# **Exercise 2**

### Collin Real

### Import Libraries/Data

```
library(mlbench)
library(dplyr)
library(e1071)
library(kernlab)
library(AppliedPredictiveModeling)
library(caret)
library(ggplot2)
library(tidyverse)
library(corrplot)
data(Glass)
```

#### **Data Structure**

```
str(Glass)
```

### **Descriptive Statistics**

### summary(Glass)

RI	Na	Mg	Al
Min. :1.511	Min. :10.73	Min. :0.000	Min. :0.290
1st Qu.:1.517	1st Qu.:12.91	1st Qu.:2.115	1st Qu.:1.190
Median :1.518	Median :13.30	Median :3.480	Median :1.360
Mean :1.518	Mean :13.41	Mean :2.685	Mean :1.445
3rd Qu.:1.519	3rd Qu.:13.82	3rd Qu.:3.600	3rd Qu.:1.630
Max. :1.534	Max. :17.38	Max. :4.490	Max. :3.500
Si	K	Ca	Ba
Min. :69.81	Min. :0.0000	Min. : 5.430	Min. :0.000
1st Qu.:72.28	1st Qu.:0.1225	1st Qu.: 8.240	1st Qu.:0.000
Median :72.79	Median :0.5550	Median : 8.600	Median :0.000
Mean :72.65	Mean :0.4971	Mean : 8.957	Mean :0.175
3rd Qu.:73.09	3rd Qu.:0.6100	3rd Qu.: 9.172	3rd Qu.:0.000
Max. :75.41	Max. :6.2100	Max. :16.190	Max. :3.150
Fe	Type		
Min. :0.00000	1:70		
1st Qu.:0.00000	2:76		
Median :0.00000	3:17		
Mean :0.05701	5:13		
3rd Qu.:0.10000	6: 9		
Max. :0.51000	7:29		

#### Variable Skewness - Calculated

```
# Skewness between -1 amd 1 is excellent, between -2 and 2 is acceptable, values beyond -2
  RI_ = Glass$RI
  Na_ = Glass$Na
  Mg_ = Glass Mg
  Al_ = Glass$Al
  Si_ = Glass$Si
  K_ = Glass$K
  Ca_ = Glass$Ca
  Ba_ = Glass\$Ba
  Fe_ = Glass$Fe
  paste0('RI: ', skewness(RI_))
[1] "RI: 1.60271508274373"
  paste0('Na: ', skewness(Na_))
[1] "Na: 0.447834258917133"
  paste0('Mg: ', skewness(Mg_))
[1] "Mg: -1.13645227846653"
  paste0('Al: ', skewness(Al_))
[1] "Al: 0.89461041611312"
  paste0('Si: ', skewness(Si_))
[1] "Si: -0.720239210805621"
  paste0('K: ', skewness(K_))
[1] "K: 6.46008889572281"
```

```
paste0('Ca: ', skewness(Ca_))

[1] "Ca: 2.01844629445302"

  paste0('Ba: ', skewness(Ba_))

[1] "Ba: 3.36867996880571"

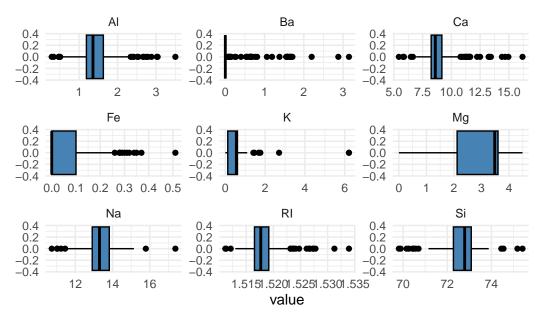
  paste0('Fe: ', skewness(Fe_))

[1] "Fe: 1.7298107095598"
```

#### **Box Plots**

```
Glass %>%
  select_if(is.numeric) %>%
  gather() %>%
  ggplot(aes(value)) +
  geom_boxplot(color='black', fill='steelblue') +
  facet_wrap(~key, scales = 'free') +
  ggtitle(("Numerical Predictors - Box Plots")) +
  theme_minimal()
```

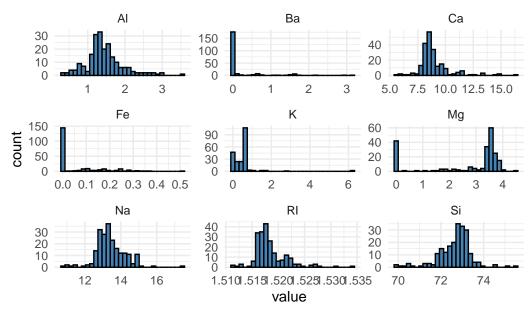
### Numerical Predictors - Box Plots



### **Histogram Plots**

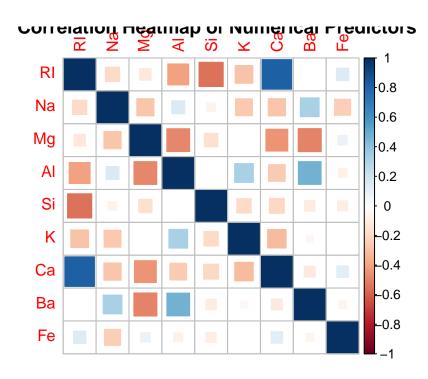
```
Glass %>%
  select_if(is.numeric) %>%
  gather() %>%
  ggplot(aes(value)) +
  geom_histogram(color='black', fill='steelblue') +
  facet_wrap(~key, scales = 'free') +
  ggtitle(("Numerical Predictors - Histograms")) +
  theme_minimal()
```

### Numerical Predictors – Histograms



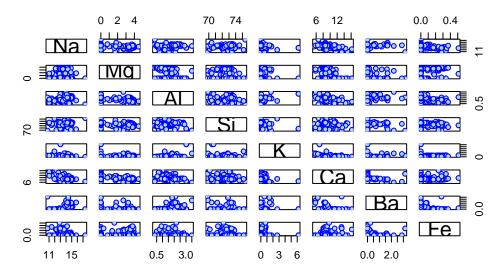
### **Heatmap Correlation**

```
Glass %>%
  select_if(is.numeric) %>%
  cor() %>%
  corrplot(method = "square", title = 'Correlation Heatmap of Numerical Predictors')
```



#### **Scatterplot Correlation**

### **Investigate Potential Variable Correlation**



#### Question A) & B)

To explore the predictor variables, I created boxplots, histograms, scatterplots, and a heatmap to understand the distributions and relationships among the predictor variables to gain a better understanding. There are outliers in our dataset for variables Ca, Fe, K, and Na. Variables Ba, Ca, Fe, and K are skewed to the right, indicating that we might improve our classification model by applying a transformation.

#### Question C)

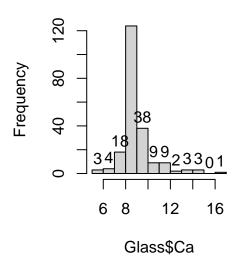
Since we identified skewness in variables Ba, Ca, Fe, and K, we applied a BoxCox transformation to each variable. After reviewing the distribution plots of our transformed variables, we concluded that the transformation was only slightly effective for the Ca variable. See the below outputs comparing the histogram plots between the original and transformed data for each variable.

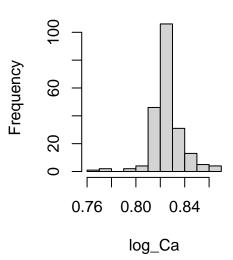
#### Make transformations on 3 skewed variables: K, Ca, and Ba

```
transform_Ca <- BoxCoxTrans(Glass$Ca)</pre>
log_Ca <- predict(transform_Ca, Glass$Ca)</pre>
#hist(log_Ca)
#log_Ca
transform_Ba <- BoxCoxTrans(Glass$Ba)</pre>
log_Ba <- predict(transform_Ba, Glass$Ba)</pre>
#hist(log_Ba)
#log_Ba
transform_Fe <- BoxCoxTrans(Glass$Fe)</pre>
log_Fe <- predict(transform_Fe, Glass$Fe)</pre>
#hist(log_Fe)
#log_Fe
transform_K <- BoxCoxTrans(Glass$K)</pre>
log_K <- predict(transform_K, Glass$K)</pre>
#hist(log_K)
#log_K
par(mfrow = c(1, 2))
ca = hist(Glass$Ca)
text(ca$mids,ca$counts,labels=ca$counts, adj=c(0.5, -0.5))
hist(log_Ca)
```

# Histogram of Glass\$Ca

# Histogram of log\_Ca

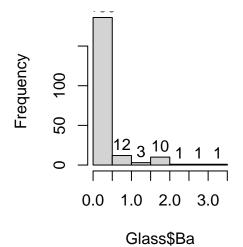


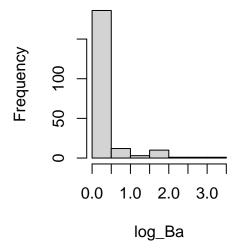


```
par(mfrow = c(1, 2))
ba = hist(Glass$Ba)
text(ba$mids,ba$counts,labels=ba$counts, adj=c(0.5, -0.5))
hist(log_Ba)
```

## **Histogram of Glass\$Ba**

# Histogram of log\_Ba





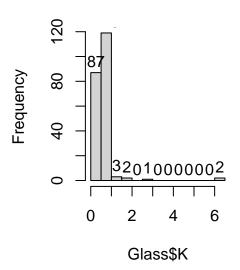
```
par(mfrow = c(1, 2))
fe = hist(Glass$Fe)
text(fe$mids,fe$counts,labels=fe$counts, adj=c(0.5, -0.5))
hist(log_Fe)
```

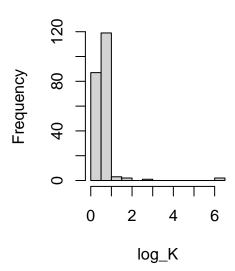
### **Histogram of Glass\$Fe** Histogram of log\_Fe 150 150 100 100 Frequency Frequency 20 20 0.4 0.0 0.0 0.2 0.2 0.4 Glass\$Fe log\_Fe

```
par(mfrow = c(1, 2))
k = hist(Glass$K)
text(k$mids,k$counts,labels=k$counts, adj=c(0.5, -0.5))
hist(log_K)
```

# Histogram of Glass\$K

# Histogram of log\_K





### Question 4)

```
set.seed(231)
  sigDist <- sigest(Type~ ., data = Glass, frac = 1)</pre>
  sigDist
       90%
                  50%
                             10%
0.03407935 0.11297847 0.62767315
  svmTuneGrid <- data.frame(sigma = as.vector(sigDist)[1], C = 2^(-2:10))</pre>
  svmTuneGrid
        sigma
                    С
1 0.03407935
                 0.25
2 0.03407935
                 0.50
3 0.03407935
               1.00
4 0.03407935
              2.00
5 0.03407935
               4.00
6 0.03407935 8.00
7 0.03407935 16.00
8 0.03407935 32.00
9 0.03407935 64.00
10 0.03407935 128.00
11 0.03407935 256.00
12 0.03407935 512.00
13 0.03407935 1024.00
  set.seed(1056)
  #It may take a while to run
  svmFit <- train(Type~ ., data = Glass, method = "svmRadial",</pre>
  preProc = c("center", "scale"),tuneGrid = svmTuneGrid,
  trControl = trainControl(method = "repeatedcv", repeats = 5))
  plot(svmFit, scales = list(x = list(log = 2)))
```

