Penkrot et al. 2018 Geosphere U1419 Supervised Classification Model

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The primary goal of this code is to test whether these sedimentary properties can discriminate amongst the different litofacies. This code will import elemental concentrations and physical property data from from Integrated Ocean Drilling Site U1419. See here for more details about this drilling location: <http://iodp.tamu.edu/scienceops/expeditions/alaska_tectonics_climate.html>

Code is available on Github at: <https://github.com/jmjak86/Penkrot_et_al_2018_Geosphere>

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# Code Information

This code will import physical property data and normalized scanning XRF elemental concentrations (NMS normalized; Lyle et al., 2012) from Integrated Ocean Drilling Site U1419, and then perform two types of supevised classification on these data. See here for more details about this drilling location: <http://iodp.tamu.edu/scienceops/expeditions/alaska_tectonics_climate.html>.

* The datasets come from samples analyzed in the Department of Geological Sciences at the University of Florida and published values from: Walczak, M. H., Mix, A. C., Willse, T., Slagle, A., Stoner, J. S., Jaeger, J., … Kioka, A. (2015). Correction of non-intrusive drill core physical properties data for variability in recovered sediment volume. Geophysical Journal International, 202(2), 1317–1323. <https://doi.org/10.1093/gji/ggv204>

### Load packages

library(plyr)  
library(dplyr)  
library(psych)  
library(caret)  
library(car)  
library(robCompositions)  
library(klaR)  
library(e1071)

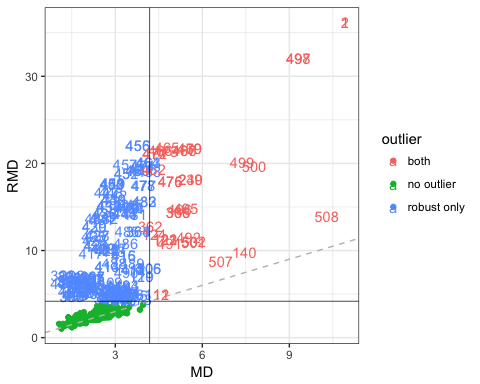
## Import the data

# load the dataset  
U1419\_all <- read.csv("../raw\_data/2018-03-20\_U1419-Penkrot\_Geosphere-2018-data.csv")   
U1419\_all<-U1419\_all[,1:15]  
U1419.all<- tbl\_df(U1419\_all)

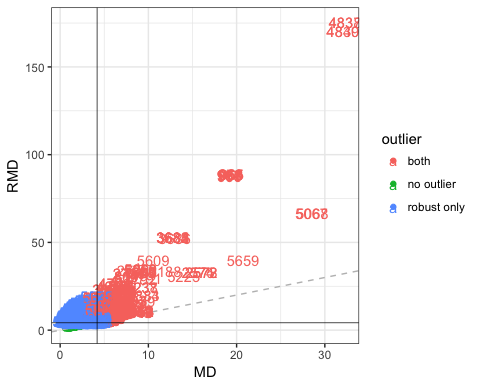
## Data preparation

We remove outlier values because they have strong influence on variance-related analyses. Because the data include compositional parameters (i.e., elemental abundances), we use a robust routine from the robCompositions package (Filzmoser, P., & Hron, K. (2008). Outlier detection for compositional data using robust methods. Mathematical Geosciences, 40(3), 233–248. <https://doi.org/10.1007/s11004-007-9141-5>).

U1419.all[,11] <- U1419.all[,11]+10 # adjust b\* so it has only positive values  
nRows <- nrow(U1419.all)  
nCols <- ncol(U1419.all)  
U1419.mud <- U1419.all[1:508,]  
U1419.diamict <- U1419.all[509:nRows,]  
  
mudout <- outCoDa(U1419.mud[5:13], quantile = 0.975, method = "robust", h = 1/2, coda=log)  
plot(mudout,which=2)



mud.outclean <- U1419.mud[!mudout$outlierIndex,]  
diaout <- outCoDa(U1419.diamict[5:13], quantile = 0.975, method = "robust", h = 1/2, coda=log)  
plot(diaout,which=2)



diamict.outclean <- U1419.diamict[!diaout$outlierIndex,]  
  
U1419.allClean <- rbind(mud.outclean,diamict.outclean)  
U1419.diamict <- U1419.allClean[509:nRows,]

## Data Inspection

### Near Zero Values

The next step is to remove any constant and almost constant predictors across samples (called zero and near-zero variance predictors) using the the function nearZeroVar from the caret package does. It not only removes predictors that have one unique value across samples (zero variance predictors), but also removes predictors that have both 1) few unique values relative to the number of samples and 2) large ratio of the frequency of the most common value to the frequency of the second most common value (near-zero variance predictors).

nearZeroVar(U1419.allClean[,5:13], saveMetrics = TRUE)

## freqRatio percentUnique zeroVar nzv  
## Al 1.454545 43.8385573 FALSE FALSE  
## Ca 1.400000 57.1275225 FALSE FALSE  
## Zr 1.200000 59.1670245 FALSE FALSE  
## K 1.500000 40.1674538 FALSE FALSE  
## Rb 1.200000 57.3207385 FALSE FALSE  
## Si 1.090909 49.0768570 FALSE FALSE  
## b\_star 1.083871 1.6745384 FALSE FALSE  
## NGR 1.656194 0.2146844 FALSE FALSE  
## MS 1.055556 11.0991842 FALSE FALSE

nearZeroVar(U1419.diamict[,5:13], saveMetrics = TRUE)

## freqRatio percentUnique zeroVar nzv  
## Al 1.454545 29.6890672 FALSE FALSE  
## Ca 1.400000 39.9699097 FALSE FALSE  
## Zr 1.200000 41.6248746 FALSE FALSE  
## K 1.500000 28.7362086 FALSE FALSE  
## Rb 1.200000 39.5854229 FALSE FALSE  
## Si 1.090909 33.7345369 FALSE FALSE  
## b\_star 1.058442 1.1200267 FALSE FALSE  
## NGR 1.720299 0.1170177 FALSE FALSE  
## MS 1.055556 7.5727182 FALSE FALSE

The results show that all variables do not have zer-zero variance so they are all included in the following data preparation steps.

### Kruskal-Wallis tests

We first perform a non-parametric Kruskal-Wallis test on each property to see if the Mud and Diamict lithofacies have unique values following Collins, A. L., Walling, D. E., & Leeks, G. J. L. (1998). Use of composite fingerprints to determine the provenance of the contemporary suspended sediment load transported by rivers. Earth Surface Processes and Landforms, 23(1), 31–52. <https://doi.org/10.1002/(SICI)1096-9837(199801)23:1><31::AID-ESP816>3.0.CO;2-Z

#Kruskal-Wallis test to see if lithofacies are unique; if P-value <<.05 significance level, we conclude that samples are nonidentical populations.  
  
U1419.allClean$Mud\_Diamict <- as.factor(U1419.allClean$Mud\_Diamict)  
  
kruskal.test(U1419.allClean$Al, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$Al and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 817.88, df = 1, p-value < 2.2e-16

kruskal.test(U1419.allClean$Ca, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$Ca and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 300.02, df = 1, p-value < 2.2e-16

kruskal.test(U1419.allClean$Zr, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$Zr and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 6.9157, df = 1, p-value = 0.008544

kruskal.test(U1419.allClean$K, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$K and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 210.07, df = 1, p-value < 2.2e-16

kruskal.test(U1419.allClean$Rb, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$Rb and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 847.85, df = 1, p-value < 2.2e-16

kruskal.test(U1419.allClean$Si, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$Si and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 764.27, df = 1, p-value < 2.2e-16

kruskal.test(U1419.allClean$b\_star, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$b\_star and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 804.61, df = 1, p-value < 2.2e-16

kruskal.test(U1419.allClean$NGR, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$NGR and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 953.45, df = 1, p-value < 2.2e-16

kruskal.test(U1419.allClean$MS, U1419.allClean$Mud\_Diamict)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.allClean$MS and U1419.allClean$Mud\_Diamict  
## Kruskal-Wallis chi-squared = 570.42, df = 1, p-value < 2.2e-16

All sedimentary properties are distinctive at p=0.05 for the Mud-Diamict binary lithofacies model.

We now repeat the same test for the Diamict-only samples.

#Kruskal-Wallis test to see if lithofacies are unique; if P-value <<.05 significance level, we conclude that samples are nonidentical populations.  
  
U1419.allClean$Diamict\_only <- as.factor(U1419.allClean$Diamict\_only)  
  
kruskal.test(U1419.diamict$Al, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$Al and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 289.59, df = 4, p-value < 2.2e-16

kruskal.test(U1419.diamict$Ca, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$Ca and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 99.87, df = 4, p-value < 2.2e-16

kruskal.test(U1419.diamict$Zr, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$Zr and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 367.27, df = 4, p-value < 2.2e-16

kruskal.test(U1419.diamict$K, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$K and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 368.06, df = 4, p-value < 2.2e-16

kruskal.test(U1419.diamict$Rb, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$Rb and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 401.9, df = 4, p-value < 2.2e-16

kruskal.test(U1419.diamict$Si, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$Si and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 614.04, df = 4, p-value < 2.2e-16

kruskal.test(U1419.diamict$b\_star, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$b\_star and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 218.76, df = 4, p-value < 2.2e-16

kruskal.test(U1419.diamict$NGR, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$NGR and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 226.42, df = 4, p-value < 2.2e-16

kruskal.test(U1419.diamict$MS, U1419.diamict$Diamict\_only)

##   
## Kruskal-Wallis rank sum test  
##   
## data: U1419.diamict$MS and U1419.diamict$Diamict\_only  
## Kruskal-Wallis chi-squared = 86.652, df = 4, p-value < 2.2e-16

All sedimentary properties are distinctive at p=0.05 for the Diamict-only lithofacies model.

### Data Correlation

The next step is to eliminate highly correlated elements following methodology here: <https://topepo.github.io/caret/pre-processing.html>

#Identifying Correlated Predictors in Mud/diamict data  
AllCor <- cor(U1419.allClean[,5:13],use="pairwise.complete.obs")  
hc <- findCorrelation(as.matrix(AllCor), cutoff=0.9) # putt any value as a "cutoff"  
hc <- sort(hc)  
print(AllCor)

## Al Ca Zr K Rb  
## Al 1.00000000 -0.69620646 -0.5278694 -0.10235944 -0.6759842  
## Ca -0.69620646 1.00000000 0.3409005 -0.08431194 0.3000243  
## Zr -0.52786938 0.34090055 1.0000000 0.12035672 0.2688239  
## K -0.10235944 -0.08431194 0.1203567 1.00000000 0.6701262  
## Rb -0.67598425 0.30002426 0.2688239 0.67012619 1.0000000  
## Si 0.86703600 -0.44302572 -0.4448555 -0.30042874 -0.7618901  
## b\_star -0.62311395 0.47376708 0.3225605 0.25490363 0.5762382  
## NGR 0.72681284 -0.52669585 -0.3173942 -0.09539348 -0.5861278  
## MS 0.02359015 0.39456129 0.1292273 -0.28970024 -0.3570453  
## Si b\_star NGR MS  
## Al 0.8670360 -0.6231140 0.72681284 0.02359015  
## Ca -0.4430257 0.4737671 -0.52669585 0.39456129  
## Zr -0.4448555 0.3225605 -0.31739421 0.12922734  
## K -0.3004287 0.2549036 -0.09539348 -0.28970024  
## Rb -0.7618901 0.5762382 -0.58612775 -0.35704530  
## Si 1.0000000 -0.5021288 0.65402498 0.22079750  
## b\_star -0.5021288 1.0000000 -0.60724293 -0.13292707  
## NGR 0.6540250 -0.6072429 1.00000000 0.21907961  
## MS 0.2207975 -0.1329271 0.21907961 1.00000000

if(length(hc)==0){  
 print(AllCor)  
}else{  
 print(AllCor[-hc,-hc])  
}

## Al Ca Zr K Rb  
## Al 1.00000000 -0.69620646 -0.5278694 -0.10235944 -0.6759842  
## Ca -0.69620646 1.00000000 0.3409005 -0.08431194 0.3000243  
## Zr -0.52786938 0.34090055 1.0000000 0.12035672 0.2688239  
## K -0.10235944 -0.08431194 0.1203567 1.00000000 0.6701262  
## Rb -0.67598425 0.30002426 0.2688239 0.67012619 1.0000000  
## Si 0.86703600 -0.44302572 -0.4448555 -0.30042874 -0.7618901  
## b\_star -0.62311395 0.47376708 0.3225605 0.25490363 0.5762382  
## NGR 0.72681284 -0.52669585 -0.3173942 -0.09539348 -0.5861278  
## MS 0.02359015 0.39456129 0.1292273 -0.28970024 -0.3570453  
## Si b\_star NGR MS  
## Al 0.8670360 -0.6231140 0.72681284 0.02359015  
## Ca -0.4430257 0.4737671 -0.52669585 0.39456129  
## Zr -0.4448555 0.3225605 -0.31739421 0.12922734  
## K -0.3004287 0.2549036 -0.09539348 -0.28970024  
## Rb -0.7618901 0.5762382 -0.58612775 -0.35704530  
## Si 1.0000000 -0.5021288 0.65402498 0.22079750  
## b\_star -0.5021288 1.0000000 -0.60724293 -0.13292707  
## NGR 0.6540250 -0.6072429 1.00000000 0.21907961  
## MS 0.2207975 -0.1329271 0.21907961 1.00000000

# no parameters are correlated at >0.9  
  
#Identifying Correlated Predictors in Diamict-only data  
DiaCor <- cor(U1419.diamict[,5:13],use="pairwise.complete.obs")  
hc2 <- findCorrelation(as.matrix(DiaCor), cutoff=0.9) # putt any value as a "cutoff"  
hc2 <- sort(hc2)  
print(DiaCor)

## Al Ca Zr K Rb  
## Al 1.00000000 -0.6913392 -0.5779896 0.06702474 -3.951456e-01  
## Ca -0.69133915 1.0000000 0.2943595 -0.11846426 1.802858e-01  
## Zr -0.57798957 0.2943595 1.0000000 0.14693810 3.267864e-01  
## K 0.06702474 -0.1184643 0.1469381 1.00000000 7.528147e-01  
## Rb -0.39514557 0.1802858 0.3267864 0.75281467 1.000000e+00  
## Si 0.75845747 -0.3260279 -0.4785979 -0.19106541 -5.332767e-01  
## b\_star -0.38320532 0.3731763 0.3685637 0.20181033 3.063185e-01  
## NGR 0.48543376 -0.4893586 -0.4065281 0.10395204 -1.081213e-01  
## MS -0.35684211 0.5875183 0.1153821 -0.14750124 -3.230785e-05  
## Si b\_star NGR MS  
## Al 0.7584575 -0.3832053 0.4854338 -3.568421e-01  
## Ca -0.3260279 0.3731763 -0.4893586 5.875183e-01  
## Zr -0.4785979 0.3685637 -0.4065281 1.153821e-01  
## K -0.1910654 0.2018103 0.1039520 -1.475012e-01  
## Rb -0.5332767 0.3063185 -0.1081213 -3.230785e-05  
## Si 1.0000000 -0.1941714 0.3616576 -7.623560e-02  
## b\_star -0.1941714 1.0000000 -0.2552473 1.586736e-01  
## NGR 0.3616576 -0.2552473 1.0000000 -1.644191e-01  
## MS -0.0762356 0.1586736 -0.1644191 1.000000e+00

if(length(hc2)==0){  
 print(DiaCor)  
}else{  
 print(DiaCor[-hc2,-hc2])  
}

## Al Ca Zr K Rb  
## Al 1.00000000 -0.6913392 -0.5779896 0.06702474 -3.951456e-01  
## Ca -0.69133915 1.0000000 0.2943595 -0.11846426 1.802858e-01  
## Zr -0.57798957 0.2943595 1.0000000 0.14693810 3.267864e-01  
## K 0.06702474 -0.1184643 0.1469381 1.00000000 7.528147e-01  
## Rb -0.39514557 0.1802858 0.3267864 0.75281467 1.000000e+00  
## Si 0.75845747 -0.3260279 -0.4785979 -0.19106541 -5.332767e-01  
## b\_star -0.38320532 0.3731763 0.3685637 0.20181033 3.063185e-01  
## NGR 0.48543376 -0.4893586 -0.4065281 0.10395204 -1.081213e-01  
## MS -0.35684211 0.5875183 0.1153821 -0.14750124 -3.230785e-05  
## Si b\_star NGR MS  
## Al 0.7584575 -0.3832053 0.4854338 -3.568421e-01  
## Ca -0.3260279 0.3731763 -0.4893586 5.875183e-01  
## Zr -0.4785979 0.3685637 -0.4065281 1.153821e-01  
## K -0.1910654 0.2018103 0.1039520 -1.475012e-01  
## Rb -0.5332767 0.3063185 -0.1081213 -3.230785e-05  
## Si 1.0000000 -0.1941714 0.3616576 -7.623560e-02  
## b\_star -0.1941714 1.0000000 -0.2552473 1.586736e-01  
## NGR 0.3616576 -0.2552473 1.0000000 -1.644191e-01  
## MS -0.0762356 0.1586736 -0.1644191 1.000000e+00

# no parameters are significantly correlated

No parameters are positvely correlated at >0.9 so all will be used in subsequent analyses.

### Levine Test for data distribution

The next processing step is to determine which type of discriminant analyses to conduct (linear or quadratic) to test for discrimation power of the chosen properties This is done with the Levene test, which is less sensistive to non-normality of data following methods here: <http://www.itl.nist.gov/div898/handbook/eda/section3/eda35a.htm>. For this section, only one element is analyzed (Ca). Replace Ca with other parameters to test.

## Tests for Homogeneity of variance, run for each element ----------------------------------------------------  
leveneTest(Ca~ Mud\_Diamict, data=U1419.allClean)#p value >0.05 means they are homogeneous; if not homogeneous, you cannot use LDA

## Levene's Test for Homogeneity of Variance (center = median)  
## Df F value Pr(>F)   
## group 1 11.982 0.0005419 \*\*\*  
## 4656   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Ca, Zr, K, Rb, Si, MS do not have homogeneous variance in the mud-diamict dataset, so a quadratic discrimination analysis will be used

## Tests for Homogeneity of variance, run for each element ----------------------------------------------------  
leveneTest(Ca~ Diamict\_only, data=U1419.diamict)#p value >0.05 means they are homogeneous; if not homogeneous, you cannot use LDA

## Levene's Test for Homogeneity of Variance (center = median)  
## Df F value Pr(>F)   
## group 4 8.9696 3.284e-07 \*\*\*  
## 4145   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Al, Zr, K, Rb, Si, b\_star, NGR, MS do not have homogeneous variance in the diamict-only dataset, so a quadratic discrimination analysis will be used

## Data Transformation-Full Dataset

The next step is to transform and scale data. A center-log ratio transformation is chosen for elemental data to remove constant-sum effects (Templ, M., Filzmoser, P., & Reimann, C. (2008). Cluster analysis applied to regional geochemical data: Problems and possibilities. Applied Geochemistry, 23(8), 2198–2213. <https://doi.org/10.1016/j.apgeochem.2008.03.004>).

mudout <- U1419.allClean[which(U1419.allClean$Mud\_Diamict== "mud"), ]  
diamictout <- U1419.allClean[which(U1419.allClean$Mud\_Diamict== "diamict"), ]  
  
dataCLRmud <- cenLR(mudout[,5:10]) #clr transformed elemental data  
dataCLRdiamict <- cenLR(diamictout[,5:10]) #clr transformed elemmental data  
  
mudCLR <- dataCLRmud$x.clr  
diamictCLR <- dataCLRdiamict$x.clr  
  
allelementdata.CLR <- rbind(mudCLR,diamictCLR)  
ppdata <- U1419.allClean[,13:nCols-2]  
  
allelements.norm <- apply(allelementdata.CLR, MARGIN = 2, FUN = function(X) (X - min(X))/diff(range(X)))  
ppdataA.norm <- apply(U1419.allClean[,13:nCols-2], MARGIN = 2, FUN = function(X) (X - min(X))/diff(range(X)))  
  
lith1 <- U1419.allClean[,3]  
lith2 <- U1419.allClean[,4]  
alldata.norm<- cbind(lith1,allelements.norm,ppdataA.norm)  
  
diamictdata<- cbind(lith2,allelementdata.CLR,ppdata)  
nRows <- nrow(diamictdata)  
diamictdataD<- diamictdata[509:nRows,]  
diamictdata.norm1 <- apply(diamictdataD[,2:10], MARGIN = 2, FUN = function(X) (X - min(X))/diff(range(X)))  
diamictdata.norm <- cbind(lith2[509:nRows,],diamictdata.norm1)

## Quadradic Discrimination Analysis of Mud-Diamict Lithofacies

The next step is to select the elements that best discriminate amongst the groups. The Greedy Wilks approach is used following methods of Gorman Sanisaca, L.E., Gellis, A.C., and Lorenz, D.L., 2017, Determining the sources of fine-grained sediment using the Sediment Source Assessment Tool (Sed\_SAT): U.S. Geological Survey Open File Report 2017–1062, 104 p., <https://doi.org/10.3133/ofr20171062>

gw\_obj<- greedy.wilks(Mud\_Diamict~., data=alldata.norm[,1:10], niveau = 0.05)## 'niveau' is probabilty that addition of variable does not contribute to model  
gw\_obj

## Formula containing included variables:   
##   
## Mud\_Diamict ~ Al + NGR + Rb + Si + MS + b\_star + Ca  
## <environment: 0x7f93e3456eb0>  
##   
##   
## Values calculated in each step of the selection procedure:   
##   
## vars Wilks.lambda F.statistics.overall p.value.overall  
## 1 Al 0.6720183 2272.383 0  
## 2 NGR 0.4488721 2857.718 0  
## 3 Rb 0.2863132 3866.975 0  
## 4 Si 0.2433640 3616.628 0  
## 5 MS 0.2289303 3133.719 0  
## 6 b\_star 0.2177738 2784.337 0  
## 7 Ca 0.2116233 2474.716 0  
## F.statistics.diff p.value.diff  
## 1 2272.3832 0  
## 2 2314.1229 0  
## 3 2642.3832 0  
## 4 821.1684 0  
## 5 293.3002 0  
## 6 238.2705 0  
## 7 135.1457 0

The next step is to test the discrimination power of the combination of the elements chosen from the Greedy Wilks routine.

Group\_mod1All<-dplyr::select(alldata.norm,Mud\_Diamict,Al,NGR,Rb,Si,MS,b\_star,Ca)  
# Select Training and Testing subsets -------------------------------------  
data <- Group\_mod1All  
nColsF <- ncol(data)  
set.seed(2969)  
sample.ind = sample(2,   
 nrow(data),  
 replace = T,  
 prob = c(0.25,0.75))  
data.test = data[sample.ind==1,]#data.dev  
data.train = data[sample.ind==2,]#data.val  
dataD.train <-data.train   
#See how balanced the test & training sets look as Group; training set should be balanced  
table(data$Mud\_Diamict)/nrow(data)

##   
## diamict mud   
## 0.93237441 0.06762559

table(data.test$Mud\_Diamict)/nrow(data.test)

##   
## diamict mud   
## 0.9374457 0.0625543

table(data.train$Mud\_Diamict)/nrow(data.train)

##   
## diamict mud   
## 0.93071001 0.06928999

#if one of the training groups is too large, you need to resample using Caret  
set.seed(9560)  
dtrainCols <- ncol(data.train)  
  
down\_train <- downSample(x = data.train[, 1:dtrainCols],  
 y = data.train$Mud\_Diamict)  
table(down\_train$Mud\_Diamict)/nrow(down\_train)

##   
## diamict mud   
## 0.5 0.5

dataD.train <- down\_train[,1:dtrainCols]  
  
# Discriminant Testing ---------------------------------------------------  
qda.fit <- qda(Mud\_Diamict ~., data=dataD.train)  
qda.fit

## Call:  
## qda(Mud\_Diamict ~ ., data = dataD.train)  
##   
## Prior probabilities of groups:  
## diamict mud   
## 0.5 0.5   
##   
## Group means:  
## Al NGR Rb Si MS b\_star  
## diamict 0.7477778 0.6451760 0.3071679 0.7141303 0.4223308 0.3603694  
## mud 0.3994768 0.1518061 0.6914481 0.4236820 0.1547725 0.7535171  
## Ca  
## diamict 0.4145803  
## mud 0.5625050

qda.class <- predict(qda.fit, data.test)$class  
qda1.table <- table(qda.class, data.test$Mud\_Diamict)  
qda1.table

##   
## qda.class diamict mud  
## diamict 1079 0  
## mud 0 72

mean(qda.class == data.test$Mud\_Diamict)

## [1] 1

fitControl <- trainControl(## 10-fold CV  
 method = "repeatedcv",  
 number = 10,  
 ## repeated ten times  
 repeats = 100)  
set.seed(825)  
qdaFit1 <- train(Mud\_Diamict~ ., data = dataD.train,   
 method = "qda",   
 trControl = fitControl,  
 finalModel=TRUE,  
 verbose = FALSE,  
 na.action = na.omit)  
qdaFit1

## Quadratic Discriminant Analysis   
##   
## 486 samples  
## 7 predictor  
## 2 classes: 'diamict', 'mud'   
##   
## No pre-processing  
## Resampling: Cross-Validated (10 fold, repeated 100 times)   
## Summary of sample sizes: 437, 438, 437, 438, 437, 438, ...   
## Resampling results:  
##   
## Accuracy Kappa  
## 1 1

qdaFit1$finalModel

## Call:  
## qda(x, grouping = y, finalModel = TRUE, verbose = FALSE)  
##   
## Prior probabilities of groups:  
## diamict mud   
## 0.5 0.5   
##   
## Group means:  
## Al NGR Rb Si MS b\_star  
## diamict 0.7477778 0.6451760 0.3071679 0.7141303 0.4223308 0.3603694  
## mud 0.3994768 0.1518061 0.6914481 0.4236820 0.1547725 0.7535171  
## Ca  
## diamict 0.4145803  
## mud 0.5625050

confusionMatrix(data.test$Mud\_Diamict, predict(qdaFit1, data.test))

## Confusion Matrix and Statistics  
##   
## Reference  
## Prediction diamict mud  
## diamict 1079 0  
## mud 0 72  
##   
## Accuracy : 1   
## 95% CI : (0.9968, 1)  
## No Information Rate : 0.9374   
## P-Value [Acc > NIR] : < 2.2e-16   
##   
## Kappa : 1   
## Mcnemar's Test P-Value : NA   
##   
## Sensitivity : 1.0000   
## Specificity : 1.0000   
## Pos Pred Value : 1.0000   
## Neg Pred Value : 1.0000   
## Prevalence : 0.9374   
## Detection Rate : 0.9374   
## Detection Prevalence : 0.9374   
## Balanced Accuracy : 1.0000   
##   
## 'Positive' Class : diamict   
##

#relative importance of variables in model  
qdaImp <- varImp(qdaFit1, scale = FALSE)  
qdaImp

## ROC curve variable importance  
##   
## Importance  
## NGR 0.9980  
## Rb 0.9928  
## b\_star 0.9761  
## Al 0.9684  
## Si 0.9389  
## MS 0.9056  
## Ca 0.7721

## Support Vector Machine Classification Analysis of Mud-Diamict Lithofacies

The SVM design follows Masaaki Tsujitani and Yusuke Tanaka, “Cross-Validation, Bootstrap, and Support Vector Machines,” Advances in Artificial Neural Systems, vol. 2011, Article ID 302572, 6 pages, 2011. <doi:10.1155/2011/302572>

Group\_mod1All<-dplyr::select(alldata.norm,Mud\_Diamict,Al,NGR,Rb,Si,MS,b\_star,Ca)  
  
## svm >  
svm.model1 <- svm(Mud\_Diamict~ ., data = dataD.train, cost = 100, gamma = 1)  
svm.pred1 <- predict(svm.model1, data.test)  
## compute svm confusion matrix >   
svmtable1 <- table(pred = svm.pred1, data.test$Mud\_Diamict)  
svmtable1

##   
## pred diamict mud  
## diamict 1079 0  
## mud 0 72

classAgreement(svmtable1,qda1.table)

## $diag  
## [1] 1  
##   
## $kappa  
## [1] 1  
##   
## $rand  
## [1] 1  
##   
## $crand  
## [1] 1

## compute rpart confusion matrix >   
fitControl <- trainControl(## 10-fold CV  
 method = "repeatedcv",  
 number = 10,#10  
 ## repeated ten times  
 repeats = 100)#100  
set.seed(645)  
#fitControl <- trainControl(number = 200)  
SVMFit1 <- train(Mud\_Diamict~ ., data = dataD.train,   
 method = "svmRadial",   
 trControl = fitControl,  
 tuneLength = 3,  
 finalModel=TRUE,  
 verbose = FALSE,  
 scaled = FALSE,  
 na.action = na.omit)

## Loading required package: kernlab

##   
## Attaching package: 'kernlab'

## The following object is masked from 'package:ggplot2':  
##   
## alpha

## The following object is masked from 'package:psych':  
##   
## alpha

SVMFit1

## Support Vector Machines with Radial Basis Function Kernel   
##   
## 486 samples  
## 7 predictor  
## 2 classes: 'diamict', 'mud'   
##   
## No pre-processing  
## Resampling: Cross-Validated (10 fold, repeated 100 times)   
## Summary of sample sizes: 438, 438, 437, 438, 437, 438, ...   
## Resampling results across tuning parameters:  
##   
## C Accuracy Kappa   
## 0.25 0.9999792 0.9999583  
## 0.50 1.0000000 1.0000000  
## 1.00 1.0000000 1.0000000  
##   
## Tuning parameter 'sigma' was held constant at a value of 0.3479712  
## Accuracy was used to select the optimal model using the largest value.  
## The final values used for the model were sigma = 0.3479712 and C = 0.5.

SVMFit1$finalModel

## Support Vector Machine object of class "ksvm"   
##   
## SV type: C-svc (classification)   
## parameter : cost C = 0.5   
##   
## Gaussian Radial Basis kernel function.   
## Hyperparameter : sigma = 0.347971239344602   
##   
## Number of Support Vectors : 61   
##   
## Objective Function Value : -17.5037   
## Training error : 0

confusionMatrix(data.test$Mud\_Diamict, predict(SVMFit1, data.test))

## Confusion Matrix and Statistics  
##   
## Reference  
## Prediction diamict mud  
## diamict 1079 0  
## mud 0 72  
##   
## Accuracy : 1   
## 95% CI : (0.9968, 1)  
## No Information Rate : 0.9374   
## P-Value [Acc > NIR] : < 2.2e-16   
##   
## Kappa : 1   
## Mcnemar's Test P-Value : NA   
##   
## Sensitivity : 1.0000   
## Specificity : 1.0000   
## Pos Pred Value : 1.0000   
## Neg Pred Value : 1.0000   
## Prevalence : 0.9374   
## Detection Rate : 0.9374   
## Detection Prevalence : 0.9374   
## Balanced Accuracy : 1.0000   
##   
## 'Positive' Class : diamict   
##

#relative importance of variables in model  
SVMImp1 <- varImp(SVMFit1, scale = FALSE)  
SVMImp1

## ROC curve variable importance  
##   
## Importance  
## NGR 0.9980  
## Rb 0.9928  
## b\_star 0.9761  
## Al 0.9684  
## Si 0.9389  
## MS 0.9056  
## Ca 0.7721

## Quadradic Discrimination Analysis of Diamict-only Lithofacies

diamictsel <- subset(diamictdata.norm, select=c("Diamict\_only", "Al", "Ca","Zr","Rb","Si","MS","b\_star","NGR")) #K and Rb are too correlated and routine crashes; Rb only is used  
  
gw\_obj2<- greedy.wilks(Diamict\_only~., data=diamictsel, niveau = 0.05)## 'niveau' is probabilty that addition of variable does not contribute to model  
gw\_obj2

## Formula containing included variables:   
##   
## Diamict\_only ~ Si + Zr + b\_star + Al + NGR + MS + Ca + Rb  
## <environment: 0x7f93c6604b80>  
##   
##   
## Values calculated in each step of the selection procedure:   
##   
## vars Wilks.lambda F.statistics.overall p.value.overall  
## 1 Si 0.8337180 206.67628 7.093025e-162  
## 2 Zr 0.7345493 172.78561 8.659758e-271  
## 3 b\_star 0.6843991 140.77478 0.000000e+00  
## 4 Al 0.6555591 117.23534 0.000000e+00  
## 5 NGR 0.6367466 100.12423 0.000000e+00  
## 6 MS 0.6203556 88.27207 0.000000e+00  
## 7 Ca 0.6123183 77.67767 0.000000e+00  
## 8 Rb 0.5983227 71.27323 0.000000e+00  
## F.statistics.diff p.value.diff  
## 1 206.67628 7.093025e-162  
## 2 139.86639 0.000000e+00  
## 3 75.89582 0.000000e+00  
## 4 45.55482 0.000000e+00  
## 5 30.58613 0.000000e+00  
## 6 27.34675 0.000000e+00  
## 7 13.58206 5.293554e-11  
## 8 24.19846 0.000000e+00

The next step is to test the discrimination power of the combination of the elements chosen from the Greedy Wilks routine.

Group\_mod2All<-dplyr::select(diamictdata.norm,Diamict\_only,Si,Zr,b\_star,Al,NGR,MS,Ca,Rb)  
  
# Select Training and Testing subsets -------------------------------------  
data <- Group\_mod2All  
nColsF <- ncol(data)  
set.seed(2969)  
sample.ind = sample(2,   
 nrow(data),  
 replace = T,  
 prob = c(0.25,0.75))  
data.test = data[sample.ind==1,]#data.dev  
data.train = data[sample.ind==2,]#data.val  
  
# #See how balanced the test & training sets look as Group; training set should be balanced  
table(data$Diamict\_only)/nrow(data)

##   
## clastrich\_diamict massive\_diamict mud\_wdropstones   
## 0.008433735 0.728915663 0.017349398   
## sandy\_diamict stratified\_diamict   
## 0.090361446 0.154939759

table(data.test$Diamict\_only)/nrow(data.test)

##   
## clastrich\_diamict massive\_diamict mud\_wdropstones   
## 0.006829268 0.728780488 0.021463415   
## sandy\_diamict stratified\_diamict   
## 0.086829268 0.156097561

table(data.train$Diamict\_only)/nrow(data.train)

##   
## clastrich\_diamict massive\_diamict mud\_wdropstones   
## 0.00896 0.72896 0.01600   
## sandy\_diamict stratified\_diamict   
## 0.09152 0.15456

#if one of the training groups is too large, you need to resample using Caret  
set.seed(9560)  
dtrainCols <- ncol(data.train)  
  
down\_train <- downSample(x = data.train[, 1:dtrainCols],  
 y = data.train$Diamict\_only)  
table(down\_train$Diamict\_only)/nrow(down\_train)

##   
## clastrich\_diamict massive\_diamict mud\_wdropstones   
## 0.2 0.2 0.2   
## sandy\_diamict stratified\_diamict   
## 0.2 0.2

dataD.train <- down\_train[,1:dtrainCols]  
  
# Discriminant Testing ---------------------------------------------------  
qda.fit2 <- qda(Diamict\_only ~., data=dataD.train)  
qda.fit2

## Call:  
## qda(Diamict\_only ~ ., data = dataD.train)  
##   
## Prior probabilities of groups:  
## clastrich\_diamict massive\_diamict mud\_wdropstones   
## 0.2 0.2 0.2   
## sandy\_diamict stratified\_diamict   
## 0.2 0.2   
##   
## Group means:  
## Si Zr b\_star Al NGR  
## clastrich\_diamict 0.7368108 0.4128705 0.2628571 0.6715367 0.5119048  
## massive\_diamict 0.6658299 0.3635199 0.4085714 0.6735068 0.5297619  
## mud\_wdropstones 0.5509637 0.3769569 0.5961905 0.4964558 0.5238095  
## sandy\_diamict 0.6857384 0.4515262 0.3000000 0.7116534 0.5178571  
## stratified\_diamict 0.4298626 0.4997714 0.4576190 0.4888311 0.3630952  
## MS Ca Rb  
## clastrich\_diamict 0.4041324 0.4482569 0.4118703  
## massive\_diamict 0.4296267 0.4479437 0.4420490  
## mud\_wdropstones 0.4429016 0.5430975 0.5388665  
## sandy\_diamict 0.3683626 0.3740992 0.4090718  
## stratified\_diamict 0.4203510 0.4663823 0.5702371

qda.class <- predict(qda.fit2, data.test)$class  
qda.table <- table(qda.class, data.test$Diamict\_only)  
qda.table

##   
## qda.class clastrich\_diamict massive\_diamict mud\_wdropstones  
## clastrich\_diamict 7 70 2  
## massive\_diamict 0 265 1  
## mud\_wdropstones 0 85 18  
## sandy\_diamict 0 207 0  
## stratified\_diamict 0 120 1  
##   
## qda.class sandy\_diamict stratified\_diamict  
## clastrich\_diamict 8 4  
## massive\_diamict 21 32  
## mud\_wdropstones 2 5  
## sandy\_diamict 55 37  
## stratified\_diamict 3 82

mean(qda.class == data.test$Diamict\_only)

## [1] 0.4165854

fitControl <- trainControl(## 10-fold CV  
 method = "repeatedcv",  
 number = 10,  
 ## repeated ten times  
 repeats = 100)  
set.seed(825)  
qdaFit3 <- train(Diamict\_only~ ., data = dataD.train,   
 method = "qda",   
 trControl = fitControl,  
 finalModel=TRUE,  
 verbose = FALSE,  
 na.action = na.omit)  
qdaFit3

## Quadratic Discriminant Analysis   
##   
## 140 samples  
## 8 predictor  
## 5 classes: 'clastrich\_diamict', 'massive\_diamict', 'mud\_wdropstones', 'sandy\_diamict', 'stratified\_diamict'   
##   
## No pre-processing  
## Resampling: Cross-Validated (10 fold, repeated 100 times)   
## Summary of sample sizes: 125, 125, 125, 126, 126, 129, ...   
## Resampling results:  
##   
## Accuracy Kappa   
## 0.5529401 0.4404742

qdaFit3$finalModel

## Call:  
## qda(x, grouping = y, finalModel = TRUE, verbose = FALSE)  
##   
## Prior probabilities of groups:  
## clastrich\_diamict massive\_diamict mud\_wdropstones   
## 0.2 0.2 0.2   
## sandy\_diamict stratified\_diamict   
## 0.2 0.2   
##   
## Group means:  
## Si Zr b\_star Al NGR  
## clastrich\_diamict 0.7368108 0.4128705 0.2628571 0.6715367 0.5119048  
## massive\_diamict 0.6658299 0.3635199 0.4085714 0.6735068 0.5297619  
## mud\_wdropstones 0.5509637 0.3769569 0.5961905 0.4964558 0.5238095  
## sandy\_diamict 0.6857384 0.4515262 0.3000000 0.7116534 0.5178571  
## stratified\_diamict 0.4298626 0.4997714 0.4576190 0.4888311 0.3630952  
## MS Ca Rb  
## clastrich\_diamict 0.4041324 0.4482569 0.4118703  
## massive\_diamict 0.4296267 0.4479437 0.4420490  
## mud\_wdropstones 0.4429016 0.5430975 0.5388665  
## sandy\_diamict 0.3683626 0.3740992 0.4090718  
## stratified\_diamict 0.4203510 0.4663823 0.5702371

confusionMatrix(data.test$Diamict\_only, predict(qdaFit3, data.test))

## Confusion Matrix and Statistics  
##   
## Reference  
## Prediction clastrich\_diamict massive\_diamict mud\_wdropstones  
## clastrich\_diamict 7 0 0  
## massive\_diamict 70 265 85  
## mud\_wdropstones 2 1 18  
## sandy\_diamict 8 21 2  
## stratified\_diamict 4 32 5  
## Reference  
## Prediction sandy\_diamict stratified\_diamict  
## clastrich\_diamict 0 0  
## massive\_diamict 207 120  
## mud\_wdropstones 0 1  
## sandy\_diamict 55 3  
## stratified\_diamict 37 82  
##   
## Overall Statistics  
##   
## Accuracy : 0.4166   
## 95% CI : (0.3862, 0.4475)  
## No Information Rate : 0.3112   
## P-Value [Acc > NIR] : 7.497e-13   
##   
## Kappa : 0.1824   
## Mcnemar's Test P-Value : < 2.2e-16   
##   
## Statistics by Class:  
##   
## Class: clastrich\_diamict Class: massive\_diamict  
## Sensitivity 0.076923 0.8307  
## Specificity 1.000000 0.3173  
## Pos Pred Value 1.000000 0.3548  
## Neg Pred Value 0.917485 0.8058  
## Prevalence 0.088780 0.3112  
## Detection Rate 0.006829 0.2585  
## Detection Prevalence 0.006829 0.7288  
## Balanced Accuracy 0.538462 0.5740  
## Class: mud\_wdropstones Class: sandy\_diamict  
## Sensitivity 0.16364 0.18395  
## Specificity 0.99563 0.95317  
## Pos Pred Value 0.81818 0.61798  
## Neg Pred Value 0.90828 0.73932  
## Prevalence 0.10732 0.29171  
## Detection Rate 0.01756 0.05366  
## Detection Prevalence 0.02146 0.08683  
## Balanced Accuracy 0.57963 0.56856  
## Class: stratified\_diamict  
## Sensitivity 0.3981  
## Specificity 0.9048  
## Pos Pred Value 0.5125  
## Neg Pred Value 0.8566  
## Prevalence 0.2010  
## Detection Rate 0.0800  
## Detection Prevalence 0.1561  
## Balanced Accuracy 0.6514

#relative importance of variables in model  
qdaImp <- varImp(qdaFit3, scale = FALSE)  
qdaImp

## ROC curve variable importance  
##   
## variables are sorted by maximum importance across the classes  
## clastrich\_diamict massive\_diamict mud\_wdropstones sandy\_diamict  
## b\_star 0.9847 0.8246 0.9145 0.8246  
## Si 0.8776 0.6709 0.9145 0.7270  
## Al 0.8954 0.6365 0.7334 0.8202  
## Rb 0.7360 0.5357 0.7934 0.6824  
## NGR 0.5408 0.5325 0.7698 0.5325  
## Zr 0.6148 0.6148 0.7041 0.6148  
## Ca 0.6875 0.7015 0.5574 0.6735  
## MS 0.5179 0.6065 0.5427 0.5153  
## stratified\_diamict  
## b\_star 0.9847  
## Si 0.8776  
## Al 0.8954  
## Rb 0.7360  
## NGR 0.5408  
## Zr 0.5702  
## Ca 0.7015  
## MS 0.6065

## Support Vector Machine Classification Analysis of Diamict-only Lithofacies

## svm >   
svm.model <- svm(Diamict\_only ~ ., data = dataD.train, cost = 100, gamma = 1)  
svm.pred <- predict(svm.model, data.test)  
## compute svm confusion matrix >   
svmtable <- table(pred = svm.pred, data.test$Diamict\_only)  
svmtable

##   
## pred clastrich\_diamict massive\_diamict mud\_wdropstones  
## clastrich\_diamict 6 66 3  
## massive\_diamict 1 431 3  
## mud\_wdropstones 0 40 16  
## sandy\_diamict 0 126 0  
## stratified\_diamict 0 84 0  
##   
## pred sandy\_diamict stratified\_diamict  
## clastrich\_diamict 6 4  
## massive\_diamict 31 39  
## mud\_wdropstones 0 0  
## sandy\_diamict 48 18  
## stratified\_diamict 4 99

classAgreement(svmtable,qda.table)

## $diag  
## [1] 0.5853659  
##   
## $kappa  
## [1] 0.3025034  
##   
## $rand  
## [1] 0.5527782  
##   
## $crand  
## [1] 0.144368

## compute rpart confusion matrix >   
fitControl <- trainControl(## 10-fold CV  
 method = "repeatedcv",  
 number = 10,#10  
 ## repeated ten times  
 repeats = 100)#100  
set.seed(645)  
#fitControl <- trainControl(number = 200)  
SVMFit2 <- train(Diamict\_only~ ., data = dataD.train,   
 method = "svmRadial",   
 trControl = fitControl,  
 tuneLength = 12,  
 finalModel=TRUE,  
 verbose = FALSE,  
 scaled = FALSE,  
 na.action = na.omit)  
SVMFit2

## Support Vector Machines with Radial Basis Function Kernel   
##   
## 140 samples  
## 8 predictor  
## 5 classes: 'clastrich\_diamict', 'massive\_diamict', 'mud\_wdropstones', 'sandy\_diamict', 'stratified\_diamict'   
##   
## No pre-processing  
## Resampling: Cross-Validated (10 fold, repeated 100 times)   
## Summary of sample sizes: 125, 125, 125, 126, 127, 125, ...   
## Resampling results across tuning parameters:  
##   
## C Accuracy Kappa   
## 0.25 0.2720610 0.1320918  
## 0.50 0.3628651 0.2250427  
## 1.00 0.4327305 0.3027396  
## 2.00 0.4541064 0.3240749  
## 4.00 0.4797717 0.3511361  
## 8.00 0.5065166 0.3835791  
## 16.00 0.5515361 0.4389786  
## 32.00 0.5739535 0.4668211  
## 64.00 0.5809287 0.4753673  
## 128.00 0.5807713 0.4751457  
## 256.00 0.5742982 0.4670105  
## 512.00 0.5509512 0.4379128  
##   
## Tuning parameter 'sigma' was held constant at a value of 0.1616777  
## Accuracy was used to select the optimal model using the largest value.  
## The final values used for the model were sigma = 0.1616777 and C = 64.

SVMFit2$finalModel

## Support Vector Machine object of class "ksvm"   
##   
## SV type: C-svc (classification)   
## parameter : cost C = 64   
##   
## Gaussian Radial Basis kernel function.   
## Hyperparameter : sigma = 0.161677737572634   
##   
## Number of Support Vectors : 115   
##   
## Objective Function Value : -1373.785 -649.626 -2035.449 -543.3263 -1449.355 -2145.998 -1597.825 -704.8161 -849.7802 -1277.091   
## Training error : 0.3

confusionMatrix(data.test$Diamict\_only, predict(SVMFit2, data.test))

## Confusion Matrix and Statistics  
##   
## Reference  
## Prediction clastrich\_diamict massive\_diamict mud\_wdropstones  
## clastrich\_diamict 7 0 0  
## massive\_diamict 142 240 99  
## mud\_wdropstones 2 0 19  
## sandy\_diamict 17 10 0  
## stratified\_diamict 8 18 6  
## Reference  
## Prediction sandy\_diamict stratified\_diamict  
## clastrich\_diamict 0 0  
## massive\_diamict 169 97  
## mud\_wdropstones 1 0  
## sandy\_diamict 52 10  
## stratified\_diamict 35 93  
##   
## Overall Statistics  
##   
## Accuracy : 0.401   
## 95% CI : (0.3708, 0.4317)  
## No Information Rate : 0.2615   
## P-Value [Acc > NIR] : < 2.2e-16   
##   
## Kappa : 0.205   
## Mcnemar's Test P-Value : < 2.2e-16   
##   
## Statistics by Class:  
##   
## Class: clastrich\_diamict Class: massive\_diamict  
## Sensitivity 0.039773 0.8955  
## Specificity 1.000000 0.3303  
## Pos Pred Value 1.000000 0.3213  
## Neg Pred Value 0.833988 0.8993  
## Prevalence 0.171707 0.2615  
## Detection Rate 0.006829 0.2341  
## Detection Prevalence 0.006829 0.7288  
## Balanced Accuracy 0.519886 0.6129  
## Class: mud\_wdropstones Class: sandy\_diamict  
## Sensitivity 0.15323 0.20233  
## Specificity 0.99667 0.95182  
## Pos Pred Value 0.86364 0.58427  
## Neg Pred Value 0.89531 0.78098  
## Prevalence 0.12098 0.25073  
## Detection Rate 0.01854 0.05073  
## Detection Prevalence 0.02146 0.08683  
## Balanced Accuracy 0.57495 0.57708  
## Class: stratified\_diamict  
## Sensitivity 0.46500  
## Specificity 0.91879  
## Pos Pred Value 0.58125  
## Neg Pred Value 0.87630  
## Prevalence 0.19512  
## Detection Rate 0.09073  
## Detection Prevalence 0.15610  
## Balanced Accuracy 0.69189

#relative importance of variables in model  
SVMImp <- varImp(SVMFit2, scale = FALSE)  
SVMImp

## ROC curve variable importance  
##   
## variables are sorted by maximum importance across the classes  
## clastrich\_diamict massive\_diamict mud\_wdropstones sandy\_diamict  
## b\_star 0.9847 0.8246 0.9145 0.8246  
## Si 0.8776 0.6709 0.9145 0.7270  
## Al 0.8954 0.6365 0.7334 0.8202  
## Rb 0.7360 0.5357 0.7934 0.6824  
## NGR 0.5408 0.5325 0.7698 0.5325  
## Zr 0.6148 0.6148 0.7041 0.6148  
## Ca 0.6875 0.7015 0.5574 0.6735  
## MS 0.5179 0.6065 0.5427 0.5153  
## stratified\_diamict  
## b\_star 0.9847  
## Si 0.8776  
## Al 0.8954  
## Rb 0.7360  
## NGR 0.5408  
## Zr 0.5702  
## Ca 0.7015  
## MS 0.6065