conf_matrix <- confusionMatrix(xgb_preds, test_data$Reason)
print(conf_matrix)
```

#### Confusion Matrix and Statistics

	Reference				
Prediction	Diaper.Change	Fussy	Hungry	Pain	Tired
Diaper.Change	6	11	7	6	8
Fussy	13	13	9	3	11
Hungry	13	10	15	12	9
Pain	14	9	14	24	14
Tired	4	7	5	5	8

#### Overall Statistics

Accuracy : 0.264  
 95% CI : (0.2105, 0.3232)  
 No Information Rate : 0.2  
 P-Value [Acc > NIR] : 0.008598

Kappa : 0.08

McNemar's Test P-Value : 0.099593

#### Statistics by Class:

	Class: Diaper.Change	Class: Fussy	Class: Hungry
Sensitivity	0.1200	0.2600	0.3000
Specificity	0.8400	0.8200	0.7800
Pos Pred Value	0.1579	0.2653	0.2542
Neg Pred Value	0.7925	0.8159	0.8168
Prevalence	0.2000	0.2000	0.2000
Detection Rate	0.0240	0.0520	0.0600
Detection Prevalence	0.1520	0.1960	0.2360
Balanced Accuracy	0.4800	0.5400	0.5400

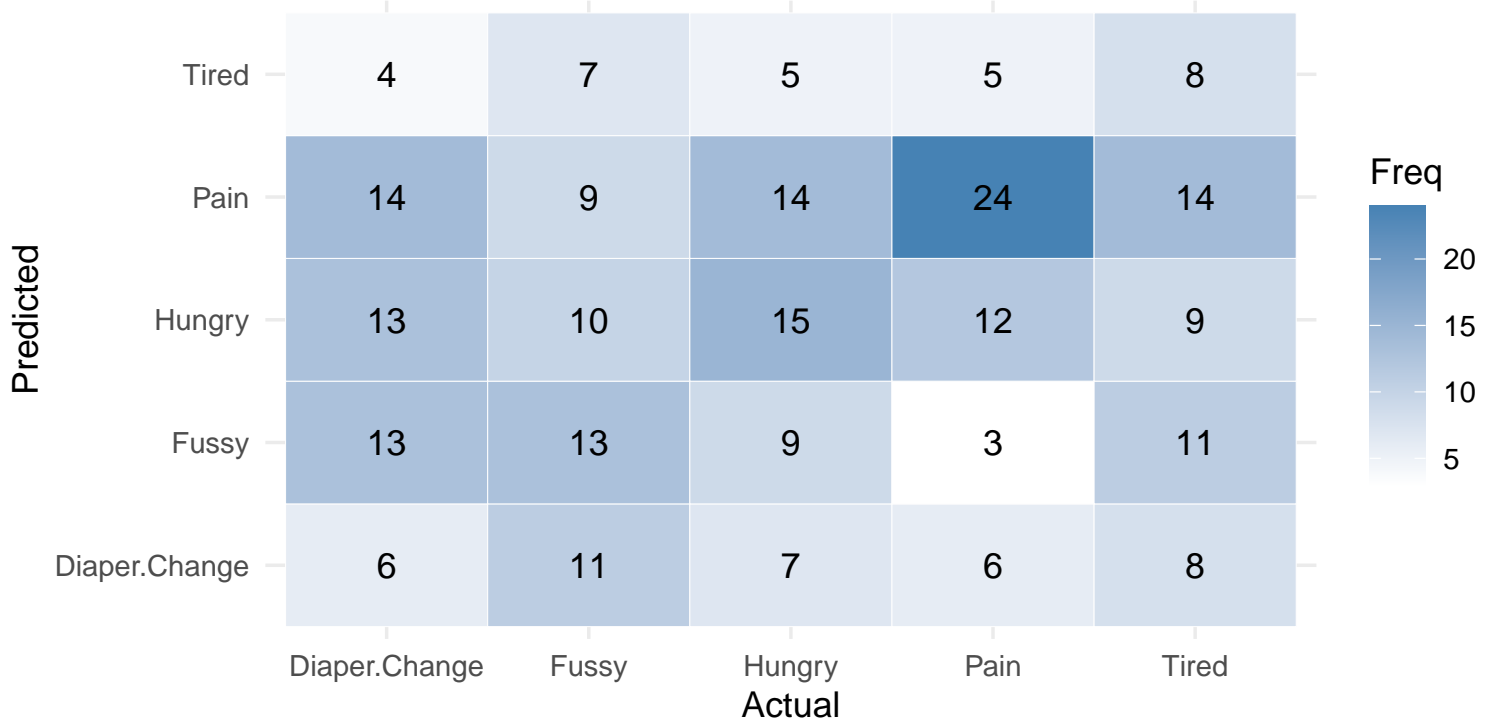
	Class: Pain	Class: Tired
Sensitivity	0.4800	0.1600
Specificity	0.7450	0.8950
Pos Pred Value	0.3200	0.2759
Neg Pred Value	0.8514	0.8100
Prevalence	0.2000	0.2000
Detection Rate	0.0960	0.0320
Detection Prevalence	0.3000	0.1160
Balanced Accuracy	0.6125	0.5275

```
accuracy <- conf_matrix$overall['Accuracy']
print(accuracy)
```

Accuracy  
0.264

```
# creating a confusion matrix heatmap (pretty)
cm_df <- as.data.frame(conf_matrix$table)
ggplot(cm_df, aes(x = Reference, y = Prediction)) +
  geom_tile(aes(fill = Freq), color = "white") +
  geom_text(aes(label = Freq), size = 4) +
  scale_fill_gradient(low = "white", high = "steelblue") +
  theme_minimal() +
  labs(title = "Confusion Matrix Heatmap (XGBoost)", x = "Actual", y = "Predicted")
```

# Confusion Matrix Heatmap (XGBoost)



```
# extract variable importance
xgb_imp <- varImp(xgb_model)$importance
xgb_imp$Variable <- rownames(xgb_imp)

# choose top 20 important features
top_n <- 20
xgb_imp <- as_tibble(xgb_imp) %>%
  arrange(desc(Overall)) %>%
  dplyr::slice(1:top_n)

# make a clean ggplot for variable importance
ggplot(xgb_imp, aes(x = reorder(Variable, Overall), y = Overall)) +
  geom_col(fill = "#1f78b4") +
  coord_flip() +
  theme_minimal(base_size = 13) +
  labs(title = "Top 20 Variable Importances",
       subtitle = "XGBoost Model (Caret)",
       x = NULL,
       y = "Importance Score") +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", size = 15),
    plot.subtitle = element_text(hjust = 0.5, size = 12),
    axis.text.y = element_text(size = 9),
    axis.text.x = element_text(size = 11)
  )
)
```

# Top 20 Variable Importances

XGBoost Model (Caret)

