ADS502 Group Project

Francisco Hernandez, Jason Morfin, Brendan Robinson, Aaron Gabriel

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```
threshold <- 0.5
drug_induced_training_data <- drug_induced_training_data[, colMeans(is.na(drug_induced_training_data))
get_mode <- function(x) {
    uniq_vals <- unique(x)
    uniq_vals[which.max(tabulate(match(x, uniq_vals)))]
}
categorical_cols <- sapply(drug_induced_training_data, is.character)
drug_induced_training_data[categorical_cols] <- lapply(
    drug_induced_training_data[categorical_cols],
    function(x) {
        x[is.na(x)] <- get_mode(x)
        return(x)
    })
write.csv(drug_induced_training_data, "DIA_trainingset_RDKit_descriptors.csv")</pre>
```

Data Cleaning

```
summary(drug_induced_training_data[, 1:6])
```

Descriptive Statistics

```
##
       Label
                      SMILES
                                        BalabanJ
                                                        BertzCT
  Min.
          :0.0000
                   Length: 477
                                     Min. :0.986
                                                          : 8.0
  1st Qu.:0.0000
                   Class :character
                                      1st Qu.:1.679
                                                     1st Qu.: 493.3
##
## Median :0.0000
                   Mode :character
                                     Median :1.964
                                                     Median: 712.4
                                           :2.143
## Mean
          :0.2474
                                     Mean
                                                     Mean : 738.6
## 3rd Qu.:0.0000
                                     3rd Qu.:2.419
                                                     3rd Qu.: 943.2
## Max.
         :1.0000
                                     Max. :5.083
                                                     Max.
                                                           :2430.9
        Chi0
##
                       Chi0n
## Min. : 3.414
                          : 1.725
                   Min.
## 1st Qu.:13.405
                   1st Qu.:10.391
## Median :17.646
                   Median :14.184
## Mean
         :18.130
                   Mean
                         :14.372
## 3rd Qu.:22.052
                   3rd Qu.:17.730
## Max. :50.120
                   Max.
                          :38.475
```

```
drug_stats <- describe(drug_data)</pre>
head(drug_stats, 10)
##
                                sd median trimmed
                                                     mad min
                                                                         range skew
            vars
                       mean
                                                                   max
                   n
               1 477
                       0.25
                                     0.00
                                             0.19
                                                    0.00 0.00
                                                                  1.00
                                                                          1.00 1.17
## Label
                              0.43
## BalabanJ
               2 477
                       2.14
                              0.71
                                     1.96
                                             2.05
                                                    0.52 0.99
                                                                  5.08
                                                                          4.10 1.49
## BertzCT
               3 477 738.63 392.97 712.42
                                          720.01 336.93 8.00 2430.93 2422.93 0.79
## ChiO
               4 477 18.13
                              7.25 17.65
                                            17.71
                                                    6.41 3.41
                                                                 50.12
                                                                         46.71 0.84
## ChiOn
               5 477 14.37
                                    14.18
                                                                 38.48
                              6.09
                                            14.05
                                                    5.50 1.73
                                                                         36.75 0.81
## ChiOv
               6 477 14.89
                              6.13 14.68
                                            14.58
                                                    5.52 1.73
                                                                 39.84
                                                                         38.11 0.77
## Chi1
               7 477 11.87
                              4.83 11.77
                                            11.67
                                                    4.29 1.73
                                                                 31.52
                                                                         29.78 0.66
## Chi1n
               8 477
                       8.43
                              3.76
                                     8.35
                                             8.26
                                                    3.54 0.61
                                                                 23.17
                                                                         22.55 0.65
## Chi1v
               9 477
                       8.96
                              3.81
                                     9.00
                                             8.79
                                                    3.39 0.61
                                                                 24.44
                                                                         23.83 0.62
## Chi2n
              10 477
                       6.67
                              3.28
                                     6.36
                                             6.48
                                                    3.04 0.25
                                                                19.35
                                                                         19.10 0.75
##
            kurtosis
                        se
               -0.64 0.02
## Label
## BalabanJ
                2.66 0.03
## BertzCT
                1.74 17.99
## ChiO
                1.73 0.33
## ChiOn
                1.77 0.28
## ChiOv
                1.62 0.28
## Chi1
                1.38 0.22
## Chi1n
                1.18 0.17
## Chi1v
                1.13 0.17
## Chi2n
                1.05 0.15
```

drug_data <- select(drug_induced_training_data, where(is.numeric))</pre>

```
data_quality_report <- data.frame(
   Variable = names(drug_induced_training_data),
   Type = sapply(drug_induced_training_data, class),
   Missing = sapply(drug_induced_training_data, function(x) sum(is.na(x))),
   Complete = sapply(drug_induced_training_data, function(x) sum(!is.na(x))),
   Unique = sapply(drug_induced_training_data, function(x) length(unique(x)))
)
knitr::kable(head(data_quality_report, 40), caption = "Drug Induced Data Quality Report (Preview)")</pre>
```

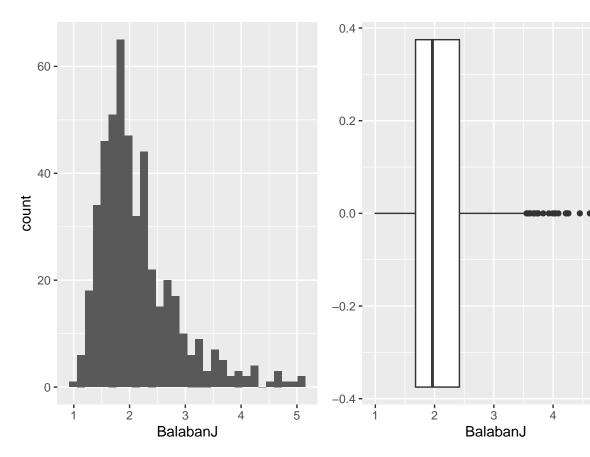
Data Quality Report

Table 1: Drug Induced Data Quality Report (Preview)

	Variable	Type	Missing	Complete	Unique
Label	Label	integer	0	477	2
SMILES	SMILES	character	0	477	477
BalabanJ	BalabanJ	numeric	0	477	406
BertzCT	$\operatorname{BertzCT}$	numeric	0	477	465
Chi0	Chi0	numeric	0	477	382
Chi0n	$\mathrm{Chi}\mathrm{0n}$	numeric	0	477	460
Chi0v	$\mathrm{Chi}0\mathrm{v}$	numeric	0	477	460
Chi1	Chi1	numeric	0	477	423

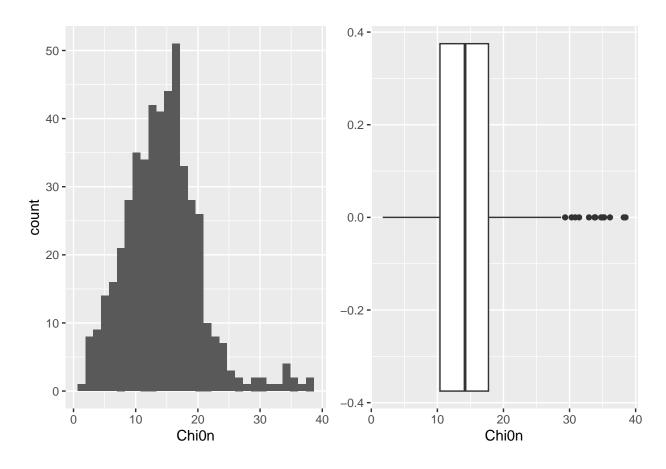
	Variable	Type	Missing	Complete	Unique
Chi1n	Chi1n	numeric	0	477	461
Chi1v	Chi1v	numeric	0	477	466
Chi2n	Chi2n	numeric	0	477	458
Chi2v	$\mathrm{Chi}2\mathrm{v}$	numeric	0	477	462
Chi3n	Chi3n	numeric	0	477	456
Chi3v	Chi3v	numeric	0	477	457
Chi4n	Chi4n	numeric	0	477	450
Chi4v	Chi4v	numeric	0	477	447
$EState_VSA1$	$EState_VSA1$	numeric	0	477	211
$EState_VSA10$	$EState_VSA10$	numeric	0	477	108
EState_VSA11	$EState_VSA11$	numeric	0	477	5
$EState_VSA2$	$EState_VSA2$	numeric	0	477	279
$EState_VSA3$	$EState_VSA3$	numeric	0	477	233
$EState_VSA4$	$EState_VSA4$	numeric	0	477	244
$EState_VSA5$	$EState_VSA5$	numeric	0	477	183
$EState_VSA6$	$EState_VSA6$	numeric	0	477	131
$EState_VSA7$	$EState_VSA7$	numeric	0	477	122
$EState_VSA8$	$EState_VSA8$	numeric	0	477	217
$EState_VSA9$	$EState_VSA9$	numeric	0	477	134
ExactMolWt	ExactMolWt	numeric	0	477	460
FractionCSP3	FractionCSP3	numeric	0	477	175
HallKierAlpha	HallKierAlpha	numeric	0	477	247
HeavyAtomCount	HeavyAtomCount	integer	0	477	53
HeavyAtomMolWt	HeavyAtomMolWt	numeric	0	477	420
Ipc	Ipc	numeric	0	477	453
Kappa1	Kappa1	numeric	0	477	450
Kappa2	Kappa2	numeric	0	477	459
Kappa3	Kappa3	numeric	0	477	448
LabuteASA	LabuteASA	numeric	0	477	466
MaxAbsEStateIndex	MaxAbsEStateIndex	numeric	0	477	452
MaxAbsPartialCharge	${\bf MaxAbsPartialCharge}$	numeric	0	477	166
MaxEStateIndex	MaxEStateIndex	numeric	0	477	452

```
hist <- ggplot(drug_induced_training_data, aes(x=BalabanJ)) + geom_histogram(bins = 30)
boxplot <- ggplot(drug_induced_training_data, aes(x=BalabanJ)) + geom_boxplot()
grid.arrange(hist, boxplot, ncol = 2)</pre>
```

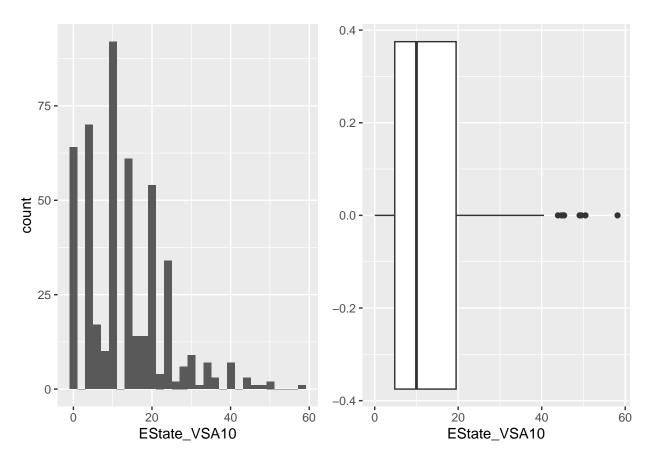


Univariate Analysis

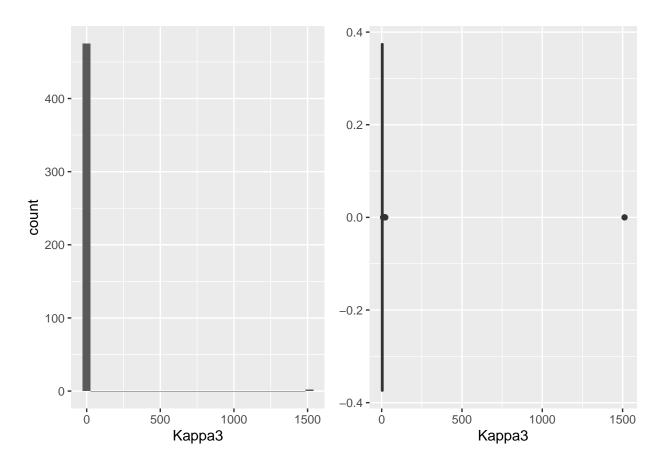
```
hist_2 <- ggplot(drug_induced_training_data, aes(x=ChiOn)) + geom_histogram(bins = 30)
boxplot_2 <- ggplot(drug_induced_training_data, aes(x=ChiOn)) + geom_boxplot()
grid.arrange(hist_2, boxplot_2, ncol = 2)
```



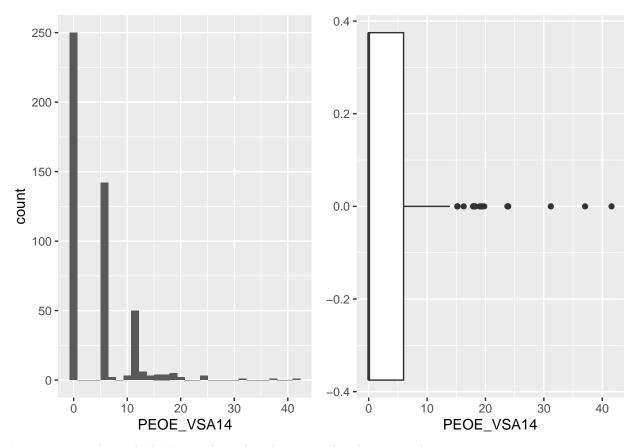
hist_3 <- ggplot(drug_induced_training_data, aes(x=EState_VSA10)) + geom_histogram(bins = 30)
boxplot_3 <- ggplot(drug_induced_training_data, aes(x=EState_VSA10)) + geom_boxplot()
grid.arrange(hist_3, boxplot_3, ncol = 2)</pre>



hist_4 <- ggplot(drug_induced_training_data, aes(x=Kappa3)) + geom_histogram(bins = 30)
boxplot_4 <- ggplot(drug_induced_training_data, aes(x=Kappa3)) + geom_boxplot()
grid.arrange(hist_4, boxplot_4, ncol = 2)</pre>



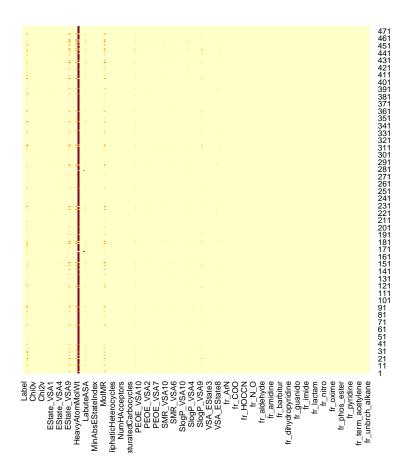
hist_5 <- ggplot(drug_induced_training_data, aes(x=PEOE_VSA14)) + geom_histogram(bins = 30)
boxplot_5 <- ggplot(drug_induced_training_data, aes(x=PEOE_VSA14)) + geom_boxplot()
grid.arrange(hist_5, boxplot_5, ncol = 2)</pre>



Features are right sweked. Few outliers that do not need to be removed.

```
numeric_cols_indexes <- sapply(drug_induced_training_data, is.numeric)
numeric_features <- drug_induced_training_data[numeric_cols_indexes]

data <- as.matrix(numeric_features)
heatmap(data,Colv = NA, Rowv = NA, scale = "row")</pre>
```



Multivariate Analysis

[1] "Post-balance class cardinality"

```
print("Pre-balance class cardinality")

Class Imbalance
## [1] "Pre-balance class cardinality"

table(drug_induced_training_data$Label)

##
## 0 1
## 359 118

# Random Undersampling
balanced_0 <- sample_n(filter(drug_induced_training_data, Label == 0), 118)
filtered_1 <- filter(drug_induced_training_data, Label == 1)
bal_drug_induced_training_data <- rbind(balanced_0, filtered_1)
print("Post-balance class cardinality")</pre>
```

```
##
    0
## 118 118
# Drop SMILES feature
bal_drug_induced_training_data <- bal_drug_induced_training_data[, colnames(bal_drug_induced_training_d
for (col_name in colnames(bal_drug_induced_training_data)){
# For binary responses
  if (length(unique(bal_drug_induced_training_data[[col_name]])) == 2){
   bal_drug_induced_training_data[[col_name]] <- as.factor(bal_drug_induced_training_data[[col_name]])
  }
  # For standarization of numeric responses
  if (is.numeric(bal_drug_induced_training_data[[col_name]])){
    if( max(bal_drug_induced_training_data[[col_name]]) != min(bal_drug_induced_training_data[[col_name]])
   bal_drug_induced_training_data[[col_name]] <- (bal_drug_induced_training_data[[col_name]] - min(bal
    (max(bal_drug_induced_training_data[[col_name]]) - min(bal_drug_induced_training_data[[col_name]]))
   }
   else{
          bal_drug_induced_training_data[[col_name]] <- 0</pre>
   }
  }
}
# Final Dataset
```

Pre-Model Data Preparation

bal_drug_induced_training_data

table(bal_drug_induced_training_data\$Label)

##

```
# Missing step --> numeric_features need to be obtained from bal_drug_induced_training_data

model_all <- lm(Label ~ ., data=numeric_features) # with all the independent variables in the datafram
# summary(model_all)
coeff <- coefficients(model_all)

# To remove correlated where coefficient = NaN -> Correlation
na_coeff_names <- names(coeff)[is.na(coeff)]
na_coeff_names</pre>
```

Feature Selection

```
## [1] "MaxEStateIndex" "NumAliphaticRings" "NumAromaticRings"
## [4] "NumRadicalElectrons" "NumSaturatedRings" "RingCount"
## [7] "SMR_VSA8" "SlogP_VSA9" "VSA_EState1"
## [10] "VSA_EState2" "VSA_EState3" "VSA_EState4"
```

```
## [13] "VSA_EState5" "VSA_EState6" "VSA_EState7"
## [16] "fr_C00" "fr_Nhpyrrole" "fr_azide"
## [19] "fr_barbitur" "fr_benzene" "fr_diazo"
## [22] "fr_isocyan" "fr_isothiocyan" "fr_prisulfonamd"
## [25] "fr_thiocyan"
```