Lab_8

Yakovenko Ivan

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Firstly we need to load data

```
nbtrain <- read.csv(
        file = "https://hyper.mephi.ru/assets/courseware/v1/66b19c28d0c9940f359aa6da5ad25a3b/asset-v1:MI
        sep = ","
)
head(nbtrain)
```

```
##     age sex   educ income
## 1 GT 45   M Others 10-50K
## 2 GT 45   F Others 10-50K
## 3 GT 45   F Others 10-50K
## 4 31-45   F Others 10-50K
## 5 GT 45   M Others 10-50K
## 6 20-30   M Others 10-50K
```

#Then we divide data frame to trainning and testing dataset

```
traindata <- as.data.frame(nbtrain[1:9010,])
testdata <- as.data.frame(nbtrain[9011:10010,])
```

```
## Loading required package: e1071

## Loading required package: caret

## Loading required package: lattice

## Loading required package: ggplot2
```

We use naiveBayes algorithm to count probabilities and create our model

```
model <- naiveBayes(as.factor(income) ~ age+sex+educ, traindata)
model
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##     10-50K     50-80K     GT 80K
## 0.80266371 0.12563818 0.07169811
##
## Conditional probabilities:
##         age
## Y             20-30      31-45      GT 45
##   10-50K 0.20796460 0.34457965 0.44745575
##   50-80K 0.08303887 0.39752650 0.51943463
##   GT 80K 0.06811146 0.34055728 0.59133127
##
##         sex
## Y                F         M
##   10-50K 0.4798119 0.5201881
##   50-80K 0.2871025 0.7128975
##   GT 80K 0.2058824 0.7941176
##
##         educ
## Y           College     Others   Prof/Phd
##   10-50K 0.24585177 0.73976770 0.01438053
##   50-80K 0.49558304 0.44257951 0.06183746
##   GT 80K 0.53869969 0.29566563 0.16563467
```

Model let us use the prediction on our testing dataset

```
results <- predict(model,testdata)
table(results)
```

```
## results
## 10-50K 50-80K GT 80K
##    981      0     19
```

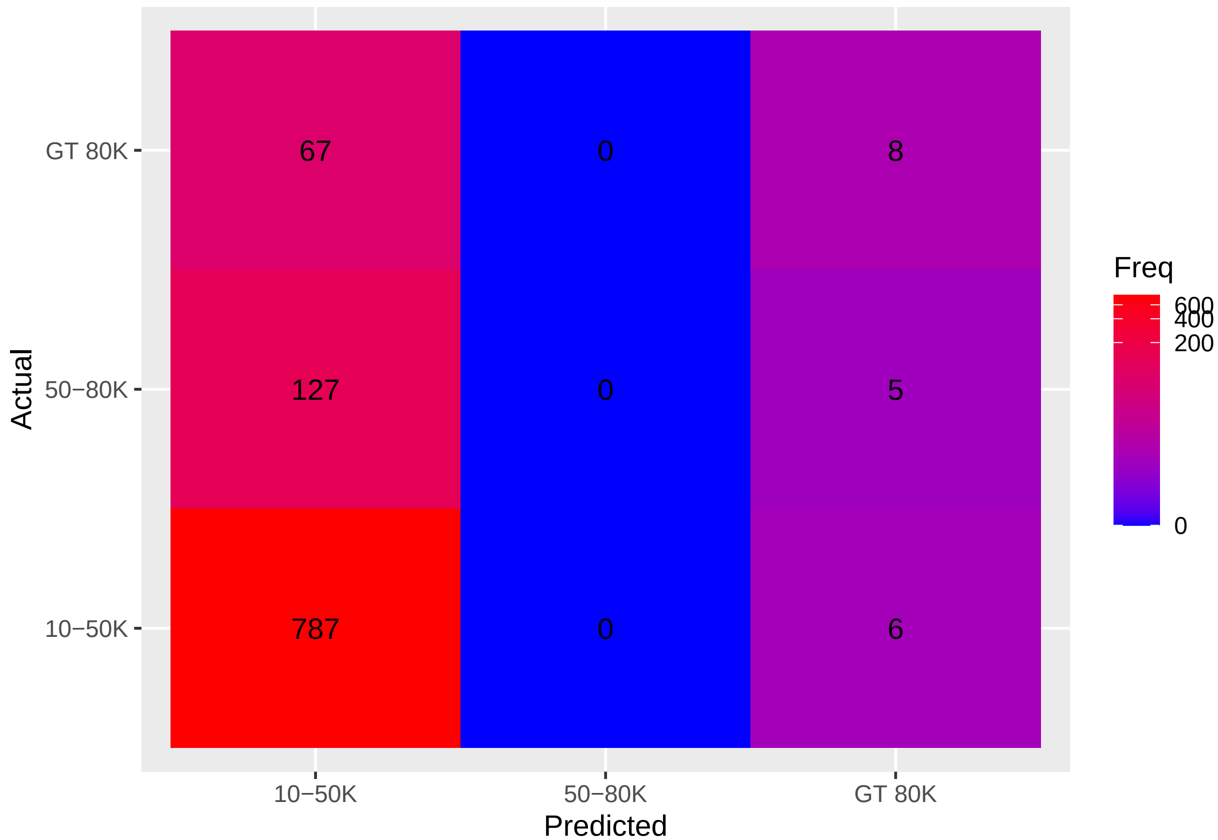
Confusion matrix gives us graphical representation of our prediction

Here we can see that our prediction give 0 to people with 50-80K income and that is not true

```
confusion_matrix <- as.data.frame(table(results, testdata$income))

ggplot(data = confusion_matrix,
       mapping = aes(x = results,
                     y = Var2)) +
```

```r
  geom_tile(aes(fill = Freq)) +
  geom_text(aes(label = Freq)) +
  scale_fill_gradient(low = "blue",
                      high = "red",
                      trans = "log1p") +
  labs(x = "Predicted", y = "Actual")
```



Misclassification rate To count it we use formula: 1-target/sum

```r
tab <- table(testdata$income,results)
all_miss <- 1 - (sum(diag(tab)) / sum(tab))
miss_10_50 <- 1 - (tab[1,1] / sum(tab[1,]))
miss_50_80 <- 1 - (tab[2,2] / sum(tab[2,]))
miss_gt_80 <- 1 - (tab[3,3] / sum(tab[3,]))
cat('for overall ')
```

```
## for overall
```

```r
all_miss
```

```
## [1] 0.205
```

```r
cat('for 10-50K ')
```

```
## for 10-50K
```

```r
miss_10_50
```

```
## [1] 0.007566204
```

```r
cat('for 50-80K ')
```

```
## for 50-80K
```

```r
miss_50_80
```

```
## [1] 1
```

```r
cat('for GT 80K ')
```

```
## for GT 80K
```

```r
miss_gt_80
```

```
## [1] 0.8933333
```

Naive Bayes for sex

now we create model for formula `sex ~ age + educ + income`

```r
model2 <- naiveBayes(as.factor(sex) ~ age + educ + income, traindata)
model2
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##       F       M
## 0.43596 0.56404
##
## Conditional probabilities:
##    age
## Y       20-30     31-45     GT 45
##   F 0.1802444 0.3475051 0.4722505
##   M 0.1837859 0.3536009 0.4626131
##
##    educ
## Y      College     Others   Prof/Phd
##   F 0.32128310 0.65707739 0.02163951
##   M 0.28040142 0.68103109 0.03856749
```

```
##
##    income
## Y       10-50K      50-80K      GT 80K
##   F 0.88340122 0.08273931 0.03385947
##   M 0.74025974 0.15879575 0.10094451
```

```r
results2 <- predict(model2,testdata)
tab2 <- table(testdata$sex,results2)
all_miss2 <- 1 - (sum(diag(tab2)) / sum(tab2))
miss_f <- 1 - (tab2[1,1] / sum(tab2[1,]))
miss_m <- 1 - (tab2[2,2] / sum(tab2[2,]))
cat('for overall ')
```

```
## for overall
```

```r
all_miss2
```

```
## [1] 0.418
```

```r
cat('for female ')
```

```
## for female
```

```r
miss_f
```

```
## [1] 0.7517564
```

```r
cat('for male ')
```

```
## for male
```

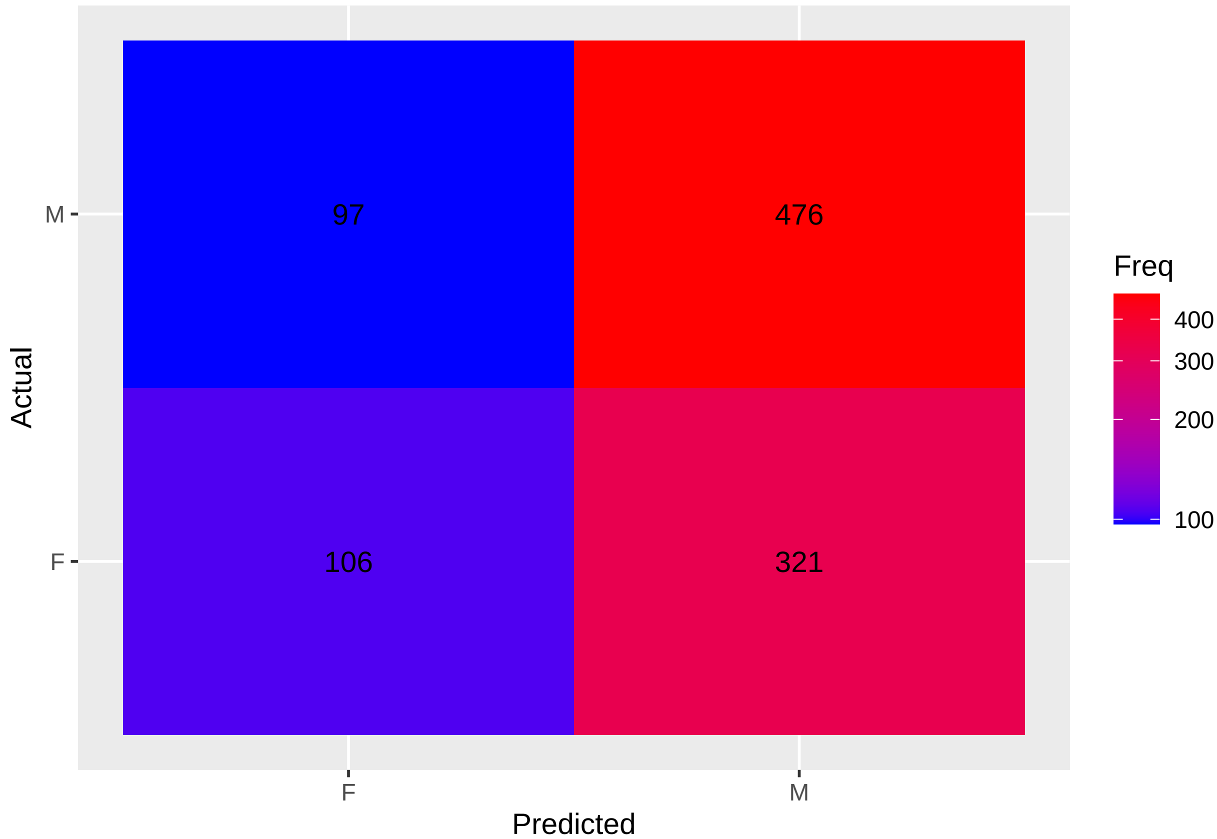
```r
miss_m
```

```
## [1] 0.1692845
```

And plot second confusion matrix

```r
confusion_matrix2 <- as.data.frame(table(results2, testdata$sex))

ggplot(data = confusion_matrix2,
       mapping = aes(x = results2,
                     y = Var2)) +
  geom_tile(aes(fill = Freq)) +
  geom_text(aes(label = Freq)) +
  scale_fill_gradient(low = "blue",
                      high = "red",
                      trans = "log1p") +
  labs(x = "Predicted", y = "Actual")
```



Test our model

we prepare data set: get 3500 from Male and 3500 from Female with random and bind them then we create `new_model` and count as previous our misclassification rate

```
f_data <- traindata[traindata$sex == 'F',]
m_data <- traindata[traindata$sex == 'M',]
library('dplyr')
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
f_data <- sample_n(f_data, 3500)
m_data <- sample_n(m_data, 3500)
union_data <- rbind(f_data, m_data)
```

```r
new_model <- naiveBayes(as.factor(sex) ~ age + educ + income, union_data)
new_model
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##   F   M
## 0.5 0.5
##
## Conditional probabilities:
##    age
## Y       20-30     31-45     GT 45
##   F 0.1808571 0.3491429 0.4700000
##   M 0.1794286 0.3465714 0.4740000
##
##    educ
## Y      College     Others   Prof/Phd
##   F 0.32000000 0.65714286 0.02285714
##   M 0.28428571 0.67685714 0.03885714
##
##    income
## Y       10-50K     50-80K     GT 80K
##   F 0.88400000 0.08142857 0.03457143
##   M 0.74171429 0.16057143 0.09771429
```

```r
results3 <- predict(new_model,testdata)
tab3 <- table(testdata$sex,results3)
all_miss3 <- 1 - (sum(diag(tab3)) / sum(tab3))
miss_f <- 1 - (tab3[1,1] / sum(tab3[1,]))
miss_m <- 1 - (tab3[2,2] / sum(tab3[2,]))
cat('for overall ')
```

```
## for overall
```

```r
all_miss2
```

```
## [1] 0.418
```

```r
cat('for female ')
```

```
## for female
```

```r
miss_f
```

```
## [1] 0.1358314
```

```r
cat('for male ')
```

```
## for male
```

```r
miss_m
```

```
## [1] 0.7190227
```

Conclusion

Naive Bayes is interesting algorithm, that can create interesting and in many cases useful models.