STAT2003 ASSIGNMENT 1

Comparison of Machine Learning Algorithms

Nina Kumagai (19389905) and Amanda Efendi (19488187)

Part 1.1 Design of Experiment

Factors	Types of Machine Learning algorithm
Levels of each factor	5 levels (Logistic Regression, Linear Discriminant Analysis, Classification and Regression Trees, Naïve Bayes, Support Vector Machines)
Experimental Unit	Each prediction run on a test set by a single algorithm trained with the corresponding training set
Response	The accuracy of the predictions made by each algorithm
Number of Replications	10. To provide more than 30 observations across all levels to achieve normality of residuals
Experimental Methodology	Using multiple random sampling seeds, the main dataset is re-sampled into 10 different sets of training and testing sets. Each machine learning algorithm is run on 10 different training sets (10 replicates), and the number of correct predictions is recorded for each replicate. This number is then converted into an accuracy percentage and listed in a longform with the type of machine learning algorithm as their grouping.

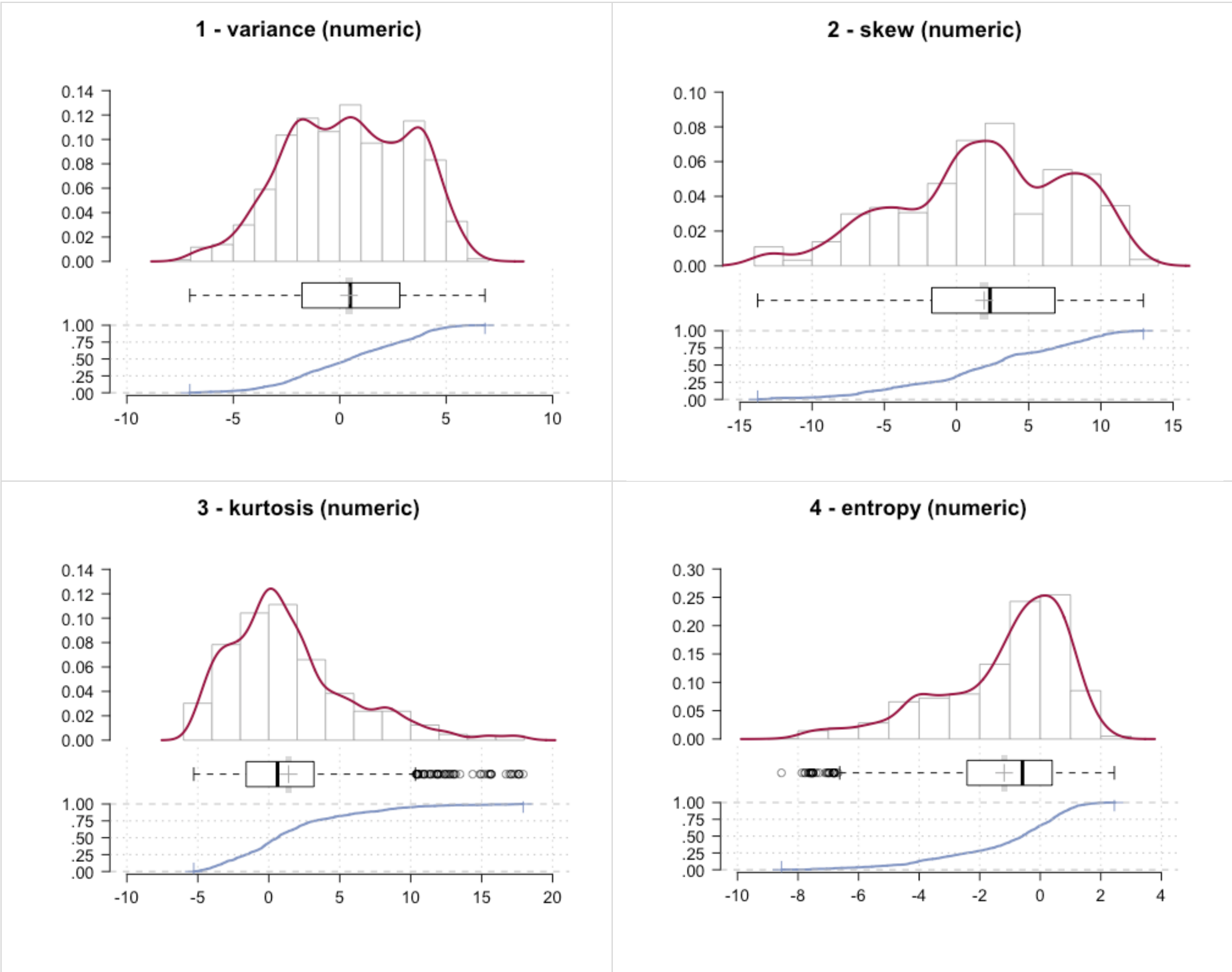
Part 1.2 Principles of Design

Randomisation is applied by the use of the sample() function in selecting the training and testing subset. Using the set.seed() function, we are able to generate 10 sets of random indexes.

Replication is achieved by generating 10 sets of different training and testing subsets of the data frame. Each Machine Learning algorithms are trained and tested on each set as a replicate. This results in 10 replicates of each machine learning algorithm

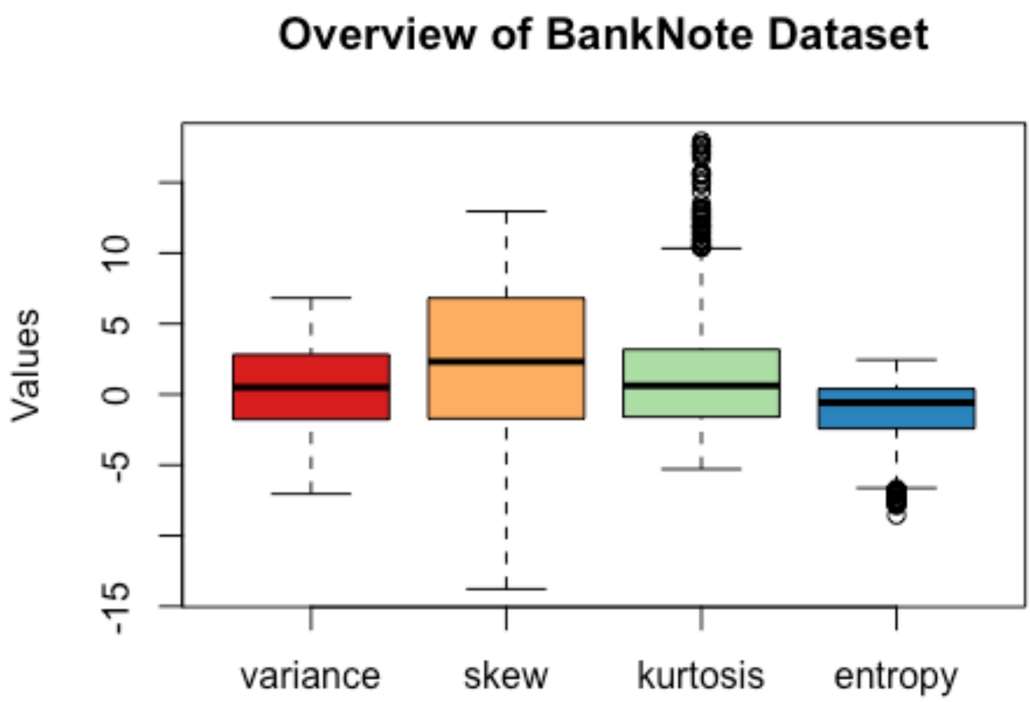
Blocking was not applied. According to the UCI site, there were no information on whether or not blocking was used in collecting the banknotes.

Part 2. EDA Graphs

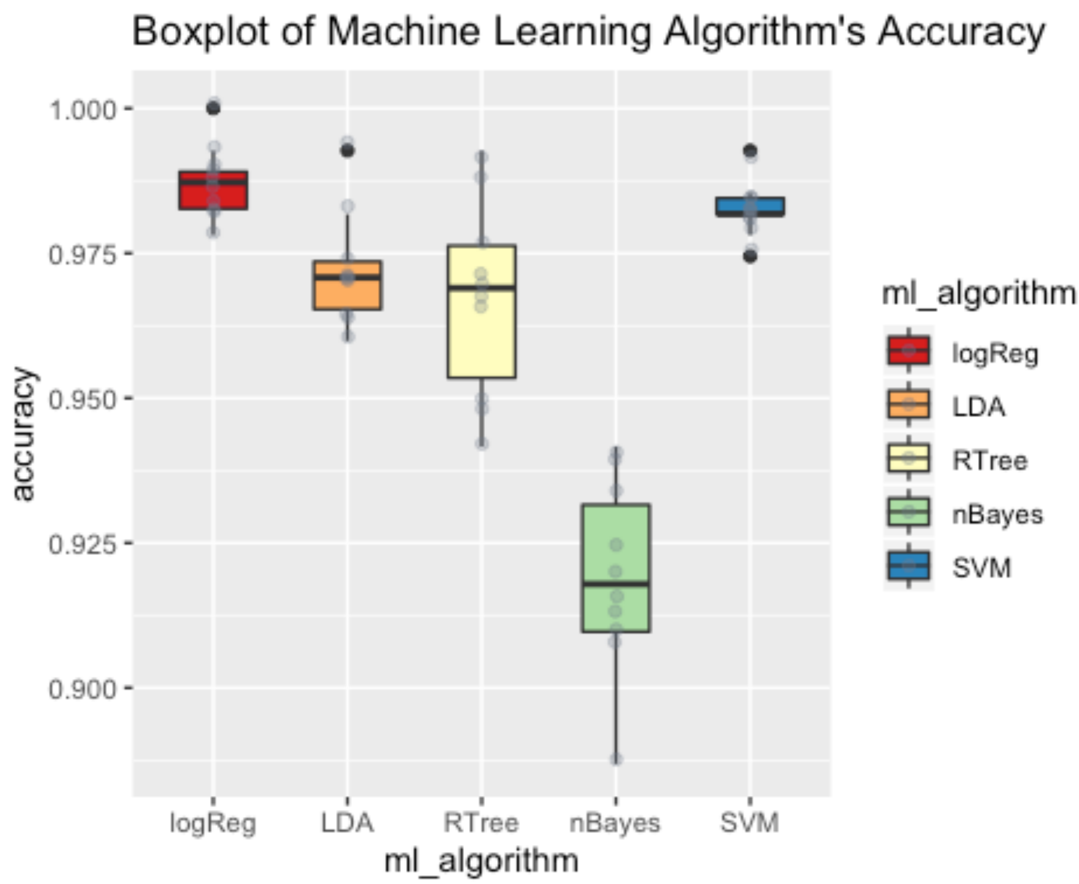


The banknote dataset has 4 variables along with the classification variable called class. As seen from above, the values for kurtosis and entropy are skewed, while the variance and skew are slightly normal with several peaks. Among the 1372 rows of data, 762 are fake and 610 are real.

```
##     variance            skew           kurtosis          entropy
##  Min.   :-7.0421   Min.   :-13.773   Min.   :-5.2861   Min.   :-8.5482
##  1st Qu.:-1.7730   1st Qu.: -1.708   1st Qu.:-1.5750   1st Qu.:-2.4135
##  Median : 0.4962   Median :  2.320   Median : 0.6166   Median :-0.5867
##  Mean   : 0.4337   Mean   :  1.922   Mean   : 1.3976   Mean   :-1.1917
##  3rd Qu.: 2.8215   3rd Qu.:  6.815   3rd Qu.: 3.1793   3rd Qu.: 0.3948
##  Max.   : 6.8248   Max.   : 12.952   Max.   :17.9274   Max.   : 2.4495
```



Part 3. Findings



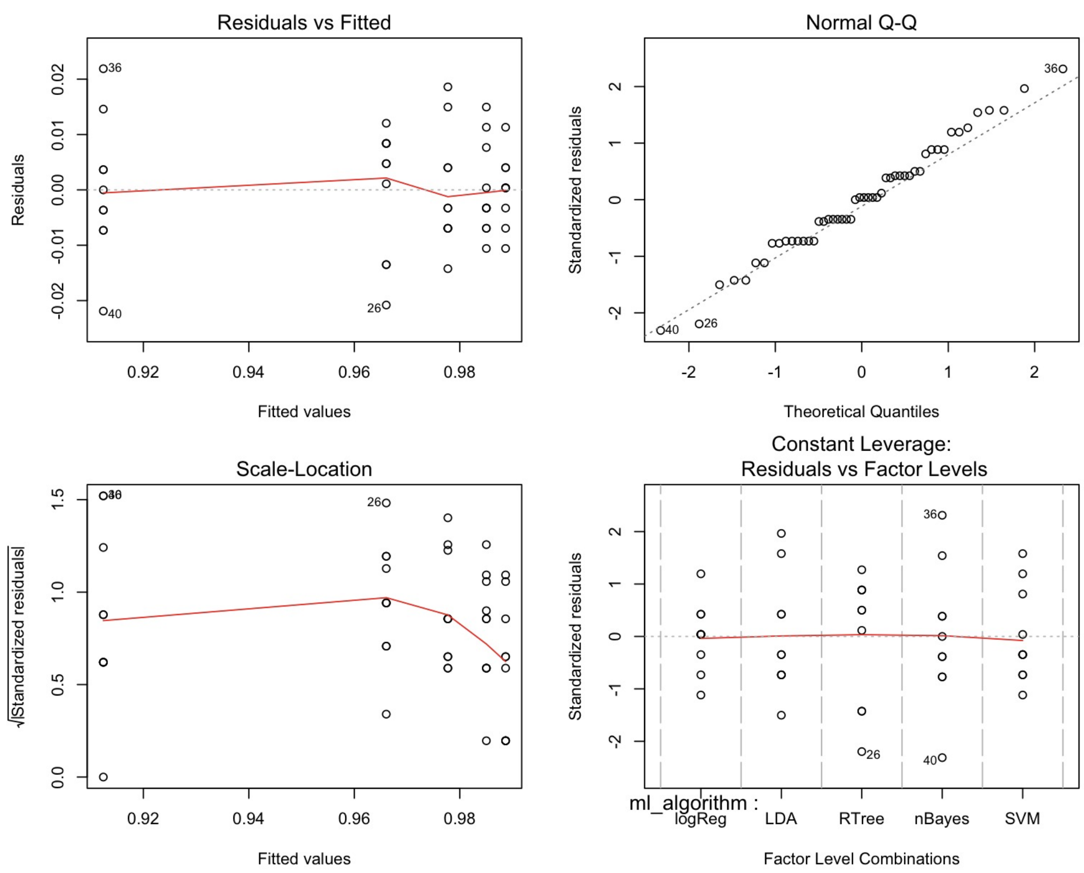
The boxplot above shows the accuracy of each machine learning algorithm over 10 replicates. The accuracy is obtained by adding up the correct (true negative and true positive) predictions and divided by the total number of observations in the test subset.

```
   logReg       LDA     RTree    nBayes       SVM 
0.9872263 0.9718978 0.9675182 0.9189781 0.9824818 
```

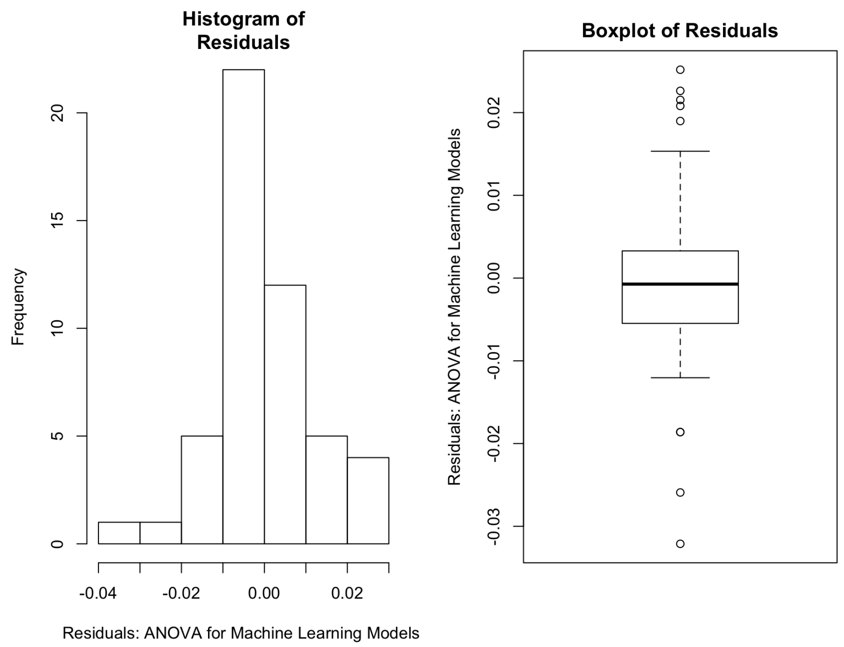
Results of analysis are reported as follows: Mean (standard deviation) of machine learning models for logistic regression, linear discriminant analysis, regression tree, naive bayes and support vector machine are 0.989(0.006), 0.9777(0.010), 0.9660(0.0115), 0.9124(0.0122), 0.985(0.0085) respectively. As seen on the table above, Logistic Regression and Support Vector Machine have the two highest mean accuracy compared to the other algorithms. The boxplot also indicates that logistic regression and support vector machine algorithm are also consistent with their findings. In contrast, Naïve Bayes, Classification and Regression Trees has a larger variety in their accuracy.

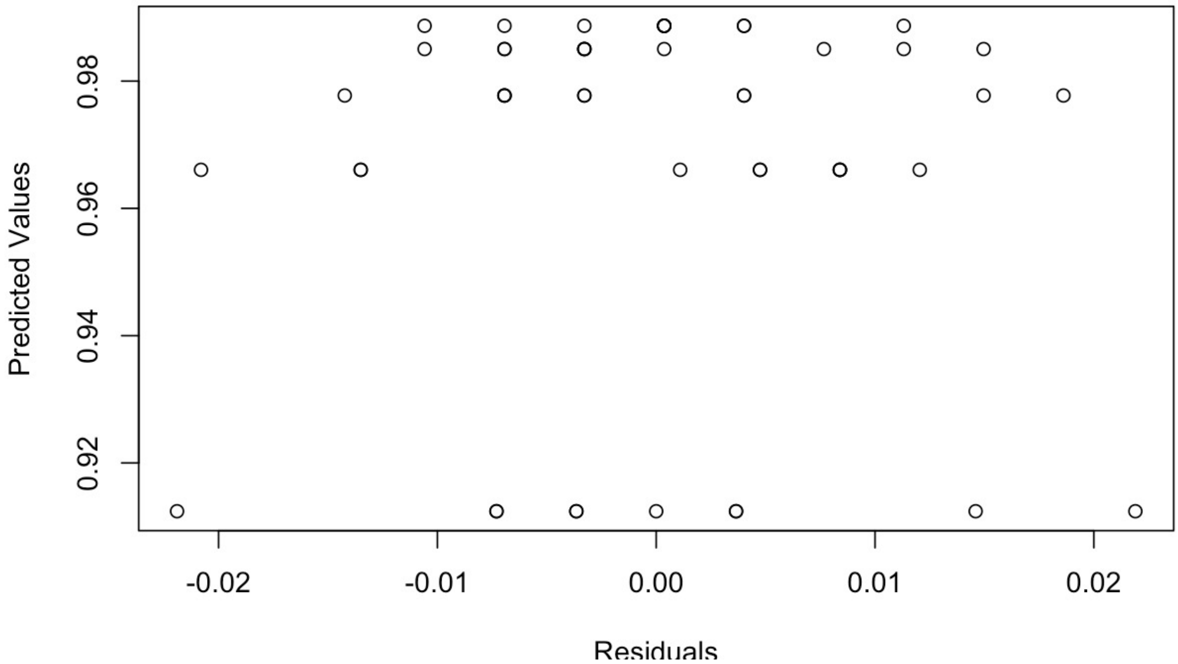
```
##              Df  Sum Sq  Mean Sq F value   Pr(>F)    
## ml_algorithm  4 0.03887 0.009717   97.47   <2e-16 ***
## Residuals    45 0.00449 0.000100                     
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The results of the analysis of variance indicates that at 5% level of significance there is sufficient evidence ($F(4,45)=97.47$, $P= 2x10^{-16}$) to conclude that average accuracy of machine learning models is not the same across model types.



A further examination of the residuals of the ANOVA can be seen below.





Plot of residuals against predicted values does not show any unusual pattern (funneling or bow shape). As normality was valid (Shapiro Wilk, P=0.7921), Bartlett test results are reliable. Bartlett test lead to high P-value (P=0.3147), indicating equality of variance in residuals across factor levels (homogeneity). Levene's test also leads to the similar result but with slightly higher p-value (p = 0.5845). Finally, as the order experiment was random with reference to each factor level setting, independence of errors can be assumed.

```
## $groups
##         accuracy groups
## logReg 0.9872263      a
## SVM    0.9824818     ab
## LDA    0.9718978     bc
## RTree  0.9675182      c
## nBayes 0.9189781      d
```

For Post-Hoc Comparison Pairwise Test, the Tukey's LSD test shows 4 distinct groups within the levels of treatment. Logistic Regression is considered different to Linear Discriminant Analysis, RTree and Naïve Bayes, while it is the same as Support Vector Machine. While Naïve Bayes, is considered the most distinct from other treatments.

Part 4. Limitations

The bank notes dataset was obtained from the UCI website. There was no information on the process undertaken to collect the data. Thus, randomisation in selecting the bank notes had to be assumed to enable the use of the dataset. The website didn't provide any information regarding any blocking that the owners of the dataset might have done while collecting the data. An example of blocking that could have been done is grouping the notes based on the country of origin.

The banknotes data is then re-sampled into 10 sets of training and testing subsets for the machine learning algorithms. To improve the accuracy of the comparison by assuming normality, more than 10 re-samples of the dataset could have been applied.

Limited understanding of each machine learning algorithms could also impact the interpretation of the results. Perhaps one machine learning algorithm are only more sensitive to large sample sizes, thus resulting in an inaccurate portrayal of its performance in this experiment.

Part 5. Application to other classification problems

As mentioned above, each machine learning algorithm requires different assumption. Logistic Regression performed well in classifying the bank notes, however, if we changed the dataset, it might be a different case. On the other hand, other model may perform better. For example, Naïve Bayes assumes that each variable in a class is independent to all the other variables within that class (Sidana, 2017). In our dataset, the Naïve Bayes performed poorly compared to the other classification algorithms due to the banknote dataset's variables such as variance and skew that are known to be dependent of each other. Due to these reasons, the results from Naïve Bayes will change with a different dataset.

Reference:

Sidana, M. (2017, Feb 28). Types of Classification Algorithms in Machine Learning [Blog post]. Retrieved from https://medium.com/@Mandysidana/machine-learning-types-of-classification-9497bd4f2e14.

Appendices

1. Loading the data

```
df = read.table("data_banknote_authentication.txt",
                  sep=",",
                  col.names=c("variance", "skew", "kurtosis", "entropy", "
class"),
                  fill=FALSE,
                  strip.white=TRUE)
```

2. Data Wrangling

```
head(df)

##   variance    skew kurtosis  entropy class
## 1  3.62160  8.6661  -2.8073 -0.44699     0
## 2  4.54590  8.1674  -2.4586 -1.46210     0
## 3  3.86600 -2.6383   1.9242  0.10645     0
## 4  3.45660  9.5228  -4.0112 -3.59440     0
## 5  0.32924 -4.4552   4.5718 -0.98880     0
## 6  4.36840  9.6718  -3.9606 -3.16250     0

summary(df)

##     variance             skew            kurtosis           entropy

##  Min.   :-7.0421   Min.   :-13.773   Min.   :-5.2861   Min.   :-8.5482

##  1st Qu.:-1.7730   1st Qu.: -1.708   1st Qu.:-1.5750   1st Qu.:-2.4135

##  Median : 0.4962   Median :  2.320   Median : 0.6166   Median :-0.5867

##  Mean   : 0.4337   Mean   :  1.922   Mean   : 1.3976   Mean   :-1.1917

##  3rd Qu.: 2.8215   3rd Qu.:  6.815   3rd Qu.: 3.1793   3rd Qu.: 0.3948

##  Max.   : 6.8248   Max.   : 12.952   Max.   :17.9274   Max.   : 2.4495

##      class
##  Min.   :0.0000
##  1st Qu.:0.0000
##  Median :0.0000
##  Mean   :0.4446
##  3rd Qu.:1.0000
##  Max.   :1.0000

#library(dlookr)
#describe_data = describe(df)

#Change class to factor
df$class <- as.factor(df$class); str(df)
```

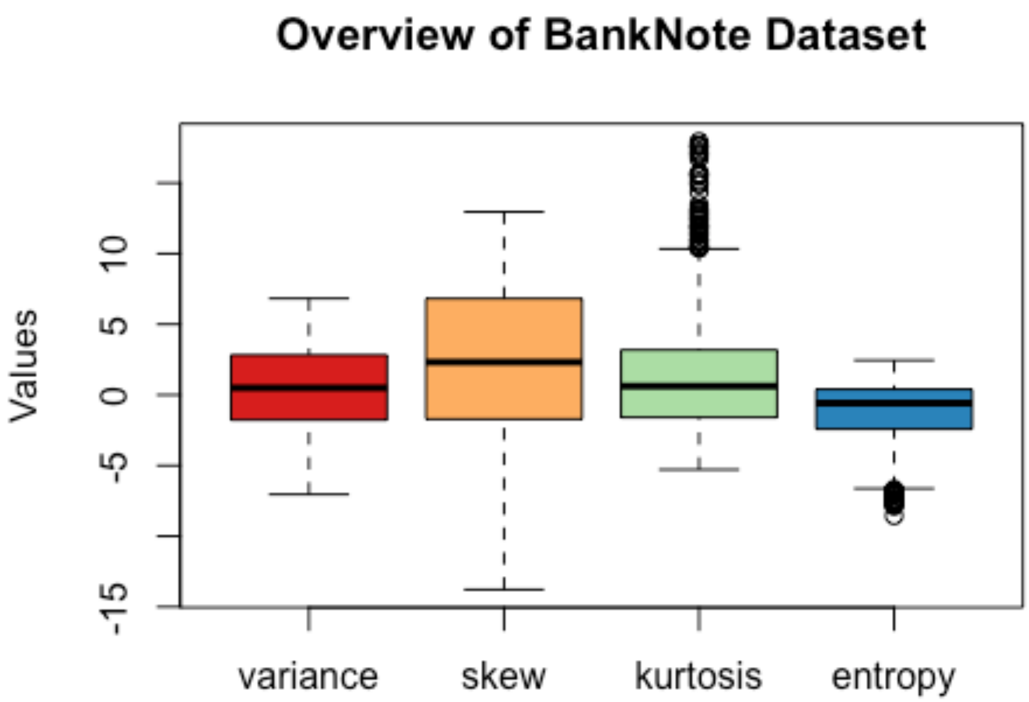
```
## 'data.frame':    1372 obs. of  5 variables:
##  $ variance: num  3.622 4.546 3.866 3.457 0.329 ...
##  $ skew    : num  8.67 8.17 -2.64 9.52 -4.46 ...
##  $ kurtosis: num  -2.81 -2.46 1.92 -4.01 4.57 ...
##  $ entropy : num  -0.447 -1.462 0.106 -3.594 -0.989 ...
##  $ class   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
```

```
#Rename the levels of class
levels(df$class) <- c("Fake", "Real"); str(df)
```

```
## 'data.frame':    1372 obs. of  5 variables:
##  $ variance: num  3.622 4.546 3.866 3.457 0.329 ...
##  $ skew    : num  8.67 8.17 -2.64 9.52 -4.46 ...
##  $ kurtosis: num  -2.81 -2.46 1.92 -4.01 4.57 ...
##  $ entropy : num  -0.447 -1.462 0.106 -3.594 -0.989 ...
##  $ class   : Factor w/ 2 levels "Fake","Real": 1 1 1 1 1 1 1 1 1 1 ...
```

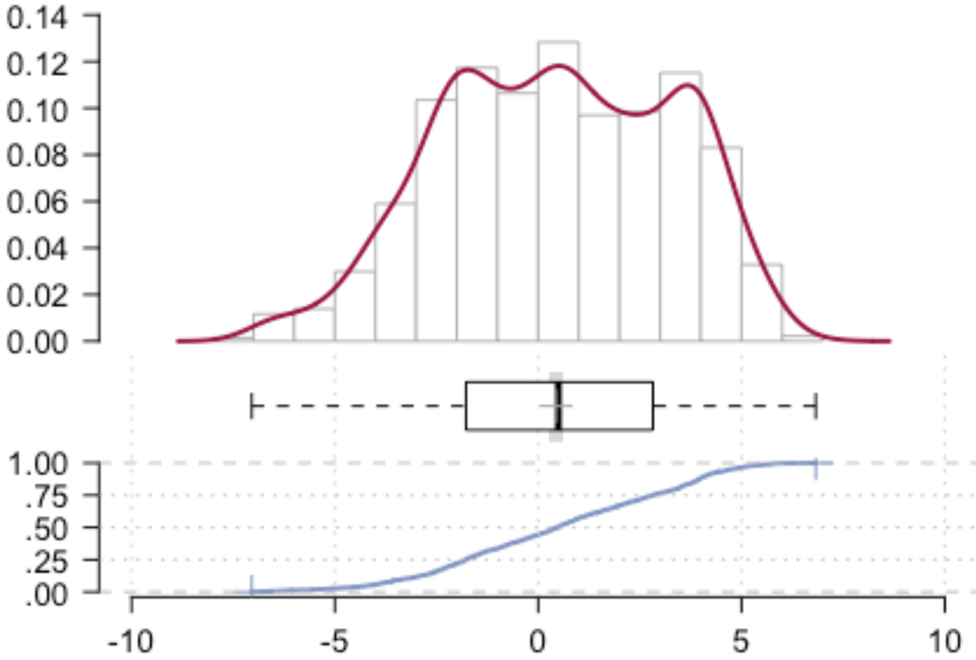
3. EDA on Data

```
library(RColorBrewer)
boxplot(df[,1:4], ylab='Values', main='Overview of BankNote Dataset', col=
c(brewer.pal(4, "Spectral")))
```

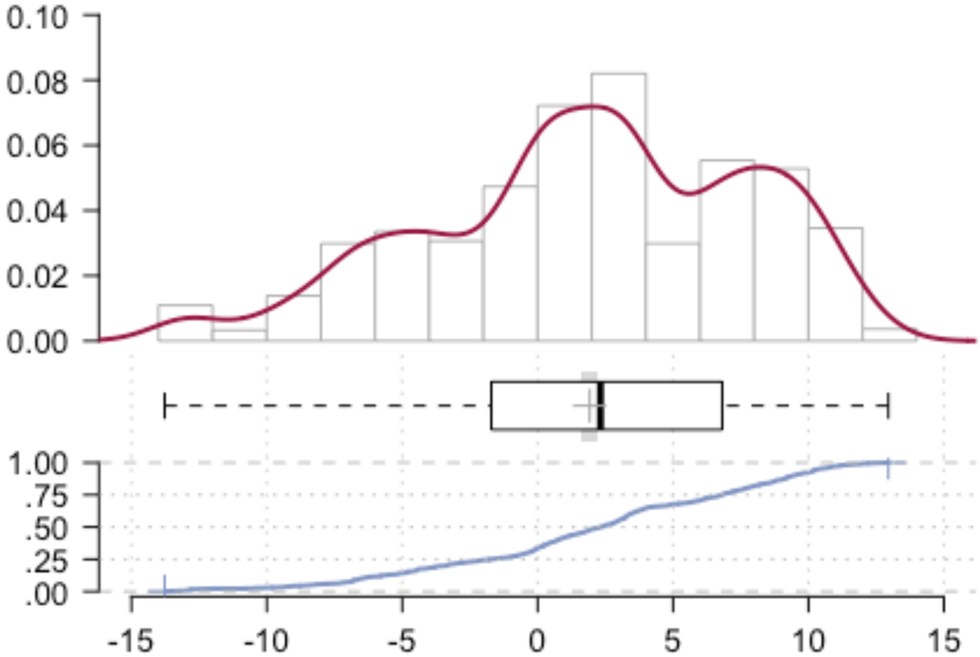



```
library(DescTools)
plot(Desc(df))
```

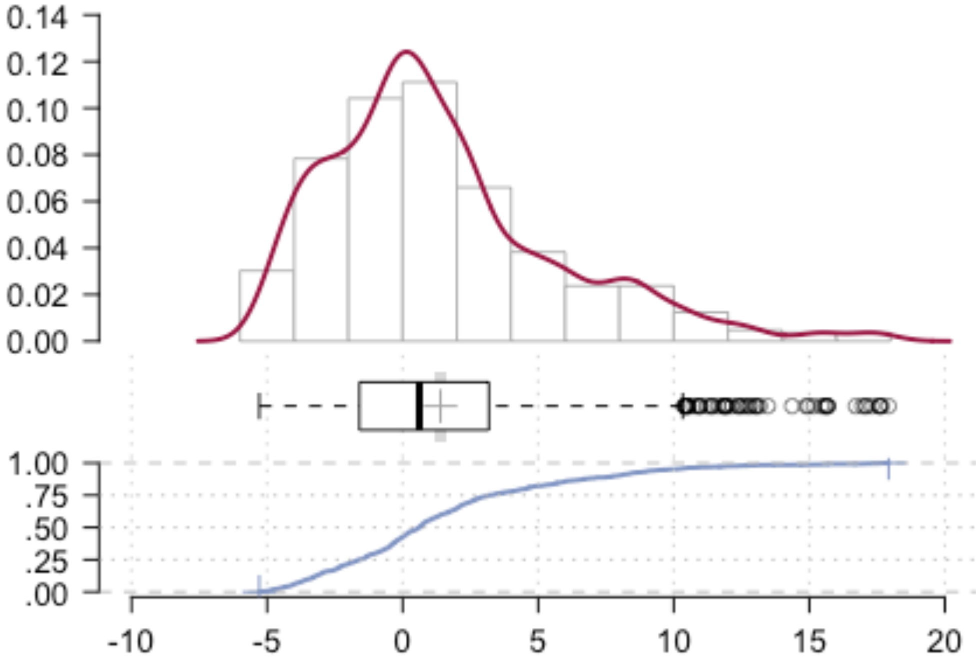
1 - variance (numeric)



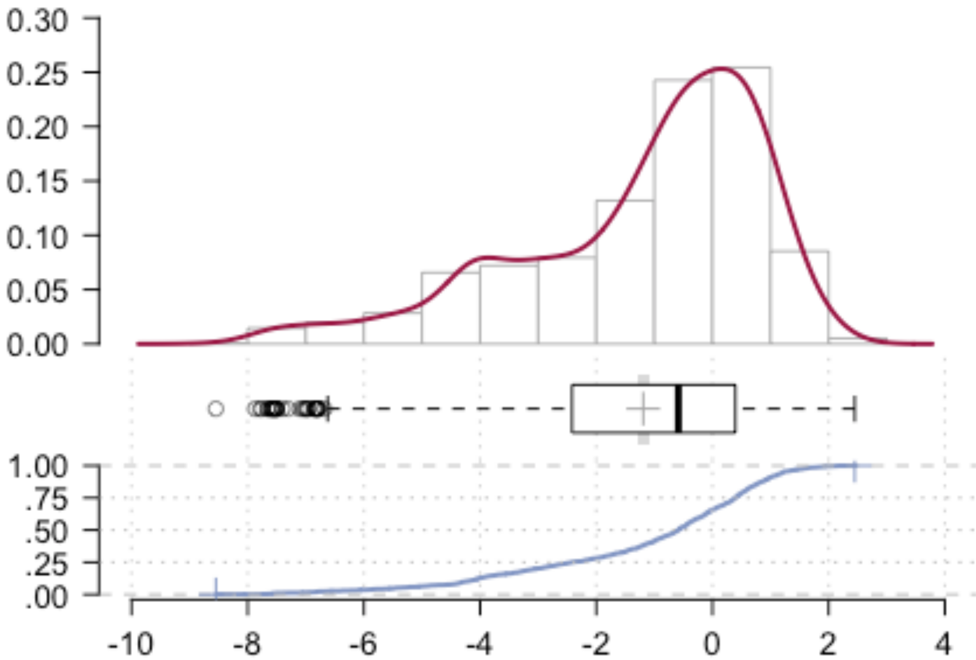
2 - skew (numeric)

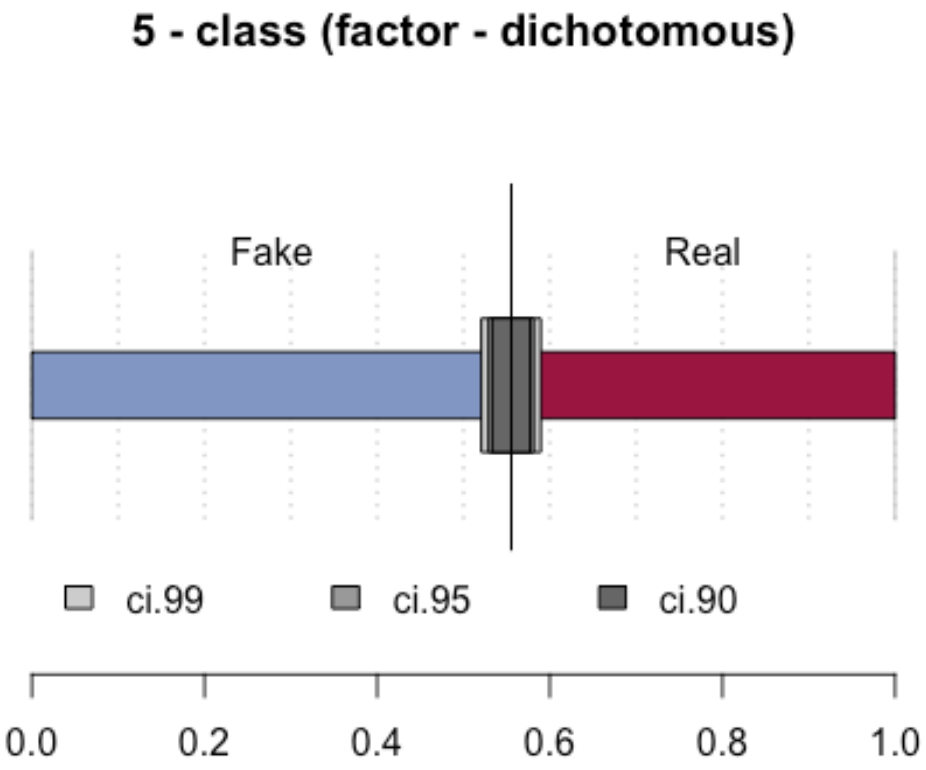


3 - kurtosis (numeric)

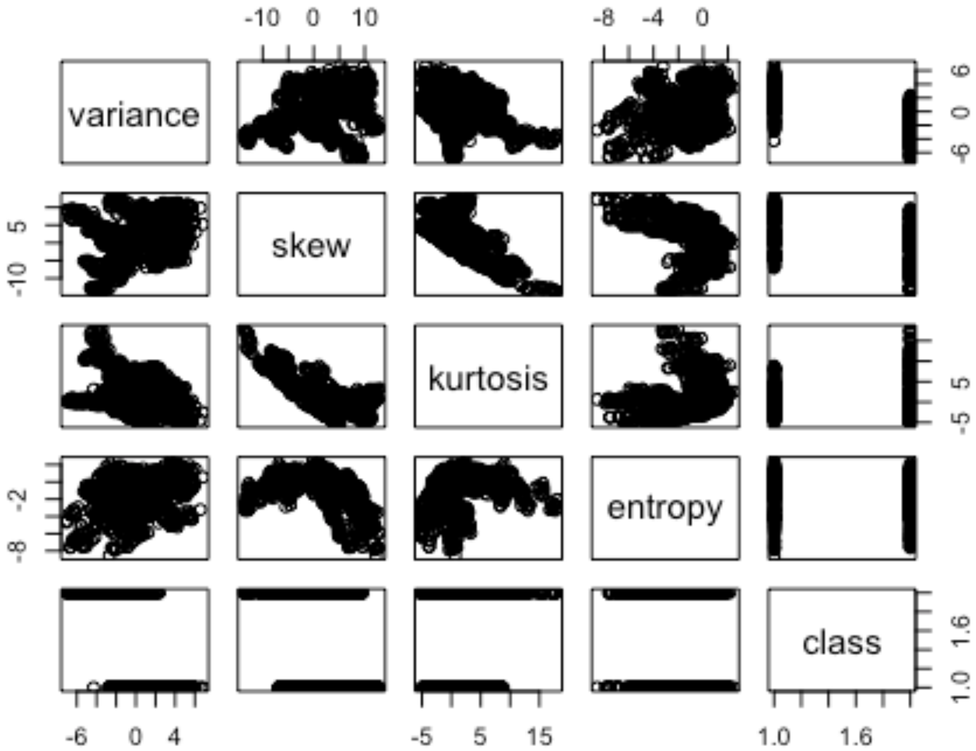


4 - entropy (numeric)






```
#hist(df)

plot(df)
```




```
library(DataExplorer)
```

4. Making TRAINING and TESTING subsets

```
make_train = function(seed_no){
  set.seed(seed_no)
  testIdx <- sample(1:nrow(df),floor(nrow(df)*0.2))
  training <- df[-testIdx,]
  return (training)
}

make_test = function(seed_no){
  set.seed(seed_no)
  testIdx <- sample(1:nrow(df),floor(nrow(df)*0.2))
  testing <- df[testIdx,]
  return (testing)
}

train1 = make_train(79)
test1 = make_test(79)

train2 = make_train(8)
test2 = make_test(8)

train3 = make_train(19)
test3 = make_test(19)

train4 = make_train(23)
```

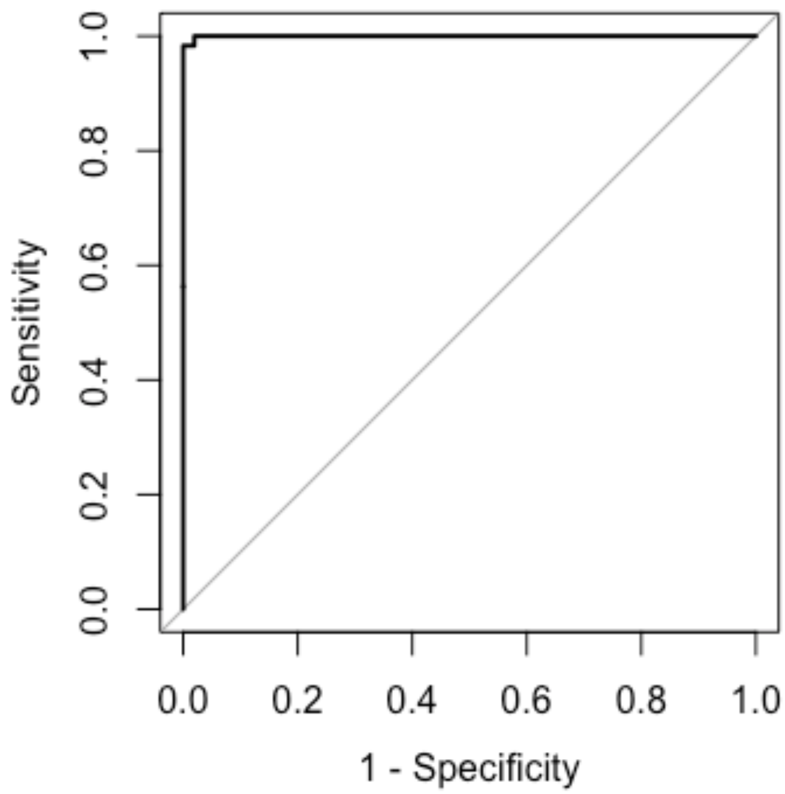
```
test4 = make_test(23)

train5 = make_train(32)
test5 = make_test(32)

train6 = make_train(75)
test6 = make_test(75)

train7 = make_train(102)
test7 = make_test(102)

train8 = make_train(421)
test8 = make_test(421)

train9 = make_train(792)
test9 = make_test(792)

train10 = make_train(1)
test10 = make_test(1)
```

5. MACHINE LEARNING ALGORITHMS

TREATMENT: Level 1 Logistic Regression

```
library(pROC)

## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var

logreg = function(training, testing){
  glm = glm(class ~ . , data = training, family = binomial(link="logit"))
  # summary(glm)
  pred.glm = predict(glm, newdata=testing, type='response')
  pred.glmclass = rep("Fake", length(pred.glm))
  pred.glmclass[pred.glm>0.5] = "Real"
  # table(pred.glmclass, test1$class, dnn=c("Predictions","Actual"))
  tn = table(pred.glmclass, testing$class, dnn=c("Predictions","Actual"))
[1,1]
  tp = table(pred.glmclass, testing$class, dnn=c("Predictions","Actual"))
[2,2]
  accuracy = (tn + tp)/nrow(testing)
  return (accuracy)
}

logreg_df = data.frame(accuracy = c(logreg(train1, test1), logreg(train2,
test2), logreg(train3, test3), logreg(train4, test4), logreg(train5, test
5), logreg(train6, test6), logreg(train7, test7), logreg(train8, test8), l
ogreg(train9, test9), logreg(train10, test10)),
           ml_algorithm = rep("logReg", 10))
```

```
logreg_df

##      accuracy ml_algorithm
## 1  0.9854015       logReg
## 2  0.9854015       logReg
## 3  0.9927007       logReg
## 4  1.0000000       logReg
## 5  0.9781022       logReg
## 6  0.9817518       logReg
## 7  0.9890511       logReg
## 8  0.9817518       logReg
## 9  0.9890511       logReg
## 10 0.9890511       logReg

par(pty='s')
glm = glm(class ~ . , data = train1, family = binomial(link="logit"))

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

pred.glm = predict(glm, newdata=test1, type='response')
plot(roc(test1$class, pred.glm), legacy.axes=TRUE)

## Setting levels: control = Fake, case = Real

## Setting direction: controls < cases
```

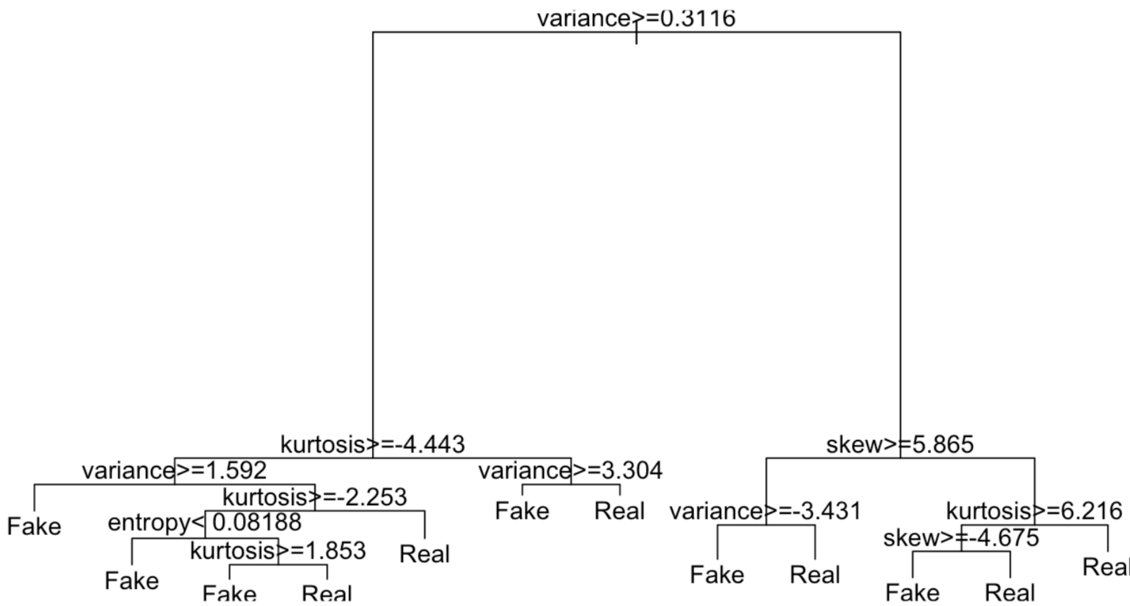


TREATMENT: Level 2 Linear Discriminant Analysis

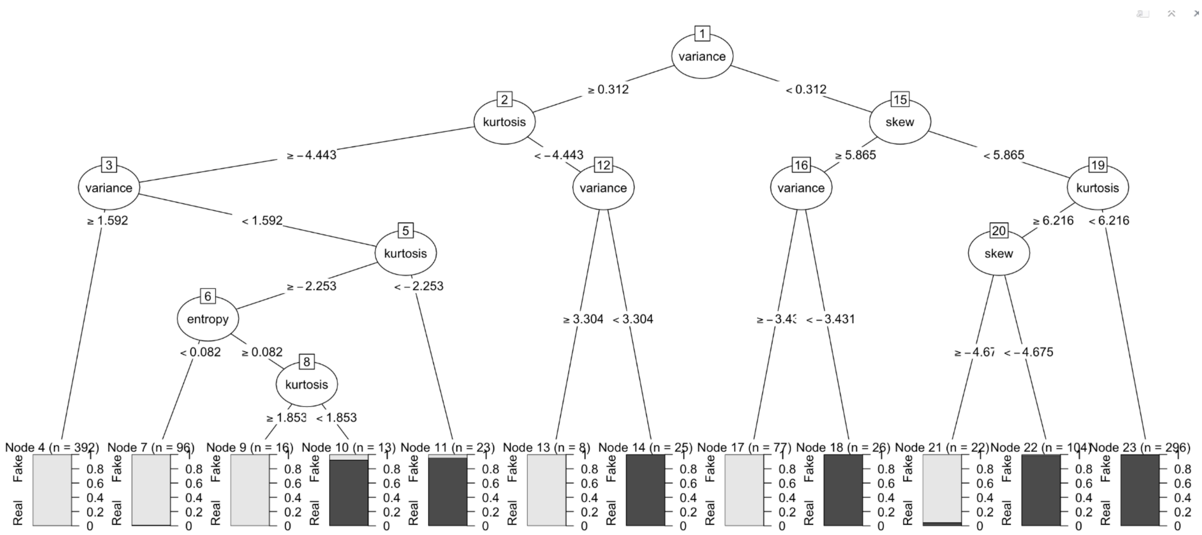
```
library(MASS)
ldareg <- function(training, testing){
  lda_fit = lda(class ~ . , data=training)
  lda_pred = predict(lda_fit, newdata=testing)
  accuracy = sum(table(testing$class, lda_pred$class)[1,1],table(testing$c
lass, lda_pred$class)[2,2])/nrow(testing)
  return(accuracy)
}

lda_df = data.frame(accuracy = c(ldareg(train1, test1), ldareg(train2, tes
t2), ldareg(train3, test3), ldareg(train4, test4), ldareg(train5, test5),
ldareg(train6, test6), ldareg(train7, test7), ldareg(train8, test8), ldare
g(train9, test9), ldareg(train10, test10)),
           ml_algorithm = rep("LDA",5))

lda_df

##     accuracy ml_algorithm
## 1  0.9817518          LDA
## 2  0.9635036          LDA
## 3  0.9927007          LDA
## 4  0.9708029          LDA
## 5  0.9635036          LDA
## 6  0.9598540          LDA
## 7  0.9708029          LDA
## 8  0.9708029          LDA
## 9  0.9708029          LDA
## 10 0.9744526          LDA
```

TREATMENT: Level 3 Classification and Regression Trees

```
library(rpart)
rpart = rpart(class ~ ., data = train1)
plot(rpart)
text(rpart)
```




```
library(partykit)

plot(as.party(rpart))
```



```
regtree = function(training, testing){
  rpart = rpart(class ~ ., data = training)
  rpart.pred = predict(rpart, newdata = testing, type = "class")
  tn = table(rpart.pred, testing$class, dnn = c("Prediction", "Actual"))
[1,1]
  tp = table(rpart.pred, testing$class, dnn = c("Prediction", "Actual"))
[2,2]
  accuracy = (tn + tp)/nrow(testing)
  return (accuracy)
}

regtree_df = data.frame(accuracy = c(regtree(train1, test1), regtree(train
2, test2), regtree(train3, test3), regtree(train4, test4), regtree(train5,
```

```r
 test5), regtree(train6, test6), regtree(train7, test7), regtree(train8, t
est8), regtree(train9, test9), regtree(train10, test10)),
           ml_algorithm = rep("RTree", 5))

regtree_df

##     accuracy ml_algorithm
## 1  0.9927007        RTree
## 2  0.9671533        RTree
## 3  0.9416058        RTree
## 4  0.9781022        RTree
## 5  0.9708029        RTree
## 6  0.9489051        RTree
## 7  0.9489051        RTree
## 8  0.9671533        RTree
## 9  0.9708029        RTree
## 10 0.9890511        RTree
```

TREATMENT: Level 4 Naive Bayes

```r
library(naivebayes)

## naivebayes 0.9.6 loaded

nBayes = function(training, testing){
  nb = naive_bayes(class ~ .,usekernel=T, data=training)
  nb.pred=predict(nb, newdata = testing, type="class")
  tn = table(nb.pred, testing$class, dnn = c("Prediction", "Actual"))[1,1]
  tp = table(nb.pred, testing$class, dnn = c("Prediction", "Actual"))[2,2]
  accuracy = (tn + tp)/nrow(testing)
  return (accuracy)
}

nbayes_df = data.frame(accuracy = c(nBayes(train1, test1), nBayes(train2,
test2), nBayes(train3, test3), nBayes(train4, test4), nBayes(train5, test
5), nBayes(train6, test6), nBayes(train7, test7), nBayes(train8, test8), n
Bayes(train9, test9), nBayes(train10, test10)),
           ml_algorithm = rep("nBayes", 5))

nbayes_df

##     accuracy ml_algorithm
## 1  0.9197080       nBayes
## 2  0.9233577       nBayes
## 3  0.9160584       nBayes
## 4  0.9416058       nBayes
## 5  0.9379562       nBayes
## 6  0.9343066       nBayes
## 7  0.9124088       nBayes
## 8  0.9087591       nBayes
## 9  0.9087591       nBayes
## 10 0.8868613       nBayes
```

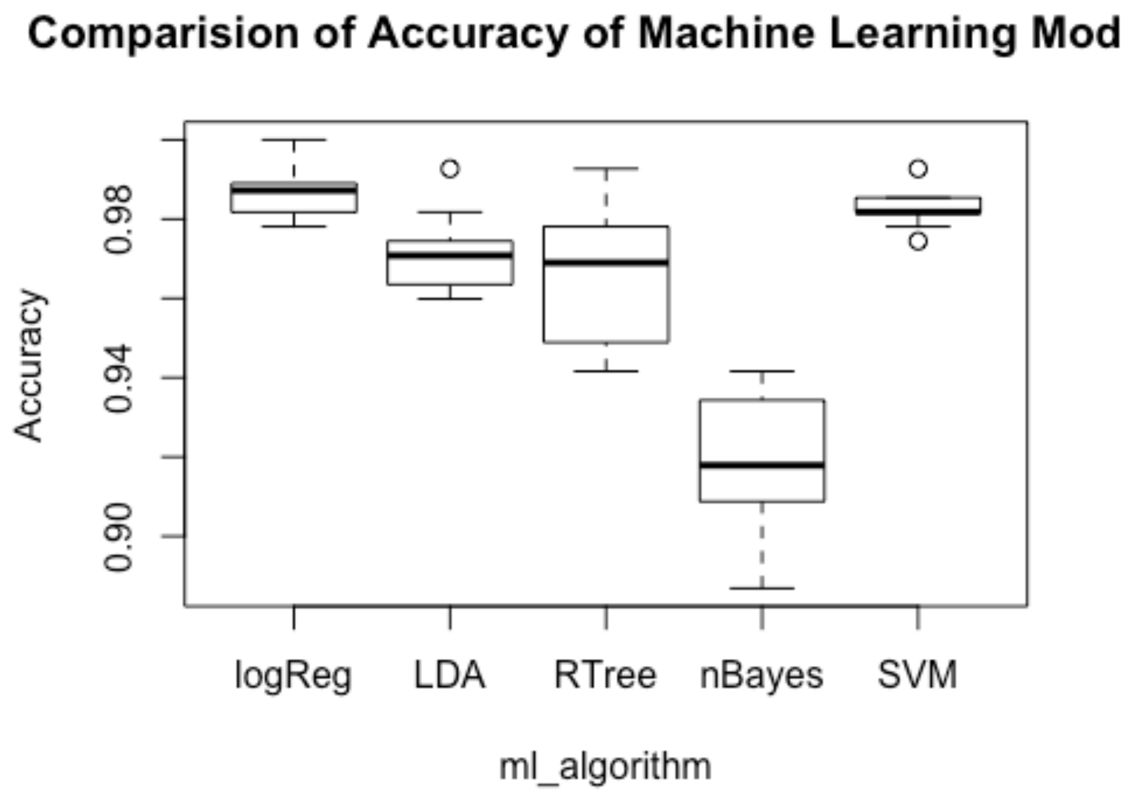
TREATMENT: Level 5 Support Vector Machines

```r
# Fitting SVM to the Training set
library(e1071)
```

```r
svm_func = function(train, testing){
  # svm_fit = svm(formula = class ~ ., data = training, type = 'C-classifi
cation', kernel = 'linear')
  training = train
  svm_fit = svm(formula = class ~ ., data = training, kernel = "linear")
  svm.pred = predict(svm_fit, newdata = testing, type = "class")
  tn = table(svm.pred, testing$class, dnn = c("Prediction", "Actual"))[1,
1]
  tp = table(svm.pred, testing$class, dnn = c("Prediction", "Actual"))[2,
2]
  # tn = table(testing[,5], svm_pred)[1,1]
  # tp = table(testing[,5], svm_pred)[2,2]
  accuracy = (tn + tp)/nrow(testing)
  return (accuracy)
}

svm_df = data.frame(accuracy = c(svm_func(train1, test1), svm_func(train2,
 test2), svm_func(train3, test3), svm_func(train4, test4), svm_func(train
5, test5), svm_func(train6, test6), svm_func(train7, test7), svm_func(trai
n8, test8), svm_func(train9, test9), svm_func(train10, test10)),
           ml_algorithm = rep("SVM", 5))

svm_df

##     accuracy ml_algorithm
## 1  0.9817518          SVM
## 2  0.9817518          SVM
## 3  0.9927007          SVM
## 4  0.9854015          SVM
## 5  0.9744526          SVM
## 6  0.9817518          SVM
## 7  0.9854015          SVM
## 8  0.9817518          SVM
## 9  0.9817518          SVM
## 10 0.9781022          SVM

# FINAL DATASET OF EACH MODEL'S ACCURACY

models_df = rbind(logreg_df, lda_df, regtree_df, nbayes_df, svm_df)
models_df

##     accuracy ml_algorithm
## 1  0.9854015       logReg
## 2  0.9854015       logReg
## 3  0.9927007       logReg
## 4  1.0000000       logReg
## 5  0.9781022       logReg
## 6  0.9817518       logReg
## 7  0.9890511       logReg
## 8  0.9817518       logReg
## 9  0.9890511       logReg
## 10 0.9890511       logReg
## 11 0.9817518          LDA
## 12 0.9635036          LDA
## 13 0.9927007          LDA
```

```
## 14 0.9708029          LDA
## 15 0.9635036          LDA
## 16 0.9598540          LDA
## 17 0.9708029          LDA
## 18 0.9708029          LDA
## 19 0.9708029          LDA
## 20 0.9744526          LDA
## 21 0.9927007        RTree
## 22 0.9671533        RTree
## 23 0.9416058        RTree
## 24 0.9781022        RTree
## 25 0.9708029        RTree
## 26 0.9489051        RTree
## 27 0.9489051        RTree
## 28 0.9671533        RTree
## 29 0.9708029        RTree
## 30 0.9890511        RTree
## 31 0.9197080       nBayes
## 32 0.9233577       nBayes
## 33 0.9160584       nBayes
## 34 0.9416058       nBayes
## 35 0.9379562       nBayes
## 36 0.9343066       nBayes
## 37 0.9124088       nBayes
## 38 0.9087591       nBayes
## 39 0.9087591       nBayes
## 40 0.8868613       nBayes
## 41 0.9817518          SVM
## 42 0.9817518          SVM
## 43 0.9927007          SVM
## 44 0.9854015          SVM
## 45 0.9744526          SVM
## 46 0.9817518          SVM
## 47 0.9854015          SVM
## 48 0.9817518          SVM
## 49 0.9817518          SVM
## 50 0.9781022          SVM
```

```
# SET DATAFRAME DATATYPE AS NUMERIC AND FACTOR
models_df$accuracy = as.numeric(models_df$accuracy)
models_df$ml_algorithm = as.factor(models_df$ml_algorithm)


boxplot(accuracy~ml_algorithm, xlab="ml_algorithm", ylab="Accuracy", main=
"Comparision of Accuracy of Machine Learning Models",data=models_df)
```



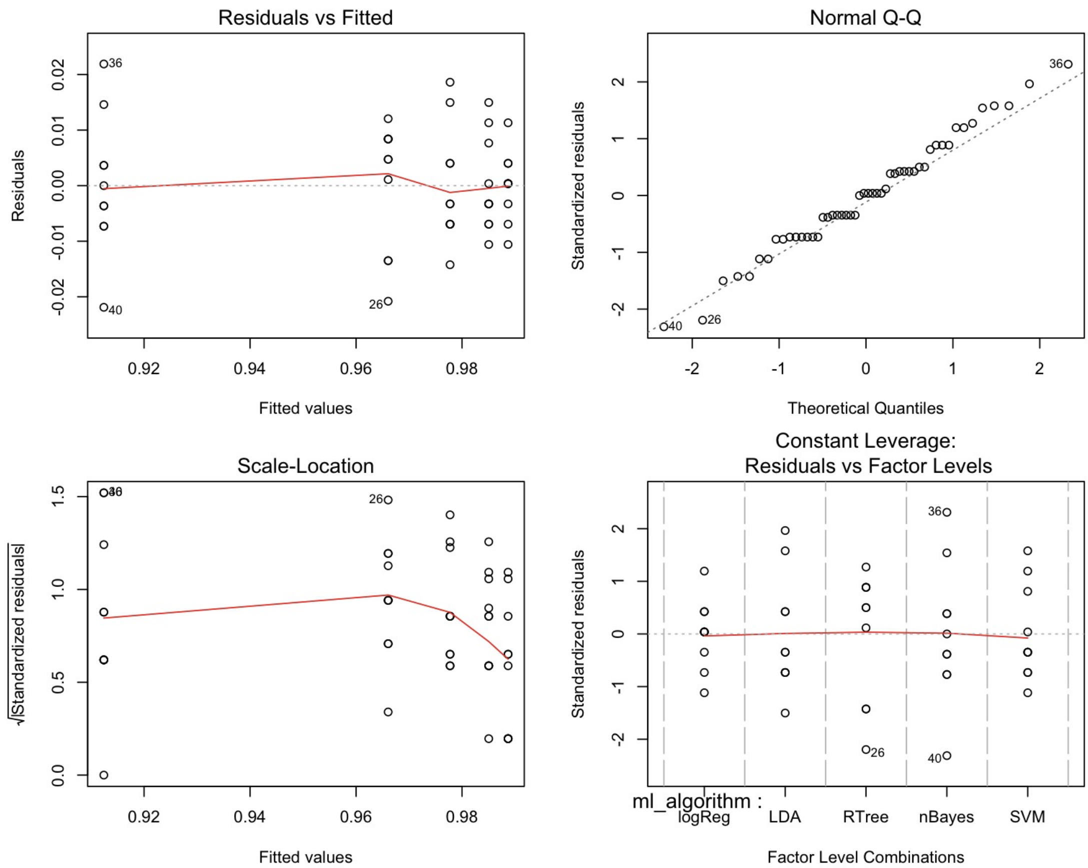
6. ANOVA Summary

```
ml_anova = aov(accuracy~ml_algorithm,data=models_df)
summary(ml_anova)

##              Df  Sum Sq  Mean Sq F value   Pr(>F)    
## ml_algorithm  4 0.03887 0.009717    97.47   <2e-16 ***
## Residuals    45 0.00449 0.000100                      
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

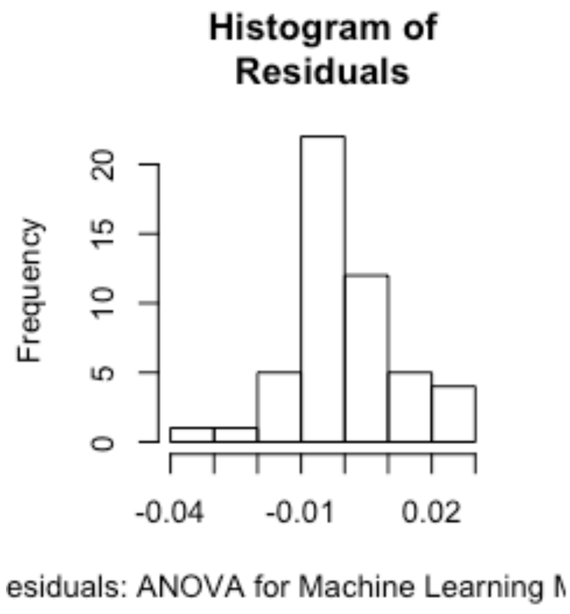
Conclusion Analysis of variance indicates that at 5% level of significance there is sufficient evidence (F(4,45)=97.47, P= < 2x10^-16) to conclude that average accuracy of machine learning models is not the same across model types.

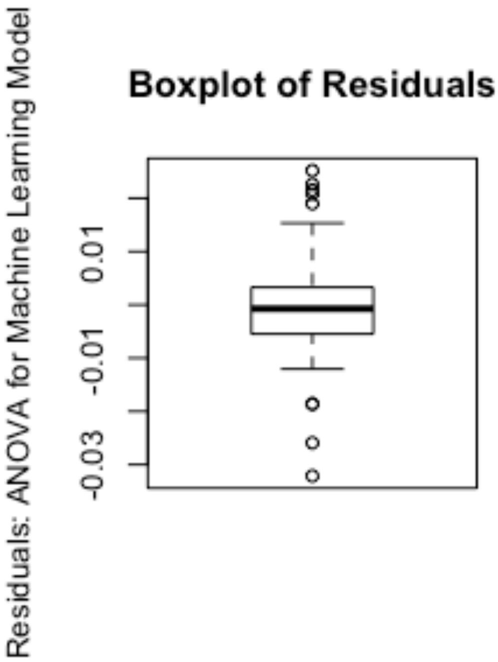
ANOVA Assumptions

```
opar <- par(mfrow=c(2,2),cex=.8)
plot(ml_anova)
```




```
# follow through from above
# comparing residuals and fitted values of anova
ml_res <-residuals(ml_anova)
ml_pre <-predict(ml_anova)


# Check for Normality of Residuals using Histogram and Boxplot
par(mfrow=c(2,2))
hist(ml_res, xlab="Residuals: ANOVA for Machine Learning Models ", main="H
istogram of
Residuals")
boxplot(ml_res, ylab="Residuals: ANOVA for Machine Learning Models", main=
"Boxplot of Residuals")
```

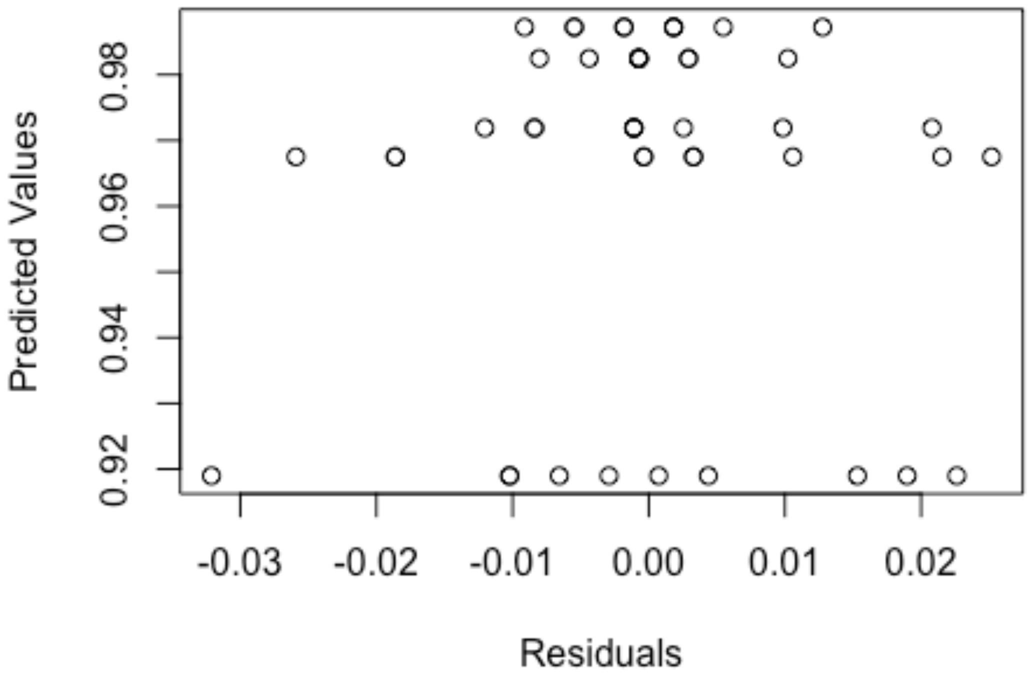





```r
shapiro.test(ml_res)

##
##  Shapiro-Wilk normality test
##
## data:  ml_res
## W = 0.98548, p-value = 0.7921
```

In qqplot not all points are close to the expected line, indicative of some departure from normality and P value for Shapiro Wilks test is high (P=0.7921) so there is normality observed here. Next we check for equality of variance of residuals.

```r
#Check for equality of variance
plot(ml_res,ml_pre,xlab = "Residuals",ylab = "Predicted Values")
```




```
bartlett.test(accuracy ~ ml_algorithm,data=models_df)

##
##  Bartlett test of homogeneity of variances
##
## data:  accuracy by ml_algorithm
## Bartlett's K-squared = 4.7431, df = 4, p-value = 0.3147

leveneTest(ml_anova)

## Levene's Test for Homogeneity of Variance (center = median)
##       Df F value  Pr(>F)
## group  4 0.7174   0.5845 *
##       45
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plot of residuals against predicted values does not show any unusual pattern (funneling or bow shape). As normality was valid, Bartlett test results are reliable. Bartlett test lead to high P-value (P=0.3147), indicating equality of variance in residuals across factor levels (homogeneity). Levene's test also leads to the similar result but with slightly higher p-value (p = 0.5845).

Finally, as the order experiment was random with reference to each factor level setting, independence of errors can be assumed. All underlying anova assumptions are satisfied.

7. Comparing Models

```
tapply(models_df$accuracy,models_df$ml_algorithm, mean)

##    logReg       LDA     RTree    nBayes       SVM
## 0.9872263 0.9718978 0.9675182 0.9189781 0.9824818

tapply(models_df$accuracy,models_df$ml_algorithm, sd)

##      logReg         LDA       RTree      nBayes         SVM
## 0.006262549 0.009586807 0.016983770 0.016394044 0.004804968
```

Results of analysis of mean are reported as follows: Mean (standard deviation) of machine learning models for logistic regression, linear discriminant analysis, regression tree, naive bayes and support vector machine are 0.989(0.006), 0.9777(0.010), 0.9660(0.0115), 0.9124(0.0122), 0.985(0.0085) respectively.

8. Multiple Comparisons

Fishers Least Significant Difference Test (Fisher's LSD)

```
library(agricolae)
MComLSD=LSD.test(ml_anova,"ml_algorithm");MComLSD

## $statistics
##        MSerror Df      Mean       CV  t.value        LSD
##   0.0001422854 45 0.9656204 1.235304 2.014103 0.01074427
##
## $parameters
##         test p.ajusted       name.t ntr alpha
##   Fisher-LSD      none ml_algorithm   5  0.05
##
## $means
##         accuracy         std  r       LCL       UCL       Min       Max
## LDA    0.9718978 0.009586807 10 0.9643005 0.9794952 0.9598540 0.9927007
## logReg 0.9872263 0.006262549 10 0.9796289 0.9948236 0.9781022 1.0000000
## nBayes 0.9189781 0.016394044 10 0.9113808 0.9265754 0.8868613 0.9416058
## RTree  0.9675182 0.016983770 10 0.9599209 0.9751156 0.9416058 0.9927007
## SVM    0.9824818 0.004804968 10 0.9748844 0.9900791 0.9744526 0.9927007
##              Q25       Q50       Q75
## LDA    0.9653285 0.9708029 0.9735401
## logReg 0.9826642 0.9872263 0.9890511
## nBayes 0.9096715 0.9178832 0.9315693
## RTree  0.9534672 0.9689781 0.9762774
## SVM    0.9817518 0.9817518 0.9844891
##
## $comparison
## NULL
##
## $groups
##         accuracy groups
## logReg 0.9872263      a
## SVM    0.9824818     ab
## LDA    0.9718978     bc
## RTree  0.9675182      c
## nBayes 0.9189781      d
```

```
##
## attr(,"class")
## [1] "group"
```

Tukey's Studentised Range Test

```
MComTukey=HSD.test(ml_anova,"ml_algorithm");MComTukey

## $statistics
##        MSerror Df      Mean       CV        MSD
##   0.0001422854 45 0.9656204 1.235304 0.01515777
##
## $parameters
##    test       name.t ntr StudentizedRange alpha
##   Tukey ml_algorithm   5         4.018417  0.05
##
## $means
##         accuracy         std  r       Min       Max       Q25       Q50
## LDA    0.9718978 0.009586807 10 0.9598540 0.9927007 0.9653285 0.9708029
## logReg 0.9872263 0.006262549 10 0.9781022 1.0000000 0.9826642 0.9872263
## nBayes 0.9189781 0.016394044 10 0.8868613 0.9416058 0.9096715 0.9178832
## RTree  0.9675182 0.016983770 10 0.9416058 0.9927007 0.9534672 0.9689781
## SVM    0.9824818 0.004804968 10 0.9744526 0.9927007 0.9817518 0.9817518
##              Q75
## LDA    0.9735401
## logReg 0.9890511
## nBayes 0.9315693
## RTree  0.9762774
## SVM    0.9844891
##
## $comparison
## NULL
##
## $groups
##         accuracy groups
## logReg 0.9872263      a
## SVM    0.9824818     ab
## LDA    0.9718978      b
## RTree  0.9675182      b
## nBayes 0.9189781      c
##
## attr(,"class")
## [1] "group"
```

Duncan's Test

```
#Use first treatment(alphanumerically)as control
library(multcomp)

MComScheffe=glht(ml_anova,Linfct=mcp(Treatment="Dunnett"))
summary(MComScheffe)

##
##   Simultaneous Tests for General Linear Hypotheses
##
## Fit: aov(formula = accuracy ~ ml_algorithm, data = models_df)
```

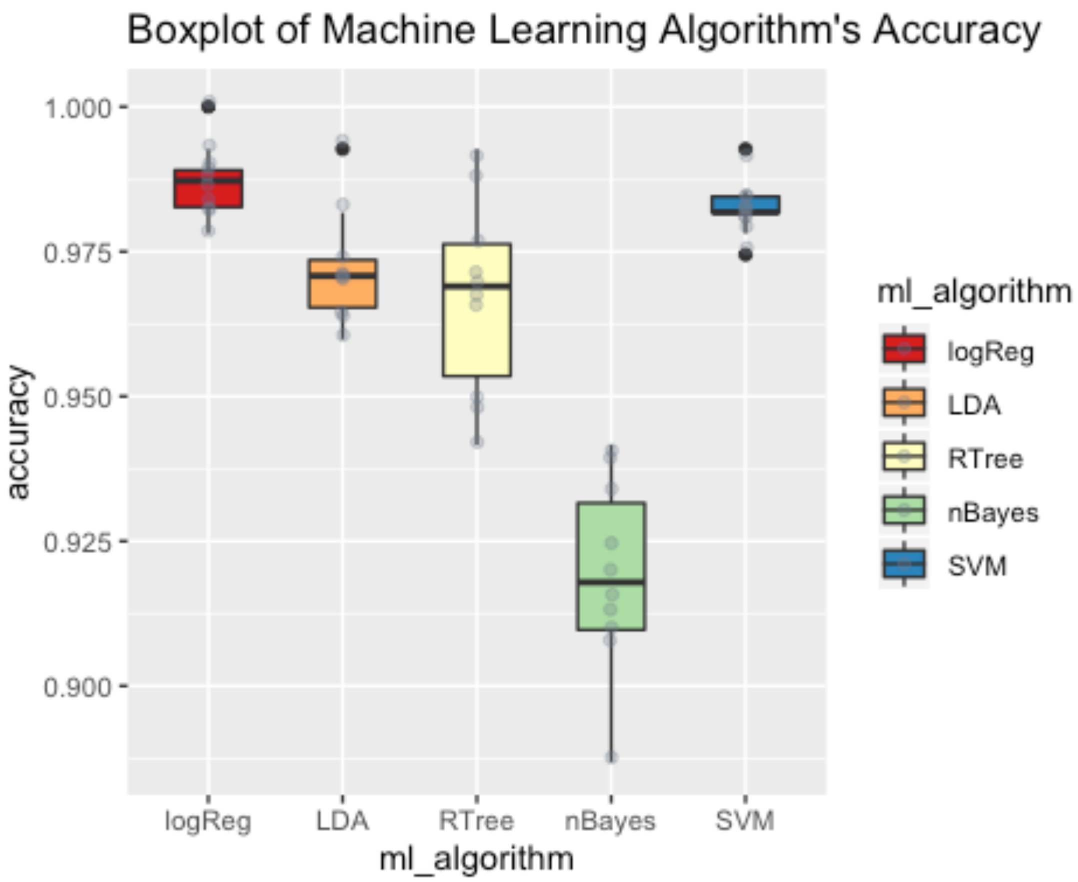
```
##
## Linear Hypotheses:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept) == 0          0.987226   0.003772 261.720  < 0.001 ***
## ml_algorithmLDA == 0     -0.015328   0.005335  -2.873  0.02315 *
## ml_algorithmRTree == 0   -0.019708   0.005335  -3.694  0.00252 **
## ml_algorithmnBayes == 0 -0.068248   0.005335 -12.794  < 0.001 ***
## ml_algorithmSVM == 0     -0.004745   0.005335  -0.889  0.80710
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
```

Pairwise T-tests using Bonferroni and Holm

```
accuracy=models_df$accuracy
ml_algorithm=models_df$ml_algorithm

MComBonferroni=pairwise.t.test(accuracy,ml_algorithm,p.adjust="bonferroni
");MComBonferroni

##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  accuracy and ml_algorithm
##
##        logReg  LDA     RTree   nBayes
## LDA    0.0618  -       -       -
## RTree  0.0059  1.0000  -       -
## nBayes 1.4e-15 6.7e-12 9.2e-11 -
## SVM    1.0000  0.5337  0.0740  1.7e-14
##
## P value adjustment method: bonferroni

attach(models_df)
MComPairwise=pairwise.t.test(accuracy,ml_algorithm);MComPairwise

##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  accuracy and ml_algorithm
##
##        logReg  LDA     RTree   nBayes
## LDA    0.0309  -       -       -
## RTree  0.0036  0.7570  -       -
## nBayes 1.4e-15 5.3e-12 6.4e-11 -
## SVM    0.7570  0.1601  0.0309  1.5e-14
##
## P value adjustment method: holm
```

RESULT PLOTTING

```
library(ggplot2)
p = ggplot(models_df, aes(ml_algorithm, accuracy, fill=ml_algorithm))
p + geom_boxplot(width=0.5) + geom_jitter(width = 0.01, colour = 'lightste
elblue4', alpha=0.3) + scale_fill_brewer(palette = "Spectral") + ggtitle("
Boxplot of Machine Learning Algorithm's Accuracy")
```



Boxplot of Machine Learning Algorithm's Accuracy
1.000
0.975
0.950
0.925
0.900
accuracy
logReg
LDA
RTree
nBayes
SVM
ml_algorithm
ml_algorithm
logReg
LDA
RTree
nBayes
SVM