Notes on the Buzz data

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10-25-2013

To run this example you need a system with R installed (see `http://cran.r-project.org`), Latex (see `http://tug.org`) and data from `https://github.com/WinVector/zmPDSwR/tree/master/Buzz`.

To run this example:

1. Download buzz.Rns and TomsHardware-Relative-Sigma-500.data.txt from the github URL.
2. Start a copy of R, use `setwd()` to move to the directory you have stored the files.
3. Make sure knitr is loaded into R (`install.packages('knitr')` and `library(knitr)`).
4. In R run: (produces buzz.tex from buzz.Rnw).

```
knit('buzz.Rnw')
system('/usr/texbin/pdflatex buzz.tex')
```

Now you can run the following data prep steps:

```
buzzdata <- read.table("TomsHardware-Relative-Sigma-500.data.txt",
                       header=F, sep=",")
makevars <- function(colname, ndays=7) {
  paste(colname, 0:ndays, sep='')
}
varnames <- c("num.new.disc",
              "burstiness",
              "number.total.disc",
              "auth.increase",
              "atomic.containers", # not documented
              "num.displays", # number of times topic displayed to user (measure of interest,
              "contribution.sparseness", # not documented
```

```r
             "avg.auths.per.disc",
             "num.authors.topic", # total authors on the topic
             "avg.disc.length",
             "attention.level.author",
             "attention.level.contrib"
)
colnames <- as.vector(sapply(varnames, FUN=makevars))
colnames <-  c(colnames, "buzz")
colnames(buzzdata) <- colnames
# Split into training and test
set.seed(2362690L)
rgroup <- runif(dim(buzzdata)[1])
buzztrain <- buzzdata[rgroup > 0.1,]
buzztest <- buzzdata[rgroup <=0.1,]
```

This currently returns a training set with 7114 rows and a test set with 791 rows, which is the same as when this document was prepared.

Notice we have exploded the basic column names into the following:

```r
print(colnames)
```

```
##  [1] "num.new.disc0"            "num.new.disc1"
##  [3] "num.new.disc2"            "num.new.disc3"
##  [5] "num.new.disc4"            "num.new.disc5"
##  [7] "num.new.disc6"            "num.new.disc7"
##  [9] "burstiness0"              "burstiness1"
## [11] "burstiness2"              "burstiness3"
## [13] "burstiness4"              "burstiness5"
## [15] "burstiness6"              "burstiness7"
## [17] "number.total.disc0"       "number.total.disc1"
## [19] "number.total.disc2"       "number.total.disc3"
## [21] "number.total.disc4"       "number.total.disc5"
## [23] "number.total.disc6"       "number.total.disc7"
## [25] "auth.increase0"           "auth.increase1"
## [27] "auth.increase2"           "auth.increase3"
## [29] "auth.increase4"           "auth.increase5"
## [31] "auth.increase6"           "auth.increase7"
## [33] "atomic.containers0"       "atomic.containers1"
## [35] "atomic.containers2"       "atomic.containers3"
## [37] "atomic.containers4"       "atomic.containers5"
## [39] "atomic.containers6"       "atomic.containers7"
## [41] "num.displays0"            "num.displays1"
## [43] "num.displays2"            "num.displays3"
## [45] "num.displays4"            "num.displays5"
## [47] "num.displays6"            "num.displays7"
## [49] "contribution.sparseness0" "contribution.sparseness1"
```

```
## [51] "contribution.sparseness2" "contribution.sparseness3"
## [53] "contribution.sparseness4" "contribution.sparseness5"
## [55] "contribution.sparseness6" "contribution.sparseness7"
## [57] "avg.auths.per.disc0"      "avg.auths.per.disc1"
## [59] "avg.auths.per.disc2"      "avg.auths.per.disc3"
## [61] "avg.auths.per.disc4"      "avg.auths.per.disc5"
## [63] "avg.auths.per.disc6"      "avg.auths.per.disc7"
## [65] "num.authors.topic0"       "num.authors.topic1"
## [67] "num.authors.topic2"       "num.authors.topic3"
## [69] "num.authors.topic4"       "num.authors.topic5"
## [71] "num.authors.topic6"       "num.authors.topic7"
## [73] "avg.disc.length0"         "avg.disc.length1"
## [75] "avg.disc.length2"         "avg.disc.length3"
## [77] "avg.disc.length4"         "avg.disc.length5"
## [79] "avg.disc.length6"         "avg.disc.length7"
## [81] "attention.level.author0"  "attention.level.author1"
## [83] "attention.level.author2"  "attention.level.author3"
## [85] "attention.level.author4"  "attention.level.author5"
## [87] "attention.level.author6"  "attention.level.author7"
## [89] "attention.level.contrib0" "attention.level.contrib1"
## [91] "attention.level.contrib2" "attention.level.contrib3"
## [93] "attention.level.contrib4" "attention.level.contrib5"
## [95] "attention.level.contrib6" "attention.level.contrib7"
## [97] "buzz"
```

We are now ready to create a simple model predicting “buzz” as function of the other columns.

```
# build a model
# let's use all the input variables
nlist = varnames
varslist = as.vector(sapply(nlist, FUN=makevars))
# these were defined previously,  in Chapter 9
loglikelihood <- function(y, py) {
  pysmooth <- ifelse(py==0, 1e-12,
                     ifelse(py==1, 1-1e-12, py))
  sum(y * log(pysmooth) + (1-y)*log(1 - pysmooth))
}
accuracyMeasures <- function(pred, truth, threshold=0.5, name="model") {
  dev.norm <- -2*loglikelihood(as.numeric(truth), pred)/length(pred)
  ctable = table(truth=truth,
                 pred=pred)
  accuracy <- sum(diag(ctable))/sum(ctable)
  precision <- ctable[2,2]/sum(ctable[,2])
  recall <- ctable[2,2]/sum(ctable[2,])
  f1 <- precision*recall
```

```
  print(paste("precision=", precision, "; recall=" , recall))
  print(ctable)
  data.frame(model=name, accuracy=accuracy, f1=f1, dev.norm)
}
library(randomForest)

## randomForest 4.6-7
## Type rfNews() to see new features/changes/bug fixes.

bzFormula <- paste('as.factor(buzz) ~ ',paste(varslist,collapse=' + '))
fmodel <- randomForest(as.formula(bzFormula),
                      data=buzztrain,
                      mtry=floor(sqrt(length(varslist))),
                      ntree=101,
                      importance=T)
print('training')

## [1] "training"

rtrain <- data.frame(truth=buzztrain$buzz, pred=predict(fmodel, newdata=buzztrain))
print(accuracyMeasures(rtrain$pred, rtrain$truth))

## [1] "precision= 1 ; recall= 0.999360613810742"
##      pred
## truth    0    1
##     0 5550    0
##     1    1 1563
##   model accuracy     f1 dev.norm
## 1 model   0.9999 0.9994 0.007768

print('test')

## [1] "test"

rtest <- data.frame(truth=buzztest$buzz, pred=predict(fmodel, newdata=buzztest))
print(accuracyMeasures(rtest$pred, rtest$truth))

## [1] "precision= 0.831460674157303 ; recall= 0.836158192090395"
##      pred
## truth   0   1
##     0 584  30
##     1  29 148
##   model accuracy     f1 dev.norm
## 1 model   0.9254 0.6952    4.122
```

Notice the extreme fall-off from training to test performance, the random forest over fit. In fact the random forest fit all the data if it sees it during training:

```
fmodel <- randomForest(as.formula(bzFormula),
                       data=buzzdata,
                       mtry=floor(sqrt(length(varslist))),
                       ntree=101,
                       importance=T)
print('all data')

## [1] "all data"

rall <- data.frame(truth=buzztrain$buzz, pred=predict(fmodel, newdata=buzztrain))
print(accuracyMeasures(rall$pred, rall$truth))

## [1] "precision= 1 ; recall= 0.999360613810742"
##      pred
## truth    0    1
##     0 5550    0
##     1    1 1563
##   model accuracy     f1 dev.norm
## 1 model   0.9999 0.9994 0.007768
```

To try and control the over-fitting we build a new model with the tree complexity limited to 100 nodes and the node size to at least 20. This is not necessarily a better model (in fact it scores slightly poorer on test), but it is one where the training procedure didn't have enough freedom to memorize the training data (and therefore maybe had visibility into some trade-offs.

```
fmodel <- randomForest(as.formula(bzFormula),
                       data=buzztrain,
                       mtry=floor(sqrt(length(varslist))),
                       ntree=101,
                       maxnodes=100,
                       nodesize=20,
                       importance=T)
print('training')

## [1] "training"

rtrain <- data.frame(truth=buzztrain$buzz, pred=predict(fmodel, newdata=buzztrain))
print(accuracyMeasures(rtrain$pred, rtrain$truth))

## [1] "precision= 0.864364981504316 ; recall= 0.896419437340154"
##      pred
## truth    0    1
##     0 5330  220
##     1  162 1402
```

```
##   model accuracy     f1 dev.norm
## 1 model   0.9463 0.7748    2.967
```

```
print('test')
```

```
## [1] "test"
```

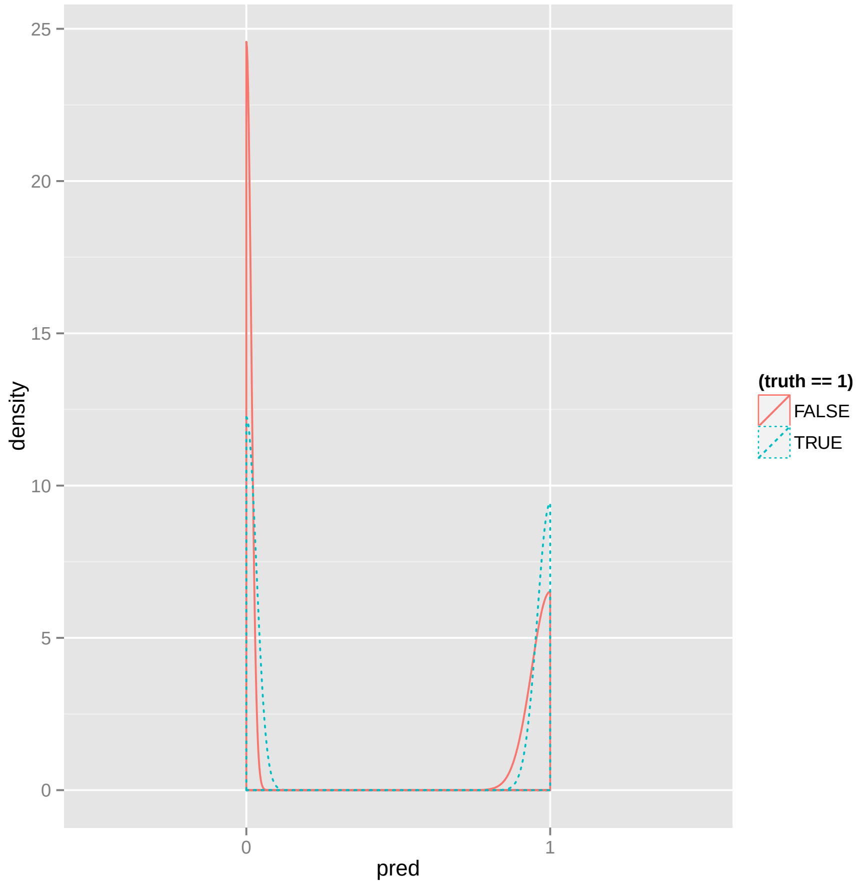
```
rtest <- data.frame(truth=buzztest$buzz, pred=predict(fmodel, newdata=buzztest))
print(accuracyMeasures(rtest$pred, rtest$truth))
```

```
## [1] "precision= 0.809782608695652 ; recall= 0.84180790960452"
##      pred
## truth   0   1
##     0 579  35
##     1  28 149
##   model accuracy     f1 dev.norm
## 1 model   0.9204 0.6817    4.401
```

And we can also make plots.

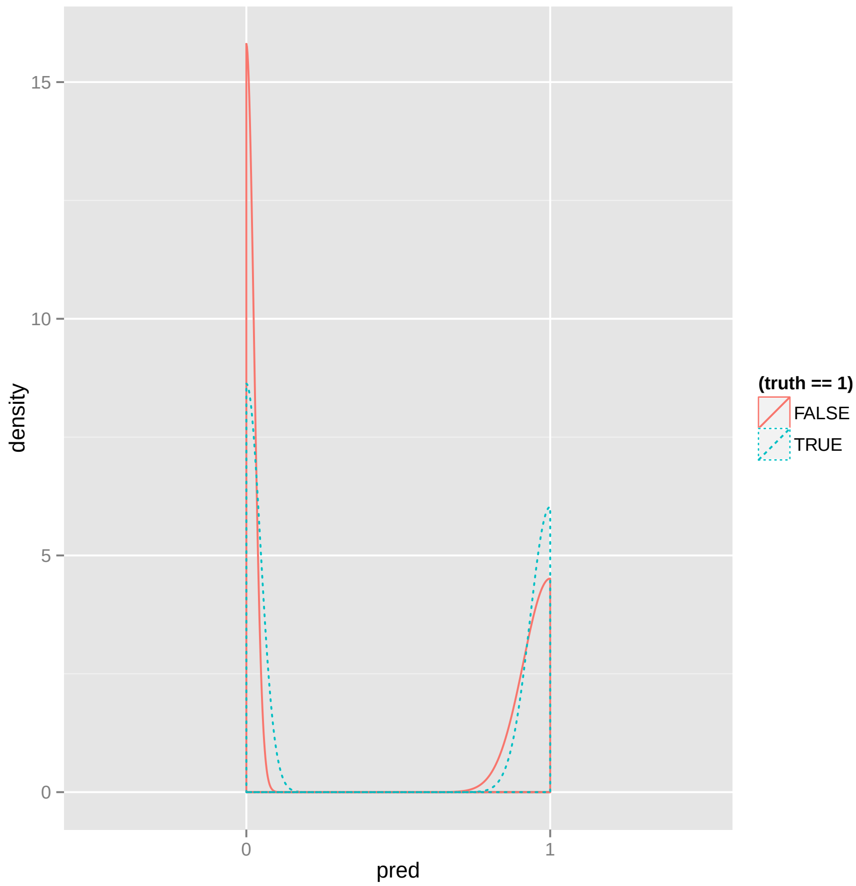
Training performance:

```
library(ggplot2)
ggplot(rtrain, aes(x=pred, color=(truth==1),linetype=(truth==1))) +
   geom_density(adjust=0.1,)
```



Test performance:

```
ggplot(rtest, aes(x=pred, color=(truth==1),linetype=(truth==1))) +
   geom_density(adjust=0.1)
```



Note the classifier scores are concentrated near zero and one (meaning the printed confusion matrices pretty much capture the whole story and the density plots or any sort of ROC plot doesn't add much value in this case).

Save prepared R environment.

```
save(list=ls(),file='thRS500.Rdata')
```