# Lab 1

## David Duffrin

### Contents

Lab 1	2
Intro	2
Data Analysis	4

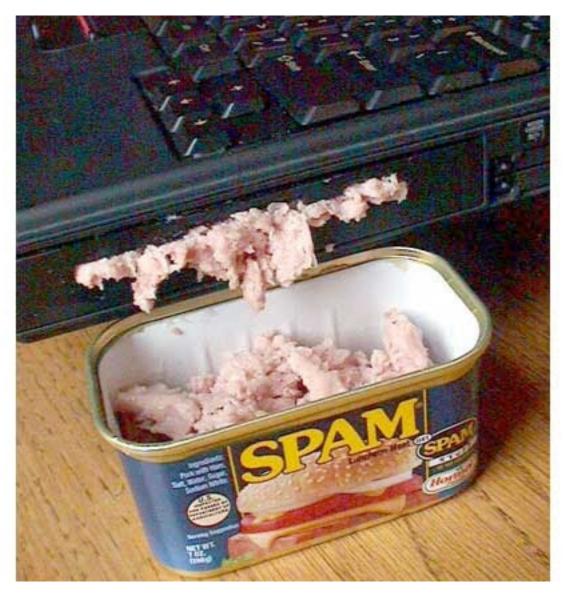


Figure 1: spammy lappy

### Lab 1

#### Intro

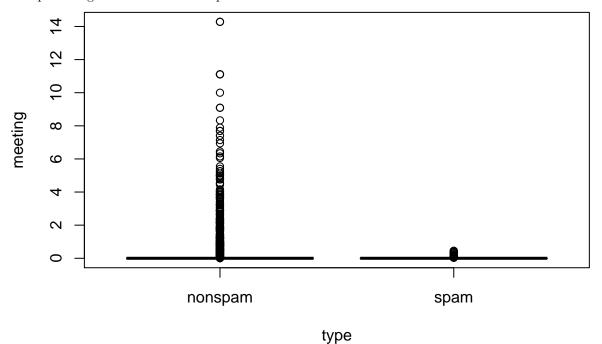
A data set collected at Hewlett-Packard Labs, that classifies 4601 e-mails as spam or non-spam. In addition to this class label there are 57 variables indicating the frequency of certain words and characters in the e-mail.

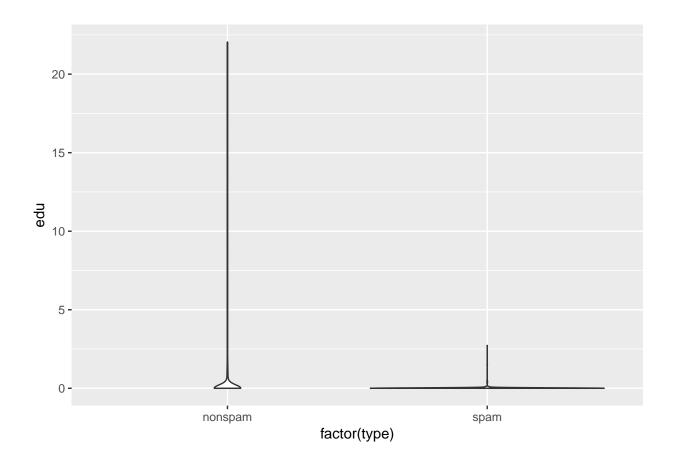
make	$\operatorname{address}$	all	${\rm num} 3{\rm d}$	our	over	remove	internet	order	$_{ m mail}$	receive	will	people	report	addres
0.00	0.64	0.64	0	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.64	0.00	0.00	0
0.21	0.28	0.50	0	0.14	0.28	0.21	0.07	0.00	0.94	0.21	0.79	0.65	0.21	G
0.06	0.00	0.71	0	1.23	0.19	0.19	0.12	0.64	0.25	0.38	0.45	0.12	0.00	1
0.00	0.00	0.00	0	0.63	0.00	0.31	0.63	0.31	0.63	0.31	0.31	0.31	0.00	C
0.00	0.00	0.00	0	0.63	0.00	0.31	0.63	0.31	0.63	0.31	0.31	0.31	0.00	(

make	address	all	num3d	our	over	remove	internet	order	mail	receive	will	people	report	addres
0.00	0.00	0.00	0	1.85	0.00	0.00	1.85	0.00	0.00	0.00	0.00	0.00	0.00	C

```
##
                              edu
                                                 type
        money
##
           : 0.00000
                                : 0.0000
                                            nonspam:2788
    Min.
                         Min.
    1st Qu.: 0.00000
                         1st Qu.: 0.0000
##
                                            spam
                                                    :1813
                         Median : 0.0000
##
    {\tt Median} \,:\, 0.00000
##
    Mean
           : 0.09427
                         Mean
                                : 0.1798
    3rd Qu.: 0.00000
                         3rd Qu.: 0.0000
##
    Max.
           :12.50000
                        Max.
                                :22.0500
```

The percentage of emails that are spam in the dataset is 0.3940448





#### Data Analysis

```
## Generalized Linear Model
##
## 2761 samples
    57 predictor
##
##
      2 classes: 'nonspam', 'spam'
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 2761, 2761, 2761, 2761, 2761, 2761, ...
## Resampling results:
##
##
     Accuracy
                Kappa
     0.9221363 0.8368392
##
## Confusion Matrix and Statistics
##
##
             Reference
## Prediction nonspam spam
                 1044
                       78
##
      nonspam
                   71 647
##
      spam
##
##
                  Accuracy: 0.919
##
                    95% CI : (0.9056, 0.9311)
       No Information Rate: 0.606
##
```

```
P-Value [Acc > NIR] : <2e-16
##
##
##
                     Kappa: 0.8301
    Mcnemar's Test P-Value : 0.623
##
##
               Sensitivity: 0.9363
##
##
               Specificity: 0.8924
            Pos Pred Value: 0.9305
##
##
            Neg Pred Value: 0.9011
                Prevalence: 0.6060
##
##
            Detection Rate: 0.5674
      Detection Prevalence: 0.6098
##
         Balanced Accuracy: 0.9144
##
##
##
          'Positive' Class : nonspam
##
##
## Call:
## roc.default(response = testing$typeNum, predictor = resultsNum)
## Data: resultsNum in 1115 controls (testing$typeNum 0) < 725 cases (testing$typeNum 1).
## Area under the curve: 0.9144
```

My test dataset contains 60.5939877 percent nonspam emails, so I will use this as a baseline for accuracy. After training a binomial model on 60.0086938 percent of the data, I predicted the type of email in the test dataset (which consisted of the remaining rows). I got an accuracy of 0.9221363 and AUC of 0.9143683.