# 621 Assignment 3

# $Brett\ Burk$

# Sunday, March 01, 2015

# Contents

1.		2
	New weights are created	2
	The weights are tested against the training and test data sets	3
	My Naive Bayes algorithm	4
2 .		-
3 .		6
4 .		7
	e1071	7
	pred.knn	7
5 .		8
	Jury data set	8
6 .		ę
	Pima data set	Ć

Assumptions: I am assuming this assignment is more about working through creating the algorithms than the results.

## 1

## New weights are created

```
# Reading in the data
folder <- "C:\\Users\\Brett\\Dropbox\\CUNY\\621\\Week3\\"</pre>
data.train <- read.csv(paste0(folder, "sample-training-data-naive-bayes.csv"))
data.test <- read.csv(paste0(folder, "sample-testing-data-naive-bayes.csv"))</pre>
# Seperating the variable of interest
var.interest <- data.train[,4]</pre>
training.vars <- data.train[,1:3]</pre>
# Creates the weights for Naive Bayes as a list of lists
create.weights <- function(training.vars, var.interest){</pre>
  split.data <- split(training.vars, var.interest)</pre>
  weights <- list()</pre>
  for(i in names(split.data)){
    temp.total <- nrow(split.data[[i]])</pre>
    weights[[i]] <- list()</pre>
    for(j in colnames(split.data[[i]])){
      weights[[i]][[j]] <- table(split.data[[i]][[j]])/temp.total</pre>
    }
  }
  return(weights)
}
new.weights <- create.weights(training.vars, var.interest)</pre>
new.weights
```

```
## $\ -1\
## $\`-1\`$Cat1
##
##
           Α
## 0.3717949 0.6282051
##
## $`-1`$Cat2
##
##
           G
## 0.4871795 0.5128205
##
## $`-1`$Cat3
##
##
           Х
                      Y
## 0.5384615 0.2692308 0.1923077
##
##
## $`1`
```

```
## $`1`$Cat1
##
##
## 0.6463415 0.3536585
##
## $`1`$Cat2
##
##
           G
                      Η
## 0.5243902 0.4756098
##
## $`1`$Cat3
##
##
           X
                      Y
## 0.1829268 0.3414634 0.4756098
```

The weights are first created

```
test.weights <- function(test.data, weights){</pre>
  results <- test.data[ncol(test.data)]
  test.data <- test.data[,1:(ncol(test.data)-1)]</pre>
  weighted.df <- data.frame(matrix(data = 0, ncol = length(weights) + 1, nrow = nrow(test.data)))</pre>
  colnames(weighted.df) <- c(names(weights), 'prediction')</pre>
  for(result in unique(unlist(results))){
    for(row in 1:nrow(test.data)){
      temp.total <- 1
      for(i in names(test.data)){
        temp.total <- temp.total * weights[[as.character(result)]][[i]][test.data[i][row,]]</pre>
    weighted.df[as.character(result)][row,] <- temp.total</pre>
    }
  for(row in 1:nrow(weighted.df)){
    weighted.df['prediction'][row,] <- names(which.max(weighted.df[row,1:(ncol(weighted.df)-1)]))</pre>
  predictions <- weighted.df['prediction']</pre>
  accuracy <- sum(predictions == results)/nrow(results)</pre>
  return(accuracy)
```

The weights are tested against the training and test data sets

```
## [1] 0.65625

test.weights(data.test, new.weights)

## [1] 0.65
```

Both are predicted with about 65% accuracy.

# My Naive Bayes algorithm

```
naive.bayes <- function(train.data, test.data){</pre>
  weights <- create.weights(train.data[,1:(ncol(train.data)-1)], train.data[ncol(train.data)])</pre>
  weighted.df <- data.frame(matrix(data = 0, ncol = length(weights) + 1, nrow = nrow(test.data)))</pre>
  colnames(weighted.df) <- c(names(weights), 'prediction')</pre>
  for(result in names(weights)){
    for(row in 1:nrow(test.data)){
      temp.total <- 1
      for(i in names(test.data)){
        temp.total <- temp.total * weights[[as.character(result)]][[i]][test.data[i][row,]]</pre>
      weighted.df[as.character(result)][row,] <- temp.total</pre>
    }
  }
  for(row in 1:nrow(weighted.df)){
    weighted.df['prediction'][row,] <- names(which.max(weighted.df[row,1:(ncol(weighted.df)-1)]))</pre>
  return(cbind(test.data, weighted.df['prediction']))
}
```

The code does not perform perfectly, but still a 65% accuracy is definitely better than just guessing. (it predicts both on the training data set and the testing data set)

```
knn.train <- read.csv(pasteO(folder, "sample-training-data-nearest-neighbor.csv"))</pre>
knn.test <- read.csv(pasteO(folder, "sample-testing-data-nearest-neighbor.csv"))</pre>
knn.train[,1:3] <- scale(knn.train[,1:3])</pre>
knn.test[,1:3] <- scale(knn.test[,1:3])</pre>
k.near.neighbors <- function(unclassified, points){</pre>
  point.classification <- points[,ncol(points)]</pre>
  points <- points[,1:(ncol(points)-1)]</pre>
  classifications <- array(data = 0, dim = nrow(unclassified))</pre>
  k < -3
  for(row in 1:nrow(unclassified)){
    distances <- data.frame(matrix(data=0, ncol=1, nrow=nrow(points)))</pre>
    for(point in 1:nrow(points)){
      distances[point,1] <- sum((points[point,] - unclassified[row,])^2)</pre>
    knns <- order(distances, decreasing=F)[1:k]</pre>
    classifications[row] <- names(which.max(table(point.classification[knns])))</pre>
  return(cbind(unclassified, classifications))
classif <- k.near.neighbors(knn.test[,1:3], knn.train)</pre>
sum(as.numeric(classif[,4]) == knn.test[,4])/length(classif[,4])
```

## [1] 0.8

80% prediction accuracy is pretty good.

 ${\bf Submitted\ as\ brettmburk@gmail.com}$ 

#### e1071

```
library(e1071)
folder <- "C:\\Users\\Brett\\Dropbox\\CUNY\\621\\Week3\\"
data.train <- read.csv(pasteO(folder, "sample-training-data-naive-bayes.csv"))
data.test <- read.csv(pasteO(folder, "sample-testing-data-naive-bayes.csv"))

model <- naiveBayes(as.factor(Class) ~ ., data = data.train)
pred <- predict(model, data.test[,1:3])

accuracy <- sum(pred == data.test[,4])/length(pred)
accuracy</pre>
```

## [1] 0.65

Exactly the same accuracy as my version

# pred.knn

```
library(class)
folder <- "C:\\Users\\Brett\\Dropbox\\CUNY\\621\\Week3\\"
knn.train <- read.csv(paste0(folder, "sample-training-data-nearest-neighbor.csv"))
knn.test <- read.csv(paste0(folder, "sample-testing-data-nearest-neighbor.csv"))

pred.knn <- knn(knn.train[,1:3], knn.test[,1:3], cl=as.factor(knn.train[,4]), k=3)
accuracy <- sum(pred.knn == knn.test[,4])/length(pred.knn)
accuracy</pre>
```

## [1] 0.725

My result was better, but as this is a n=1 trial, no real assumptions can/should be made, this may also have to do with feature scaling

# Jury data set

```
jury.train <- read.csv(paste0(folder, "jury-training-data.csv"))
jury.public <- read.csv(paste0(folder, "jury-learning-data-public.csv"))
jury.private <- read.csv(paste0(folder, "jury-learning-data-private.csv"))

jury.public <- jury.public[complete.cases(jury.public),]
jury.predictions <- naive.bayes(jury.train, jury.public[,-5])
accuracy <- sum(jury.predictions[,5] == jury.public[,5])/length(jury.predictions[,5])
accuracy</pre>
```

## ## [1] 0.6302521

```
model <- naiveBayes(as.factor(tendency) ~ ., data = jury.train)
jury.pred <- predict(model, jury.public[,-5])
accuracy <- sum(jury.pred == jury.public[,5])/length(jury.pred)
accuracy</pre>
```

# ## [1] 0.6302521

It came up with exactly the same accuracy as my naive bayes implementation (although it runs significantly faster).

## Pima data set

```
pima.train <- read.csv(paste0(folder, "pima-training-data.csv"))
pima.test <- read.csv(paste0(folder, "pima-learning-data-public.csv"))

pima.train[,1:8] <- scale(pima.train[,1:8])
pima.test[,1:8] <- scale(pima.test[,1:8])

my.preds <- k.near.neighbors(pima.test[,-9], pima.train)
accuracy <- sum(my.preds[,9] == pima.test[,9])/length(my.preds[,9])
accuracy

## [1] 0.7037037

pred.knn <- knn(pima.train[,1:8], pima.test[,1:8], cl=as.factor(pima.train[,9]), k=3)
accuracy <- sum(pred.knn == pima.test[,9])/length(pred.knn)
accuracy</pre>
```

## [1] 0.7037037

Both models came up with the same accuracy—that of  $\sim 70\%$