Structure of a Data Analysis

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Steps in a data analysis

- Define the question
- Define the ideal data set
- Determine what data you can access
- Obtain the data
- Clean the data
- Exploratory data analysis
- Statistical prediction/modeling
- Interpret results
- Challenge results
- Synthesize/write up results
- Create reproducible code

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An example

Start with a general question

Can I automatically detect emails that are SPAM or not?

Make it concrete

Can I use quantitative characteristics of the emails to classify them as SPAM/HAM?

Our data set

R: Spam E-mail Database

rss.acs.unt.edu/Rdoc/library/kernlab/html/spam.html

spam {kernlab} R Documentation

Spam E-mail Database

Description

A data set collected at Hewlett-Packard Labs, that classifies 4601 e-mails as spam or non-spam. In addition to this class label there are 57 variables indicating the frequency of certain words and characters in the e-mail.

Usage

`data(spam)`

Format

A data frame with 4601 observations and 58 variables.

The first 48 variables contain the frequency of the variable name (e.g., business) in the e-mail. If the variable name starts with num (e.g., num650) the it indicates the frequency of the corresponding number (e.g., 650). The variables 49-54 indicate the frequency of the characters \`;', \`(', \`[', \`!', \`$', and \`#'. The variables 55-57 contain the average, longest and total run-length of captial letters. Variable 58 indicates the type of the mail and is either `"nonspam"` or `"spam"`, i.e. unsolicited commercial e-mail.

Details

The data set contains 2788 e-mails classified as `"nonspam"` and 1813 classified as `"spam"`.

The \`\`spam'' concept is diverse: advertisements for products/web sites, make money fast schemes, chain letters, pornography... This collection of spam e-mails came from the collectors' postmaster and individuals who had filed spam. The collection of non-spam e-mails came from filed work and personal e-mails, and hence the word 'george' and the area code '650' are indicators of non-spam. These are useful when constructing a personalized spam filter. One would either have to blind such non-spam indicators or get a very wide collection of non-spam to generate a general purpose spam filter.

Source

- Creators: Mark Hopkins, Erik Reeber, George Forman, Jaap Suermondt at Hewlett-Packard Labs, 1501 Page Mill Rd., Palo Alto, CA 94304
- Donor: George Forman (gforman at nospam hpl.hp.com) 650-857-7835

These data have been taken from the UCI Repository Of Machine Learning Databases at http://www.ics.uci.edu/~mlearn/MLRepository.html

References

T. Hastie, R. Tibshirani, J.H. Friedman. *The Elements of Statistical Learning*. Springer, 2001.

`http://search.r-project.org/library/kernlab/html/spam.html`

Subsampling our data set

We need to generate a test and training set (prediction)

```
# If it isn't installed, install the kernlab package
library(kernlab)
data(spam)
# Perform the subsampling
set.seed(3435)
trainIndicator = rbinom(4601,size=1,prob=0.5)
table(trainIndicator)
```

```
## trainIndicator
##    0    1
## 2314 2287
```

```
trainSpam = spam[trainIndicator==1,]
testSpam = spam[trainIndicator==0,]
```

Exploratory data analysis

- Look at summaries of the data
- Check for missing data
- Create exploratory plots
- Perform exploratory analyses (e.g. clustering)

Names

```
names(trainSpam)
```

```
##  [1] "make"              "address"           "all"
##  [4] "num3d"             "our"               "over"
##  [7] "remove"            "internet"          "order"
## [10] "mail"              "receive"           "will"
## [13] "people"            "report"            "addresses'
## [16] "free"              "business"          "email"
## [19] "you"               "credit"            "your"
## [22] "font"              "num000"            "money"
## [25] "hp"                "hpl"               "george"
## [28] "num650"            "lab"               "labs"
## [31] "telnet"            "num857"            "data"
## [34] "num415"            "num85"             "technolog
## [37] "num1999"           "parts"             "pm"
## [40] "direct"            "cs"                "meeting"
## [43] "original"          "project"           "re"
## [46] "edu"               "table"             "conference
```

Head

```r
head(trainSpam)
```

```
##    make address  all num3d  our over remove internet or
## 1  0.00    0.64 0.64     0 0.32 0.00   0.00        0  0.
## 7  0.00    0.00 0.00     0 1.92 0.00   0.00        0  0.
## 9  0.15    0.00 0.46     0 0.61 0.00   0.30        0  0.
## 12 0.00    0.00 0.25     0 0.38 0.25   0.25        0  0.
## 14 0.00    0.00 0.00     0 0.90 0.00   0.90        0  0.
## 16 0.00    0.42 0.42     0 1.27 0.00   0.42        0  0.
##    will people report addresses free business email  you
## 1  0.64   0.00      0         0 0.32        0  1.29 1.93
## 7  1.28   0.00      0         0 0.96        0  0.32 3.85
## 9  0.92   0.00      0         0 0.00        0  0.15 1.23
## 12 0.12   0.12      0         0 0.00        0  0.00 1.16
## 14 0.00   0.90      0         0 0.00        0  0.00 2.72
## 16 0.00   0.00      0         0 1.27        0  0.00 1.70
##    num000 money hp hpl george num650 lab labs telnet nu
## 1       0  0.00  0   0      0      0   0    0      0
```

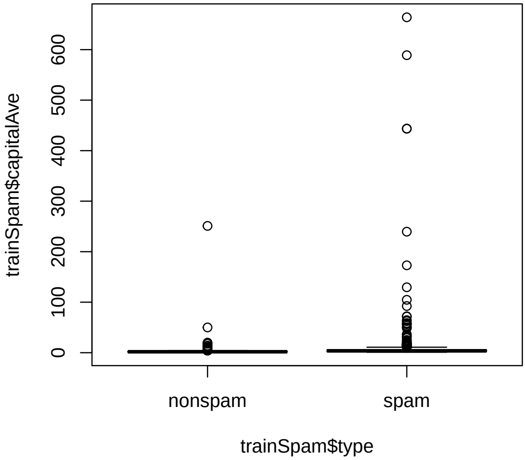
Summaries

```r
table(trainSpam$type)
```

```
##
## nonspam    spam
##    1381     906
```

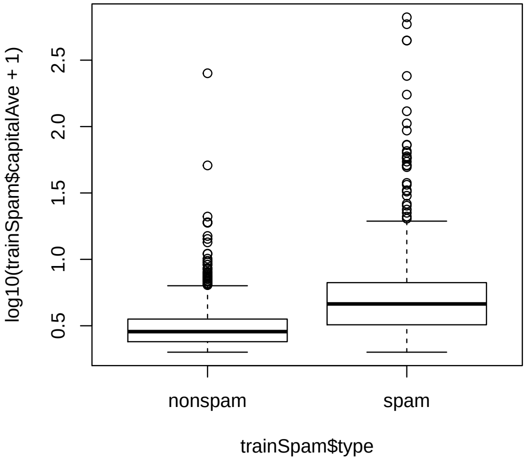
Plots

```r
plot(trainSpam$capitalAve ~ trainSpam$type)
```



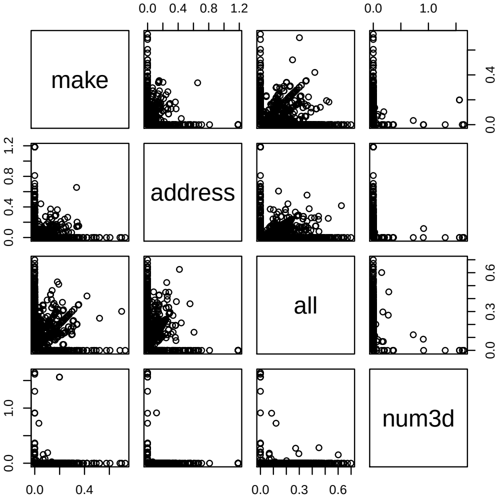
Plots

```
plot(log10(trainSpam$capitalAve + 1) ~ trainSpam$type)
```



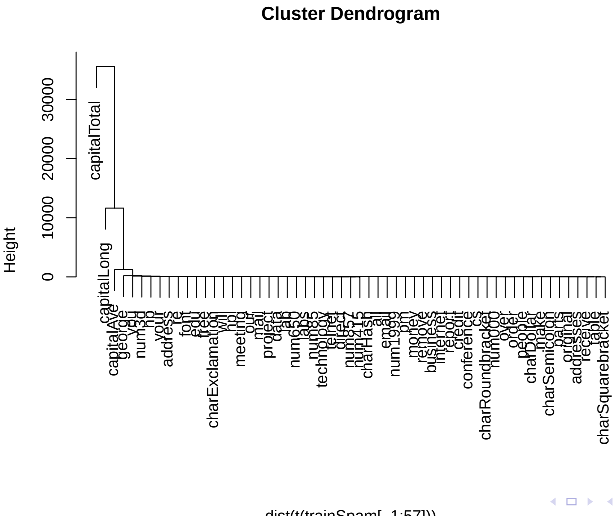
Relationships between predictors

```
plot(log10(trainSpam[,1:4]+1))
```



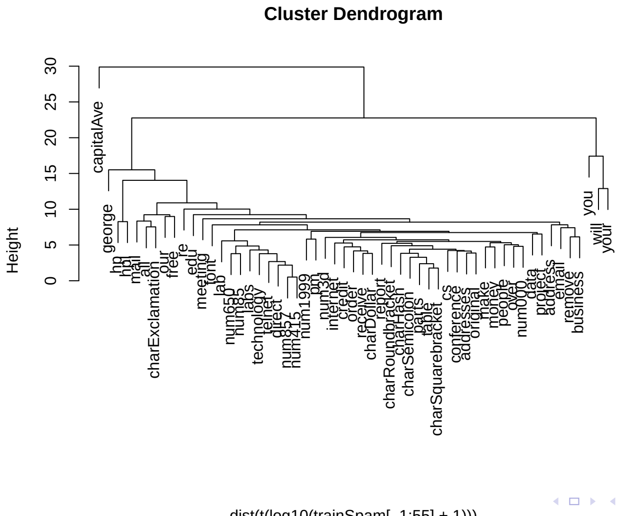
Clustering

```r
hCluster = hclust(dist(t(trainSpam[,1:57])))
plot(hCluster)
```



New clustering

```r
hClusterUpdated = hclust(dist(t(log10(trainSpam[,1:55]+1))))
plot(hClusterUpdated)
```



Statistical prediction/modeling

- Should be informed by the results of your exploratory analysis
- Exact methods depend on the question of interest
- Transformations/processing should be accounted for when necessary
- Measures of uncertainty should be reported

Statistical prediction/modeling

```
trainSpam$numType = as.numeric(trainSpam$type)-1
costFunction = function(x,y) sum(x!=(y > 0.5))
cvError = rep(NA,55)
library(boot)
for(i in 1:55){
  lmFormula = reformulate(names(trainSpam)[i], response = '
  glmFit = glm(lmFormula,family="binomial",data=trainSpam)
  cvError[i] = cv.glm(trainSpam,glmFit,costFunction,2)$delt
}

## Which predictor has minimum cross-validated error?
names(trainSpam)[which.min(cvError)]
```

```
## [1] "charDollar"
```

Get a measure of uncertainty

```
## Use the best model from the group
predictionModel = glm(numType ~ charDollar,family="binomial

## Get predictions on the test set
predictionTest = predict(predictionModel,testSpam)
predictedSpam = rep("nonspam",dim(testSpam)[1])

## Classify as `spam' for those with prob > 0.5
predictedSpam[predictionModel$fitted > 0.5] = "spam"
```

Get a measure of uncertainty

```r
## Classification table
table(predictedSpam,testSpam$type)
```

```
##
## predictedSpam nonspam spam
##       nonspam    1346  458
##       spam         61  449
```

```r
## Error rate
(61+458)/(1346+458 + 61 + 449)
```

```
## [1] 0.2242869
```

Interpret results

- Use the appropriate language
- describes
- correlates with/associated with
- leads to/causes
- predicts
- Give an explanation
- Interpret coefficients
- Interpret measures of uncertainty

Our example

- The fraction of charcters that are dollar signs can be used to predict if an email is Spam
- Anything with more than 6.6% dollar signs is classified as Spam
- More dollar signs always means more Spam under our prediction
- Our test set error rate was 22.4%

Challenge results

- Challenge all steps:
- Question
- Data source
- Processing
- Analysis
- Conclusions
- Challenge measures of uncertainty
- Challenge choices of terms to include in models
- Think of potential alternative analyses

Synthesize/write-up results

- Lead with the question
- Summarize the analyses into the story
- Don't include every analysis, include it
- If it is needed for the story
- If it is needed to address a challenge
- Order analyses according to the story, rather than chronologically
- Include "pretty" figures that contribute to the story

In our example

- Lead with the question
- Can I use quantitative characteristics of the emails to classify them as SPAM/HAM?
- Describe the approach
- Collected data from UCI -> created training/test sets
- Explored relationships
- Choose logistic model on training set by cross validation
- Applied to test, 78% test set accuracy
- Interpret results
- Number of dollar signs seems reasonable, e.g. "Make money with Viagra \$ \$ \$ \$!"
- Challenge results
- 78% isn't that great
- I could use more variables
- Why logistic regression?

Create reproducible code

````
---
## New clustering
```{r, fig.height =6,fig.width=6}
hClusterUpdated = hclust(dist(t(log10(trainSpam[,1:55]+1))))
plot(hClusterUpdated)
```

---
## Statistical prediction/modeling

* Should be informed by the results of your exploratory analysis
* Exact methods depend on the question of interest
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---
## Statistical prediction/modeling
```{r,cache=TRUE}
trainSpam$numType = as.numeric(trainSpam$type)-1
costFunction = function(x,y){sum(x!=(y > 0.5))}
cvError = rep(NA,55)
library(boot)
for(i in 1:55){
  lmFormula = as.formula(paste("numType~",names(trainSpam)[i],sep=""))
  glmFit = glm(lmFormula,family="binomial",data=trainSpam)
  cvError[i] = cv.glm(trainSpam,glmFit,costFunction,2)$delta[2]
}
which.min(cvError)
names(trainSpam)[which.min(cvError)]

```

---
````