# The Influence of Text Characteristics for Email Classification

Group 22

```
library(ggplot2)
library(dplyr)
library(moderndive)
library(gapminder)
library(skimr)
library(tidyverse)
library(gt)
library(patchwork)
library(gridExtra)
library(broom)
library(knitr)
library(GGally)
library(sjPlot)
```

email<-read.csv("C:/Users/70652/Desktop/STATS5085 Data Analysis Skills/Project 2/DAS-Group-2

```
email$yesno<-as.factor(email$yesno)
```

- 1 Introduction
- 2 Exploratory Data Analysis
- 2.1 Correlation

```
ggpairs(email[,1:6]) +
  theme(plot.background = element_rect(
    fill = "transparent",
    colour = NA,
    size = 1))
```

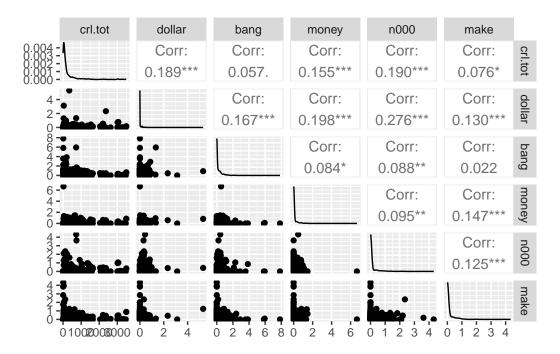


Figure 1: Correlations between each variables.

#### 2.2 Data Visualization

## Spam indictor with total length of uninterrupted sequences of

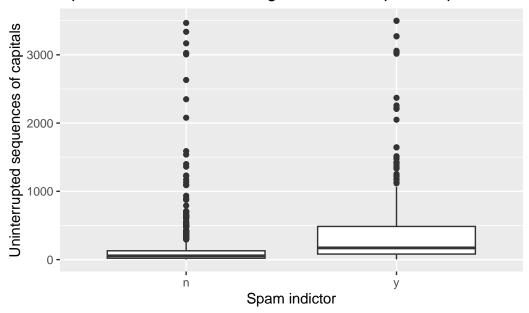


Figure 2: Boxplot of total length of uninterrupted sequences of capitals.

```
ggplot(email, aes(x = yesno, y = dollar)) +
  geom_boxplot() +
  labs(x = "Spam indictor", y = "Occurrences of the dollar sign",
      title = "Spam indictor with occurrences of the dollar sign")
```

# Spam indictor with occurrences of the dollar sign

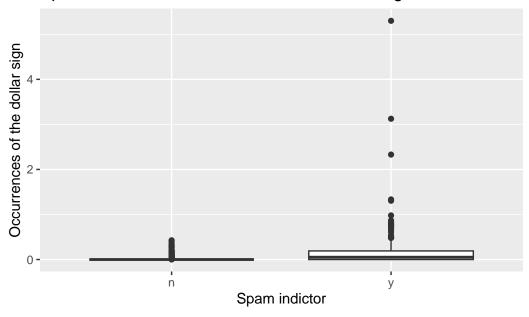


Figure 3: Boxplot of occurrences of the dollar sign.

```
ggplot(email, aes(x = yesno, y = bang)) +
  geom_boxplot() +
  labs(x = "Spam indictor", y = 'Occurrences of "!"',
      title = 'Spam indictor with occurrences of "!"')
```

# Spam indictor with occurrences of "!"

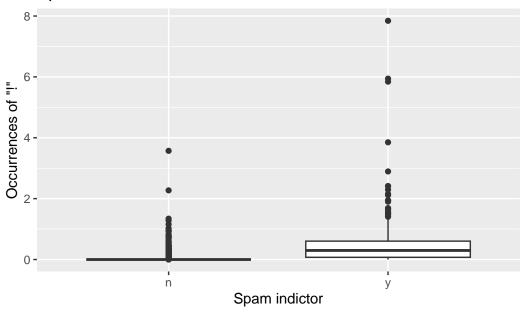


Figure 4: Boxplot of occurrences of '!'.

# Spam indictor with occurrences of "money"

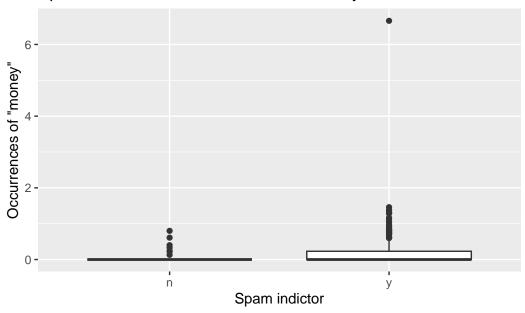


Figure 5: Boxplot of occurrences of "money".

```
ggplot(email, aes(x = yesno, y = n000)) +
  geom_boxplot() +
  labs(x = "Spam indictor", y = 'Occurrences of "000"',
     title = 'Spam indictor with occurrences of "000"')
```

# Spam indictor with occurrences of "000"

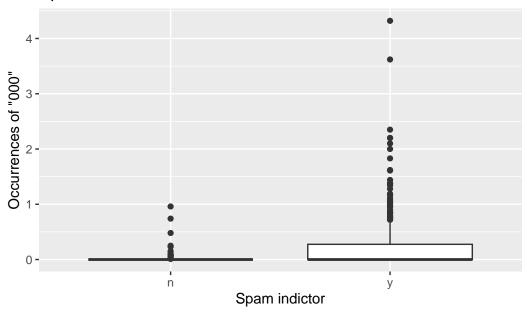


Figure 6: Boxplot of occurrences of '000'.

```
ggplot(email, aes(x = yesno, y = make)) +
  geom_boxplot() +
  labs(x = "Spam indictor", y = 'Occurrences of "make"',
       title = 'Spam indictor with occurrences of "make"')
```

## Spam indictor with occurrences of "make"

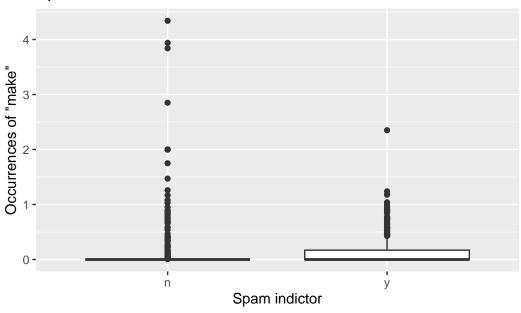


Figure 7: Boxplot of occurrences of 'make'.

#### 3 Formal Data Analysis

#### 3.1 Fitting Model in Log-odds

```
dollar
            8.1346140 1.5396484 5.283 1.27e-07 ***
bang
            2.9172085 0.3363971 8.672 < 2e-16 ***
            5.9724851 1.2455257 4.795 1.63e-06 ***
money
n000
            3.4827736 1.0261134 3.394 0.000688 ***
           -0.4553154  0.4065463  -1.120  0.262731
make
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 1234.17 on 919 degrees of freedom
Residual deviance: 752.44 on 913 degrees of freedom
AIC: 766.44
Number of Fisher Scoring iterations: 7
mod1coefs <- round(coef(model1), 2)</pre>
model2 <- glm(yesno ~ crl.tot+dollar+bang+money+n000, data = email,</pre>
            family = binomial(link = "logit"))
summary(model2)
Call:
glm(formula = yesno ~ crl.tot + dollar + bang + money + n000,
    family = binomial(link = "logit"), data = email)
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.8455026 0.1229712 -15.008 < 2e-16 ***
crl.tot
            0.0005579 0.0001887 2.956 0.003115 **
dollar
            8.1812828 1.5395890 5.314 1.07e-07 ***
            2.9348590 0.3371484 8.705 < 2e-16 ***
bang
            5.8334954 1.2421522 4.696 2.65e-06 ***
money
n000
            3.4273127 1.0224981 3.352 0.000803 ***
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
```

Null deviance: 1234.17 on 919 degrees of freedom Residual deviance: 754.04 on 914 degrees of freedom

AIC: 766.04

Number of Fisher Scoring iterations: 7

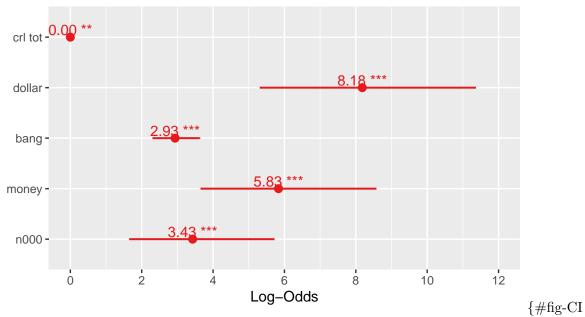
```
mod2coefs <- round(coef(model2), 3)</pre>
```

#### levels(email\$yesno)

$$\begin{split} \ln\left(\frac{p}{1-p}\right) &= \alpha + \beta_{crl.tot} \cdot \text{crl.tot} + \beta_{dollar} \cdot \text{dollar} + \beta_{bang} \cdot \text{bang} + \\ &\beta_{money} \cdot \text{money} + \beta_{n000} \cdot \text{n000} \\ &= -1.846 + 0.001 \cdot \text{crl.tot} + 8.181 \cdot \text{dollar} + 2.935 \cdot \text{bang} + 5.833 \cdot \text{money} + 3.427 \cdot \text{n000} \end{split}$$

	2.5~%	97.5~%
(Intercept)	-2.0926399	-1.610104
crl.tot	0.0001855	0.000936
dollar	5.3097543	11.355237
bang	2.3039250	3.626788
money	3.6506969	8.565015
n000	1.6521512	5.709387

## Log-Odds (Email indicator)



of Log-odds fig-pos='H'}

#### 3.2 Odds

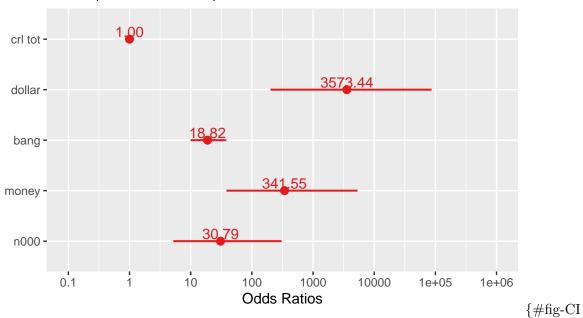
We can obtain the odds scale  $p = \frac{p}{1-p}$  by

$$\frac{p}{1-p} = exp(-1.846 + 0.001 \cdot \text{crl.tot} + 8.181 \cdot \text{dollar} + 2.935 \cdot \text{bang} + 5.833 \cdot \text{money} + 3.427 \cdot \text{n}000)$$

```
model2 %>%
coef() %>%
exp()
```

```
(Intercept) crl.tot dollar bang money n000 0.1579459 1.0005580 3573.4357177 18.8188489 341.5504504 30.7937797
```

## Odds (Email indicator)



of odds scale fig-pos='H'}

#### 3.3 Probabilities

We can obtain the probability p = Prob(spam) by

$$p = \frac{exp(-1.846 + 0.001 \cdot \text{crl.tot} + 8.181 \cdot \text{dollar} + 2.935 \cdot \text{bang} + 5.833 \cdot \text{money} + 3.427 \cdot \text{n000})}{1 + exp(-1.846 + 0.001 \cdot \text{crl.tot} + 8.181 \cdot \text{dollar} + 2.935 \cdot \text{bang} + 5.833 \cdot \text{money} + 3.427 \cdot \text{n000})}$$

# 4 Conclusion