Predicting Genetic Disorders

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Objective and Hypothesis

[...]

Data Load and Validation

```
# Load dataset(s)
gd_df <- read.csv("../data/train_genetic_disorders.csv", header = TRUE)
# Data validation and understanding, including structure, content, and statistical characteristics covered below</pre>
```

Data Structure Review

```
# Summarize base dataset and [optionally] sample rows str(gd_df)
```

```
'data.frame': 22083 obs. of 45 variables:
                                                 : chr "PID0x6418" "PID0x25d5" "PID0x4a82" "PID0x4ac8" ...
$ Patient.Id
                                                 : int 2 4 6 12 11 14 3 3 11 4 ...
$ Patient.Age
                                                 : chr "Yes" "Yes" "Yes" "Yes" ...
$ Genes.in.mother.s.side
                                                 : chr "No" "Yes" "No" "No" ...
$ Inherited.from.father
                                                 : chr "Yes" "No" "No" "Yes" ...
$ Maternal.gene
                                                        "No" "No" "No" "No" ...
$ Paternal.gene
                                                 : chr
                                                 : num 4.76 4.91 4.89 4.71 4.72 ...
$ Blood.cell.count..mcL.
                                                 : chr "Richard" "Mike" "Kimberly" "Jeffery" ...
$ Patient.First.Name
                                                 : chr "" "" "Hoelscher" ...
$ Family.Name
                                                 : chr "Larre" "Brycen" "Nashon" "Aayaan" ...
$ Father.s.name
                                                 : int NA NA 41 21 32 NA NA 40 45 44 ...
$ Mother.s.age
                                                 : int NA 23 22 NA NA NA 63 NA 44 42 ...
$ Father.s.age
                                                        "Boston Specialty & Rehabilitation Hospital" "St. Margaret's Ho
$ Institute.Name
                                                 : chr
spital For Women" "" "" ...
$ Location.of.Institute
                                                 : chr "55 FRUIT ST\nCENTRAL, MA 02114\n(42.36247485742686, -71.069247
24545246)" "1515 COMMONWEALTH AV\nALLSTON/BRIGHTON, MA 02135\n(42.34665771451756, -71.14136122385321)" "-" "55 FRUIT ST\n
CENTRAL, MA 02114\n(42.36247485742686, -71.06924724545246)" ...
                                                 : chr "Alive" "Deceased" "Alive" "Deceased" ...
$ Status
                                                 : chr "Normal (30-60)" "Tachypnea" "Normal (30-60)" "Tachypnea" ...
$ Respiratory.Rate..breaths.min.
$ Heart.Rate..rates.min
                                                 : chr "Normal" "Normal" "Tachycardia" "Normal" ...
                                                 : int 0 NA 0 0 0 0 NA 0 0 0 ...
$ Test.1
                                                 : int NA 0 0 0 0 0 0 0 0 ...
$ Test.2
$ Test 3
                                                 : int NA 0 0 0 0 0 NA 0 0 ...
                                                 : int 1 1 1 1 1 1 1 1 1 1 ...
$ Test.4
                                                 : int 0000000000...
$ Test.5
                                                        "Yes" "Yes" "Yes" "Yes"
$ Parental.consent
                                                 : chr
                                                 : chr "High" "High" "Low" "High" ...
$ Follow.up
                                                 : chr "" "" "Male" ...
$ Gender
                                                 : chr "" "No" "No record" "Not available" ...
$ Birth.asphyxia
$ Autopsy.shows.birth.defect..if.applicable.
                                                : chr "Not applicable" "None" "Not applicable" "No" ...
                                                 : chr "Institute" "" "Institute" ...
$ Place.of.birth
                                                        "No" "Yes" "Yes" "No" ...
$ Folic.acid.details..peri.conceptional.
                                                 : chr
                                                 : chr "" "Yes" "No" "Yes" ..
$ H.O.serious.maternal.illness
                                                 : chr "No" "Not applicable" "Yes" "-" ...
$ H.O.radiation.exposure..x.ray.
                                                 : chr "No" "Not applicable" "" "Not applicable" ...
$ H.O.substance.abuse
                                                 : chr "No" "No" "Yes" "" ...
$ Assisted.conception.IVF.ART
$ History.of.anomalies.in.previous.pregnancies : chr "Yes" "Yes" "Yes" "Yes" ...
                                                 : int NA NA 4 1 4 0 3 1 0 1 ..
$ No..of.previous.abortion
                                                        "" "Multiple" "Singular" "Singular" ...
$ Birth.defects
                                                 : chr
$ White.Blood.cell.count..thousand.per.microliter.: num 9.86 5.52 NA 7.92 4.1 ...
                                                 : chr "" "normal" "normal" "inconclusive" ...
$ Blood.test.result
$ Symptom.1
                                                  : int
                                                        1 1 0 0 0 1 0 0 1 0 ...
$ Symptom.2
                                                 : int 1 NA 1 0 0 0 0 1 0 ...
                                                 : int 1 1 1 1 0 0 0 1 1 1 ...
$ Symptom.3
                                                        1 1 1 0 0 1 0 NA 0 1 ...
$ Symptom.4
                                                 : int 1 0 1 0 NA 0 0 0 1 1 ...
$ Symptom.5
$ Genetic.Disorder
                                                 : chr "Mitochondrial genetic inheritance disorders" "" "Multifactoria
l genetic inheritance disorders" "Mitochondrial genetic inheritance disorders" ...
                                                 : chr "Leber's hereditary optic neuropathy" "Cystic fibrosis" "Diabet
$ Disorder.Subclass
```

```
es" "Leigh syndrome" ...
```

```
#head(gd_df, 3)
```

Preliminary Feature Reduction (clearly n/a to Objective and Hypothesis)

```
# Define n/a columns and subset dataframe; Note retaining "some" informational variables like "Institute.Name" for
  possible descriptive analytic purposes
drop_cols <- c("Patient.Id",</pre>
               "Patient.First.Name",
               "Family.Name",
               "Father.s.name"
               "Institute.Name",
               "Location.of.Institute",
               "Status",
               "Test.1",
               "Test.2",
               "Test.3",
               "Test.4",
               "Test.5",
               "Parental.consent",
               "Place.of.birth")
gd_df <- gd_df[ , !(names(gd_df) %in% drop_cols)]</pre>
```

Class Target and Label Review

```
# Check for missing labels; set aside where missing
missing_target <- which(is.na(gd_df$Disorder.Subclass) | (gd_df$Disorder.Subclass == ""))
cat("Rows pre-subset for missing labels: ", format(nrow(gd_df), format = "d", big.mark = ","), sep = "")</pre>
```

```
Rows pre-subset for missing labels: 22,083
```

```
gd_hold_df <- gd_df[missing_target, ]
gd_df <- gd_df[-missing_target, ]
cat("Held rows with missing labels: ", format(nrow(gd_hold_df), format = "d", big.mark = ","), sep = "")</pre>
```

```
Held rows with missing labels: 3,140
```

```
cat("Net rows (labeled): ", format(nrow(gd_df), format = "d", big.mark = ","), sep = "")
```

```
Net rows (labeled): 18,943
```

```
# Show frequency distribution for [prospective] target class(es)
show_frequency <- function(desc, c) {
    t <- as.data.frame(prop.table(table(c)))
    colnames(t) <- c("Class", "Frequency")
    cat(desc, "\n"); print(t[order(-t$Freq, t$Class), 1:2], row.names = FALSE)
}
show_frequency("Pre-Split Frequency Distribution", gd_df$Disorder.Subclass)</pre>
```

```
Pre-Split Frequency Distribution
                              Class Frequency
                                       0.258
                     Leigh syndrome
             Mitochondrial myopathy
                                        0.222
                    Cystic fibrosis
                          Tav-Sachs
                                       0.142
                           Diabetes
                                       0.092
                    Hemochromatosis
                                        0.068
Leber's hereditary optic neuropathy
                                       0.032
                        Alzheimer's
                                       0.008
                                       0.005
                             Cancer
```

```
# Move the target class to "top" of dataframe so column removals don't impact
gd_df <- gd_df[ , c(ncol(gd_df), 1:(ncol(gd_df) - 1))]
target_col = 1

# Clean (prelim) target class values
gd_df$Disorder.Subclass <- gsub("'", "", gd_df$Disorder.Subclass, fixed = TRUE)
gd_df$Disorder.Subclass <- gsub(" ", ".", gd_df$Disorder.Subclass, fixed = TRUE)
gd_df$Disorder.Subclass <- gsub("-", ".", gd_df$Disorder.Subclass, fixed = TRUE)</pre>
```

Data Splitting

```
# Split data 80/20 train/test, using caret's inherent stratified split to compensate for class imbalance
set.seed(1)
train_index <- createDataPartition(gd_df$Disorder.Subclass, times = 1, p = 0.80, list = FALSE)
train_df <- gd_df[train_index, ]
test_df <- gd_df[-train_index, ]
show_frequency("Post-Split Frequency Distribution (Train)", train_df$Disorder.Subclass)</pre>
```

```
Post-Split Frequency Distribution (Train)
                           Class Frequency
                  Leigh.syndrome 0.258
            Mitochondrial.myopathy
                                    0.222
                                    0.173
0.142
                  Cystic.fibrosis
                        Tay.Sachs
                        Diabetes
                                   0.092
                  Hemochromatosis
                                     0.068
Lebers.hereditary.optic.neuropathy
                                     0.032
                                    0.008
                       Alzheimers
                                    0.005
                           Cancer
```

Data Cleaning (and reduction)

Data (Sample) Characteristic Review for Pre-Processing

(Suppressing custom code for simplicity)

```
# Generate a summary (cursory) view of base dataset for initial understanding and pre-processing direction univariate(train_df)
```

	Type	NA	BlankZ	Unique	Min	Max	Mean	Median	Outlier<	>Outlier	Kurtosis	Skewness
Disorder.Subclass	character			9								
Patient.Age	integer	6%	6%	15		14		7	No	Yes	0.017	-1.211
Genes.in.mother.s	character			2								
<pre>Inherited.from.fa</pre>	character		1%	3								
Maternal.gene	character		12%	3								
Paternal.gene	character			2								
Blood.cell.count	numeric			15,158	4.093	5.610	4.900	4.902	No	Yes	-0.011	-0.037
Mother.s.age	integer	26%		34	18	51		35	No	Yes	-0.006	-1.219
Father.s.age	integer	25%		45	20	64		42	No	Yes	-0.002	-1.210
Respiratory.Rate	character		9%	3								
Heart.Raterates	character		9%	3								
Follow.up	character		9%	3								
Gender	character		9%	4								
Birth.asphyxia	character		9%	5								
Autopsy.shows.bir	character		4%	5								
Folic.acid.detail	character		9%	3								
H.O.serious.mater	character		8%	3								
H.O.radiation.exp	character		9%	5								
H.O.substance.abuse	character		9%	5								
Assisted.concepti	character		9%	3								
History.of.anomal	character		9%	3								
Noof.previous.a	integer	9%	18%	5		4		2	No	Yes	0.001	-1.292
Birth.defects	character		9%	3								
White.Blood.cell	numeric	9%		11,858	3.000	12.000	7.460	7.443	No	Yes	0.020	-0.979
Blood.test.result	character		9%	5								
Symptom.1	integer	9%	37%	2		1		1	No	Yes	-0.369	-1.864
Symptom.2	integer	9%	40%	2		1		1	No	Yes	-0.197	-1.961
Symptom.3	integer	8%	41%	2		1		1	No	Yes	-0.166	-1.973
Symptom.4	integer	9%	45%	2		1			No	Yes	0.010	-2.000
Symptom.5	integer	9%	48%	2		1			No	Yes	0.146	-1.979
Genetic.Disorder	character		9%	4								

Missing Values

```
# Genes.in.mother.s.side, Paternal.gene, Blood.cell.count..mcL., Status - n/a
# Impute basic integer values with medians
medianf <- function(x) {
  result <- median(x, na.rm = TRUE)</pre>
```

```
if (is.integer(x))
    result <- as.integer(result)
 return(result)
median cols = c("Patient.Age", "Mother.s.age", "Father.s.age", "No..of.previous.abortion")
for (n in median cols) {
  train_df[n][is.na(train_df[n])] <- apply(train_df[n], 2, medianf)</pre>
  test df[n][is.na(test df[n])] <- apply(test df[n], 2, medianf)
# Impute categorical blanks with common "notprovided"; note we could also impute these with categorical mode,
# or most frequent categorical value of each column using the cmode() function below
cols_tofill <- c("Inherited.from.father",</pre>
                         "Maternal.gene",
                        "Respiratory.Rate..breaths.min.",
                         "Heart.Rate..rates.min",
                         "Follow.up",
                        "Gender",
                         "Birth.asphyxia",
                         "Autopsy.shows.birth.defect..if.applicable.",
                        "Folic.acid.details..peri.conceptional.",
                         "H.O.serious.maternal.illness",
                         "H.O.radiation.exposure..x.ray."
                        "H.O.substance.abuse",
                         "Assisted.conception.IVF.ART",
                         "History.of.anomalies.in.previous.pregnancies",
                        "Birth.defects",
                        "Blood.test.result")
train_df[cols_tofill][train_df[cols_tofill] == ""] <- "notprovided"</pre>
test_df[cols_tofill][test_df[cols_tofill] == ""] <- "notprovided"
cmode <- function(x) {</pre>
  uniqx <- unique(na.omit(x))
  uniqx[which.max(tabulate(match(x, uniqx)))]
# Impute what appear to be masked "flag" columns iwth placeholder -1 values. .
flag_cols <- c("Symptom.1", "Symptom.2", "Symptom.3", "Symptom.4", "Symptom.5")
train_df[flag_cols][is.na(train_df[flag_cols])] <- as.integer(-1)</pre>
test_df[flag_cols][is.na(test_df[flag_cols])] <- as.integer(-1)</pre>
# Impute mean for one numeric column
train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.[is.na(train\_df\$White.Blood.cell.count..thousand.per.microliter.]]
) ] <-
  mean(train df$White.Blood.cell.count..thousand.per.microliter., na.rm = TRUE)
test df$White.Blood.cell.count..thousand.per.microliter.[is.na(test df$White.Blood.cell.count..thousand.per.microliter.)]
 mean(test df$White.Blood.cell.count..thousand.per.microliter., na.rm = TRUE)
# Note not using knnImpute for the limited number of numerical [prospective] features given that it
# centers/scales, which is illogical for the values in this dataset
#test df[ , -target col] <- predict(pp, test df[ , -target col, drop = FALSE])</pre>
# Last on the list: Genetic.Disorder - we're not classifying to this but it is relevant/informational as a
   superclass to the target Disorder. Subclass and shuold ultimately be imputed using similar Disorder. Subclass
     observations which do have valid Genetic. Disorder values
```

Feature Updates (including variable types/formats, names)

```
# Re-type variables
factor_cols <- c("Disorder.Subclass",</pre>
                 "Genes.in.mother.s.side",
                 "Inherited.from.father",
                 "Maternal.gene",
                 "Paternal.gene",
                 "Respiratory.Rate..breaths.min.",
                 "Heart.Rate..rates.min",
                 "Follow.up",
                 "Gender",
                 "Birth.asphyxia",
                 "Autopsy.shows.birth.defect..if.applicable.",
                 "Folic.acid.details..peri.conceptional.",
                 "H.O.serious.maternal.illness",
                 "H.O.radiation.exposure..x.ray."
                 "H.O.substance.abuse",
                 "Assisted.conception.IVF.ART",
                 "History.of.anomalies.in.previous.pregnancies",
                 "Birth.defects",
                 "Blood.test.result",
                 "Genetic.Disorder")
```

```
train_df[factor_cols] <- lapply(train_df[factor_cols], factor)</pre>
test_df[factor_cols] <- lapply(test_df[factor_cols], factor)</pre>
# Note dummy variables may be introduced below (model-dependent)
# Simplify variable naming
rename_cols <- c("Disorder_Subclass",</pre>
                  "Patient_Age",
                 "Genes_in_mothers_side",
                 "Inherited_from_father",
                 "Maternal_gene",
"Paternal_gene",
                 "Blood_cell_count_mcL",
                 "Mothers_age",
                 "Fathers_age",
                 "Respiratory_Rate_breaths_min",
                  "Heart_Rate_min",
                 "Follow_up",
                 "Gender",
                 "Birth_asphyxia",
                 "Autopsy_shows_birth_defect",
                 "Folic_acid_details_peri_conceptional",
                 "HO_serious_maternal_illness",
                 "HO_radiation_exposure_xray",
                 "HO_substance_abuse",
                 "Assisted_conception_IVF_ART",
                  "History_of_anomalies_in_previous_pregnancies",
                  "No_of_previous_abortion",
                 "Birth_defects",
                  "White_Blood_cell_count_thousand_per_microliter",
                  "Blood_test_result",
                 "Symptom_1",
                  "Symptom_2",
                  "Symptom_3",
                 "Symptom_4",
                 "Symptom_5",
                 "Genetic Disorder")
colnames(train_df) <- rename_cols</pre>
colnames(test_df) <- rename_cols</pre>
# Generate updated summary of base dataset
univariate(train df)
```

	Type	NA BlankZ	Unique	Min	Max	Mean	Median	Outlier<	>Outlier	Kurtosis	Skewness
Disorder_Subclass	factor		9								
Patient_Age	integer	6%	15		14		7	No	Yes	0.016	-1.090
Genes_in_mothers	factor		2								
Inherited_from_fa	factor		3								
Maternal gene	factor		3								
Paternal_gene	factor		2								
Blood_cell_count_mcL	numeric		15,158	4.093	5.610	4.900	4.902	No	Yes	-0.011	-0.037
Mothers_age	integer		34	18	51		35	No	Yes	-0.048	-0.593
Tathers_age	integer		45	20	64		42	No	Yes	-0.007	-0.600
Respiratory_Rate	factor		3								
Heart Rate min	factor		3								
Follow up	factor		3								
Gender	factor		4								
Birth asphyxia	factor		5								
Autopsy shows bir	factor		5								
Folic acid detail	factor		3								
HO serious matern	factor		3								
HO radiation expo	factor		5								
HO_substance_abuse	factor		5								
Assisted concepti			3								
Listory of anomal	factor		3								
To of previous ab		18%	5		4		2	No	Yes		-1.116
Birth defects	_		3								
White Blood cell			11,859	3.000	12.000	7.460	7.460	No	Yes	0.021	-0.768
Blood test result	factor		5								
	integer	37%	3	-1	1		1	No	Yes	-0.769	-0.496
	integer	40%	3	-1	1			No	Yes	-0.643	-0.624
<u>-</u>	integer	41%	3	-1	1			No	Yes	-0.626	-0.613
	integer	45%	3	-1	1			No	Yes	-0.502	
	integer	48%	3	-1	1			No	Yes	-0.413	-0.702
Genetic Disorder	factor		4								

Zero/Near-Zero Variances

Duplicate Values

```
# n/a for this dataset
```

"Noisy" Data

```
# n/a for this dataset
```

Data Transformation

Centering/Scaling (standardizing/normalizing)

```
# n/a for this dataset?
```

Statistical Characteristics (including distribution, skewness, outliers)

```
#summary(train_df)
```

Other Feature Engineering (transformation, aggregation, enrichment)

```
# n/a for this dataset?
```

Multivariate Analysis (and reduction)

Collinearity and Dependencies

```
# Calculate Cramer's V "measure of association" between nominal factor variables (uses Chi-square statistic)
cscorr <- PairApply(train_df[ , sapply(train_df, is.factor)], CramerV, symmetric = TRUE)

# Shorten variable names for ease of reviewing output matrix
rn <- rownames(cscorr)
for (n in 1:length(rownames(cscorr))) {
   rn[n] <- paste(rownames(cscorr)[n], " (", AscToChar(64 + n), ")", sep = "")
   rownames(cscorr)[n] <- paste(AscToChar(64 + n))
}
for (n in 1:length(colnames(cscorr)))
   colnames(cscorr)[n] <- paste(AscToChar(64 + n))

# Show master list of variable names along with output ("correlation") matrix
cat(rn, sep = "\n")</pre>
```

```
Disorder Subclass (A)
Genes_in_mothers_side (B)
Inherited_from_father (C)
Maternal_gene (D)
Paternal_gene (E)
Respiratory Rate breaths min (F)
Heart_Rate_min (G)
Follow_up (H)
Gender (I)
Birth_asphyxia (J)
Autopsy_shows_birth_defect (K)
Folic_acid_details_peri_conceptional (L)
HO_serious_maternal_illness (M)
HO radiation exposure xray (N)
HO_substance_abuse (0)
Assisted_conception_IVF_ART (P)
History of anomalies in previous pregnancies (Q)
Birth_defects (R)
Blood test result (S)
Genetic Disorder (T)
```

cscorr

```
G
                                                                                                                                                                                                                  Н
                                                                                                                                                                                                                                                I
                                                                                                                                                                                                                                                                             J
                                                                                                                                                                                                                                                                                                   K
                                                                                                                                                                                                                                                                                                                                 L
                                                                                                                                                                                                                                                                                                                                                            M
                                                                                                                                                                                                                                                                                                                                                                                          N
\texttt{A} \ \texttt{1.00} \ \texttt{0.198} \ \texttt{0.131} \ \texttt{0.123} \ \texttt{0.168} \ \texttt{0.019} \ \texttt{0.026} \ \texttt{0.02} \ \texttt{0.02} \ \texttt{0.022} \ \texttt{0.022} \ \texttt{0.020} \ \texttt{0.019} \ \texttt{0.024} \ \texttt{0.02} \ \texttt{0.019} \ \texttt{0.026} \ \texttt{0.025} \ \texttt{0.03} \ \texttt{0.78}
B 0.20 1.000 0.005 0.097 0.012 0.005 0.005 0.01 0.01 0.008 0.01 0.013 0.009 0.016 0.01 0.003 0.017 0.008 0.01 0.08
C 0.13 0.005 1.000 0.013 0.093 0.018 0.020 0.01 0.02 0.022 0.02 0.021 0.013 0.030 0.02 0.013 0.018 0.016 0.02 0.07
 \texttt{D} \ \ 0.12 \ \ 0.097 \ \ 0.013 \ \ 1.000 \ \ 0.008 \ \ 0.048 \ \ 0.040 \ \ 0.05 \ \ 0.054 \ \ 0.044 \ \ 0.053 \ \ 0.048 \ \ 0.052 \ \ 0.04 \ \ 0.055 \ \ 0.047 \ \ 0.044 \ \ 0.05 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 \ \ 0.066 
E 0.17 0.012 0.093 0.008 1.000 0.003 0.009 0.01 0.01 0.023 0.02 0.003 0.001 0.008 0.02 0.003 0.008 0.006 0.02 0.06
 \texttt{F} \ 0.02 \ 0.005 \ 0.018 \ 0.048 \ 0.003 \ 1.000 \ 0.045 \ 0.03 \ 0.05 \ 0.036 \ 0.02 \ 0.043 \ 0.028 \ 0.030 \ 0.04 \ 0.035 \ 0.036 \ 0.042 \ 0.04 \ 0.05 \\ 0.020 \ 0.030 \ 0.040 \ 0.035 \ 0.036 \ 0.042 \ 0.04 \ 0.05 \\ 0.030 \ 0.040 \ 0.040 \ 0.05 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 \ 0.040 
\texttt{G} \ \ 0.03 \ \ 0.005 \ \ 0.020 \ \ 0.040 \ \ 0.009 \ \ 0.045 \ \ 1.000 \ \ 0.04 \ \ 0.05 \ \ 0.034 \ \ 0.02 \ \ 0.035 \ \ 0.029 \ \ 0.047 \ \ 0.03 \ \ 0.055 \ \ 0.042 \ \ 0.041 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \ \ 0.05 \
H 0.02 0.015 0.012 0.046 0.011 0.029 0.040 1.00 0.04 0.033 0.04 0.041 0.043 0.032 0.04 0.043 0.051 0.038 0.05 0.04
I 0.02 0.010 0.023 0.047 0.010 0.054 0.045 0.04 1.00 0.042 0.02 0.032 0.051 0.045 0.04 0.035 0.028 0.036 0.04 0.04
\texttt{J} \ \texttt{0.02} \ \texttt{0.008} \ \texttt{0.022} \ \texttt{0.054} \ \texttt{0.023} \ \texttt{0.036} \ \texttt{0.034} \ \texttt{0.03} \ \texttt{0.04} \ \texttt{1.000} \ \texttt{0.03} \ \texttt{0.035} \ \texttt{0.026} \ \texttt{0.020} \ \texttt{0.03} \ \texttt{0.047} \ \texttt{0.048} \ \texttt{0.036} \ \texttt{0.03} \ \texttt{0.03}
K 0.02 0.010 0.016 0.035 0.025 0.019 0.023 0.04 0.02 0.025 1.00 0.030 0.022 0.028 0.03 0.021 0.024 0.029 0.03 0.03
L 0.02 0.013 0.021 0.053 0.003 0.043 0.035 0.04 0.03 0.035 0.03 1.000 0.020 0.049 0.04 0.028 0.032 0.030 0.04 0.04
M 0.02 0.009 0.013 0.048 0.001 0.028 0.029 0.04 0.05 0.026 0.02 0.020 1.000 0.048 0.04 0.043 0.042 0.032 0.04 0.05
 \begin{smallmatrix} N \end{smallmatrix} 0.02 \end{smallmatrix} 0.016 \end{smallmatrix} 0.030 \end{smallmatrix} 0.052 \end{smallmatrix} 0.008 \end{smallmatrix} 0.030 \end{smallmatrix} 0.047 \end{smallmatrix} 0.03 \end{smallmatrix} 0.04 \end{smallmatrix} 0.020 \end{smallmatrix} 0.03 \end{smallmatrix} 0.049 \end{smallmatrix} 0.048 \end{smallmatrix} 1.000 \end{smallmatrix} 0.03 \end{smallmatrix} 0.046 \end{smallmatrix} 0.047 \end{smallmatrix} 0.052 \end{smallmatrix} 0.04 \end{smallmatrix} 0.04
\begin{smallmatrix} 0 & 0.02 & 0.011 & 0.015 & 0.043 & 0.016 & 0.035 & 0.032 & 0.04 & 0.04 & 0.032 & 0.03 & 0.042 & 0.037 & 0.026 & 1.00 & 0.033 & 0.050 & 0.049 & 0.03 & 0.038 & 0.050 & 0.049 & 0.03 & 0.038 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048 & 0.048
P 0.02 0.003 0.013 0.055 0.003 0.035 0.055 0.04 0.03 0.047 0.02 0.028 0.043 0.046 0.03 1.000 0.035 0.032 0.03 0.03
 \texttt{Q} \ \ 0.03 \ \ 0.017 \ \ 0.018 \ \ 0.047 \ \ 0.008 \ \ 0.036 \ \ 0.042 \ \ 0.03 \ \ 0.048 \ \ 0.02 \ \ 0.032 \ \ 0.042 \ \ 0.047 \ \ 0.05 \ \ 0.035 \ \ 1.000 \ \ 0.032 \ \ 0.04 \ \ 0.03 
R 0.02 0.008 0.016 0.044 0.006 0.042 0.041 0.04 0.04 0.036 0.03 0.030 0.032 0.052 0.05 0.032 0.032 1.000 0.04 0.05
\mathtt{S} 0.03 0.013 0.018 0.052 0.016 0.036 0.046 0.05 0.04 0.029 0.03 0.042 0.041 0.037 0.03 0.031 0.041 0.044 1.00 0.04
 T 0.78 0.082 0.065 0.063 0.064 0.054 0.045 0.04 0.04 0.028 0.03 0.035 0.046 0.042 0.03 0.034 0.030 0.053 0.04 1.00
```

Predictor Transformations (e.g., PCA)

Modeling

Feature Selection

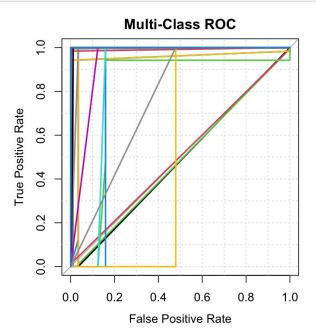
Training, Testing (validating), and Evaluation (iteration n)

```
# Convert factors to dummies (retaining non-factors and also keeping the target as a factor)
dummies <- dummyVars(Disorder Subclass ~. , data = train df[ , sapply(train df, is.factor)])</pre>
train_df <- cbind(Disorder_Subclass = train_df$Disorder_Subclass, train_df[ , !sapply(train_df, is.factor)], data.frame(p</pre>
redict(dummies, newdata = train df)))
dummies <- dummyVars(Disorder_Subclass ~. , data = test_df[ , sapply(test_df, is.factor)])</pre>
test df <- cbind(Disorder Subclass = test df$Disorder Subclass, test df[ , !sapply(test df, is.factor)], data.frame(predi
ct(dummies, newdata = test df)))
# Create Random Forest weight vector based on class priors
priors <- as.list(prop.table(table(train df$Disorder Subclass)))</pre>
wts <- data.frame(Disorder_Subclass = train_df$Disorder_Subclass, w = 0.0)
for (n in 1:length(priors))
 wts[wts$Disorder_Subclass == names(priors[n]), ]$w <- priors[[n]]</pre>
# Train the model (using defaults)
rf fit <- randomForest(x = train df,
                       y = train_df$Disorder_Subclass,
                       xtest = test df,
                       ytest = test df$Disorder Subclass,
                       weights = as.vector(wts$w),
                       importance = TRUE)
# Simplify class names for more coherent confusion matrix, and output
for (n in 1:length(rownames(rf_fit$confusion)))
 rownames(rf fit$confusion)[n] <- paste(rownames(rf fit$confusion)[n], " (", AscToChar(64 + n), ")", sep = "")
for (n in 1:length(rownames(rf fit$confusion)))
 colnames(rf fit$confusion)[n] <- paste("Class", AscToChar(64 + n))</pre>
for (n in 1:length(rownames(rf fit$test$confusion)))
 rownames(rf_fit$test$confusion)[n] <- paste(rownames(rf_fit$test$confusion)[n], " (", AscToChar(64 + n), ")", sep = "")
for (n in 1:length(rownames(rf fit$test$confusion)))
 colnames(rf_fit$test$confusion)[n] <- paste("Class", AscToChar(64 + n))</pre>
rf_fit
```

```
randomForest(x = train_df, y = train_df$Disorder_Subclass, xtest = test_df,
                                                                              ytest = test df$Disorder Subclass, weig
                        importance = TRUE)
hts = as.vector(wts$w),
              Type of random forest: classification
                    Number of trees: 500
No. of variables tried at each split: 8
       OOB estimate of error rate: 4%
Confusion matrix:
                                      Class A Class B Class C Class D Class E Class F Class G Class H Class I class.erro
Alzheimers (A)
                                                   Ω
                                                           4
                                                                 112
                                                                           Ω
                                                                                   Ω
                                                                                           0
                                                                                                   3
                                                                                                          Ω
                                                                                                                  1.00
```

0										
Cancer (B)	0	0	0	69	0	0	0	0	5	1.00
0										
Cystic.fibrosis (C)	0	0	2619	0	0	0	0	3	0	0.00
1										
Diabetes (D) 6	0	0	5	1359	0	0	0	27	4	0.02
6 Hemochromatosis (E)	0	0	2	0	853	0	0	41	137	0.17
4	U	0	۷	U	033	0	0	4.1	137	0.17
Lebers.hereditary.optic.neuropathy (F)	0	0	16	17	0	270	0	178	5	0.44
4 Leigh.syndrome (G)	0	0	0	0	0	0	3915	0	0	0.00
0	U	0	0	0	U	0	3913	O	0	0.00
Mitochondrial.myopathy (H)	0	0	0	0	0	0	0	3362	0	0.00
0										
Tay.Sachs (I)	0	0	0	0	0	0	0	7	2145	0.00
3										
Test set error rate: 4% Confusion matrix:										
	lass A (Class B	Class C	Class D	Class E	Class F	Class G	Class H	Class T	class.erro
r	1400 11	01400 D	01400 0	01400 5	01400 1	01400 1	01400 0	01000 11	01400 1	01400.0110
Alzheimers (A)	0	0	0	28	0	0	0	0	1	1.00
0										
Cancer (B) 0	0	0	0	18	0	0	0	0	0	1.00
Cystic.fibrosis (C)	0	0	654	0	0	0	0	0	1	0.00
2										
Diabetes (D) 7	0	0	2	342	0	0	0	3	1	0.01
Hemochromatosis (E)	0	0	0	0	217	0	0	9	32	0.15
9	Ŭ					Ŭ			02	0.10
Lebers.hereditary.optic.neuropathy (F)	0	0	2	5	0	56	0	58	0	0.53
7										
Leigh.syndrome (G)	0	0	0	0	0	0	978	0	0	0.00
O	0	0	0	0	0	0	0	0.40	0	0.00
Mitochondrial.myopathy (H) O	0	0	0	0	0	0	0	840	0	0.00
Tay.Sachs (I)	0	0	0	0	0	0	0	0	538	0.00
0										

Multi-class area under the curve: 0.9



Optimization, Tuning, Selection

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