

R Notebook

Code ▾

s...	to_multiple	fr...	cc	sent_email	time	im...	attach	dollar	win...					
<fctr><fctr>		<fctr><int><fctr>			<S3: POSIXct>	<dbl>	<dbl>	<dbl>	<fctr>					
0	0	1	0	0	2012-01-01 07:16:41	0	0	0	no					
0	0	1	0	0	2012-01-01 08:03:59	0	0	0	no					
0	0	1	0	0	2012-01-01 17:00:32	0	0	4	no					
0	0	1	0	0	2012-01-01 10:09:49	0	0	0	no					
0	0	1	0	0	2012-01-01 11:00:01	0	0	0	no					
0	0	1	0	0	2012-01-01 11:04:46	0	0	0	no					
0	1	1	0	1	2012-01-01 18:55:06	0	0	0	no					
0	1	1	1	1	2012-01-01 19:45:21	1	1	0	no					
0	0	1	0	0	2012-01-01 22:08:59	0	0	0	no					
0	0	1	0	0	2012-01-01 19:12:00	0	0	0	no					
1-10 of 3,921 rows   1-10 of 21 columns					Previous	1	2	3	4	5	6	...	100	Next

Hide

```
dim(email)
```

```
[1] 3921  21
```

1 - Variables categoricas binomiales: to\_multiple, from, sent\_email, image, winner, format, re\_subj, exclaim\_subj, urgent\_subj. Variables categoricas ordinales: number.

2 - variables cuantitativas: cc, time, attach, dollar, password, num\_char, line\_breaks, exclaim\_mess

Hide

```
write.csv(x = email, file = "email.csv", row.names = FALSE, col.names = TRUE)
```

```
attempt to set 'col.names' ignored
```

Hide

```
sum(is.na(email))
```

```
[1] 0
```

La variable dependiente a predecir es spam, en el que se recoge si un mail va a la bandeja de spam del correo del destinatario, o por el contrario va a la bandeja de recibidos.

Se trata de una variable categorica binomial: (0 - NO / 1 - SI)

Hide

```
library(summarytools)

table(email$spam)
```

```
  0    1
3554 367
```

Hide

```
freq(email$spam, style = "rmarkdown")
```

```
### Frequencies
#### email$spam
**Type:** Factor
```

		Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
**0**		3554	90.64	90.64	90.64	90.64
**1**		367	9.36	100.00	9.36	100.00
**\<NA\>**		0			0.00	100.00
**Total**		3921	100.00	100.00	100.00	100.00

Podemos ver en esta tabla de frecuencias de los 3921 mails analizados, 3554(90.64%) son catalogados como NO spam(en caso de que 0 sea que no) y 367 (9.36%) son catalogados como si spam. No tenemos valores nulos en esta variable.

## Vamos a comenzar analizando las variables cuantitativas

### CC

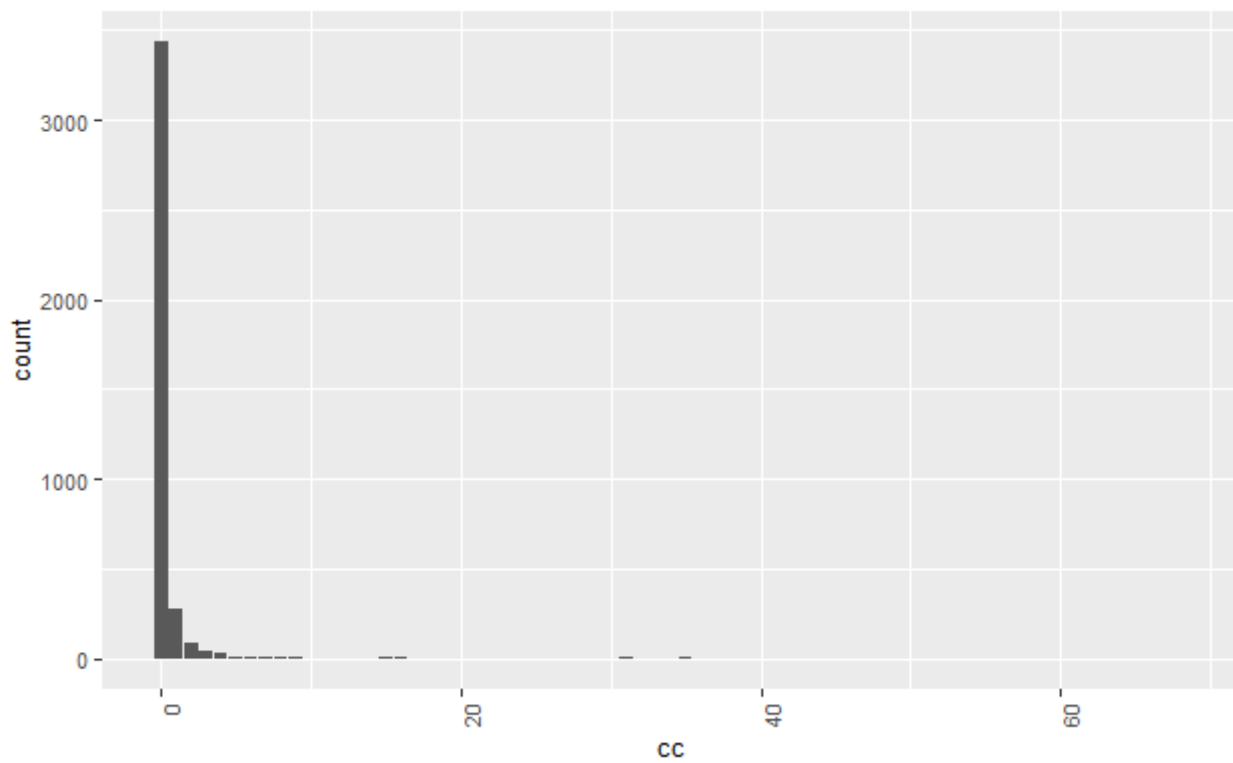
Hide

```
summary(email$cc)
```

```
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.0000  0.0000  0.0000  0.4045  0.0000 68.0000
```

¿ Cuanta gente suele ir en copia en estos correos?

Vamos a realizar un histograma y un grafico de bigotes

[Hide](#)

```
ctable(email$cc, email$spam)
```

## Cross-Tabulation, Row Proportions

cc \* spam

Data Frame: email

	spam	0	1	Total
cc				
0	3087 ( 89.8%)	349 ( 10.2%)	3436 (100.0%)	
1	278 (100.0%)	0 ( 0.0%)	278 (100.0%)	
2	80 (100.0%)	0 ( 0.0%)	80 (100.0%)	
3	39 ( 95.1%)	2 ( 4.9%)	41 (100.0%)	
4	21 ( 63.6%)	12 ( 36.4%)	33 (100.0%)	
5	7 (100.0%)	0 ( 0.0%)	7 (100.0%)	
6	9 (100.0%)	0 ( 0.0%)	9 (100.0%)	
7	8 (100.0%)	0 ( 0.0%)	8 (100.0%)	
8	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
9	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
12	0 ( 0.0%)	1 (100.0%)	1 (100.0%)	
13	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
15	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
16	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
18	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
19	0 ( 0.0%)	1 (100.0%)	1 (100.0%)	
21	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
23	0 ( 0.0%)	1 (100.0%)	1 (100.0%)	
25	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
31	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
33	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
35	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
38	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
50	0 ( 0.0%)	1 (100.0%)	1 (100.0%)	
64	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
68	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	

Vamos a convertir esta variable en binaria, entre los que si van en copia y los que no.

[Hide](#)

```
ctable(email$cc_binary, email$spam)
```

## Cross-Tabulation, Row Proportions

cc\_binary \* spam

Data Frame: email

	spam	0	1	Total
cc_binary				
0	3087 (89.8%)	349 (10.2%)	3436 (100.0%)	
1	467 (96.3%)	18 ( 3.7%)	485 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

# attach

Cuantos documentos adjuntos suelen llevar estos mails ??

[Hide](#)

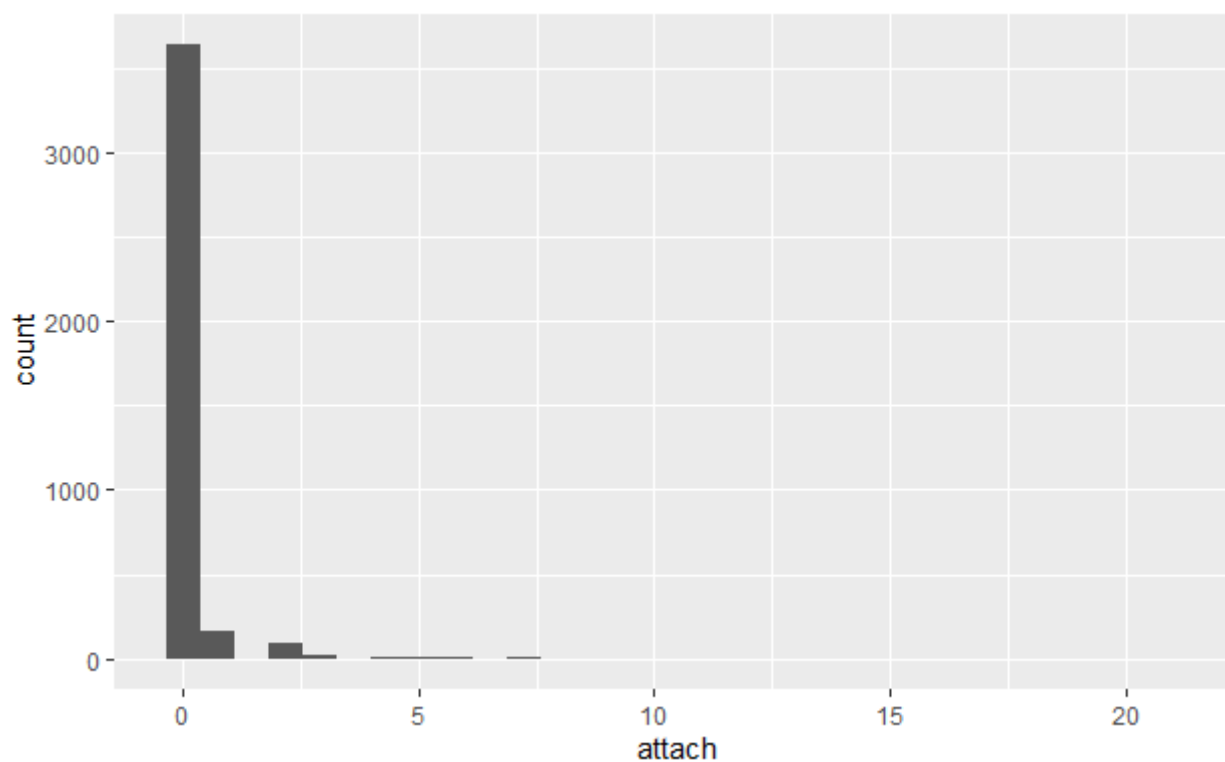
```
table(email$attach)
```

0	1	2	3	4	5	6	7	8	9	10	20	21
3638	158	90	19	3	4	2	2	1	1	1	1	1

[Hide](#)

```
summary(email$attach)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.0000	0.0000	0.0000	0.1329	0.0000	21.0000

[Hide](#)

```
ctable(email$attach, email$spam)
```

Cross-Tabulation, Row Proportions

attach \* spam

Data Frame: email

	spam	0	1	Total
attach				
0	3315 ( 91.1%)	323 ( 8.9%)	3638 (100.0%)	
1	150 ( 94.9%)	8 ( 5.1%)	158 (100.0%)	
2	54 ( 60.0%)	36 (40.0%)	90 (100.0%)	
3	19 (100.0%)	0 ( 0.0%)	19 (100.0%)	
4	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
5	4 (100.0%)	0 ( 0.0%)	4 (100.0%)	
6	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
7	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
8	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
9	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
10	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
20	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
21	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	

Vamos a convertir esta variable en binaria, de tal forma que los correos que NO lleven adjunto será un 0 y los que si un 1

Hide

```
ctable(email$attach_binary, email$spam)
```

Cross-Tabulation, Row Proportions

attach\_binary \* spam

Data Frame: email

	spam	0	1	Total
attach_binary				
0	3315 (91.1%)	323 ( 8.9%)	3638 (100.0%)	
1	239 (84.5%)	44 (15.5%)	283 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

Podemos ver como el 15.5% de los correos que contiene algun adjunto es catalogado como spam.

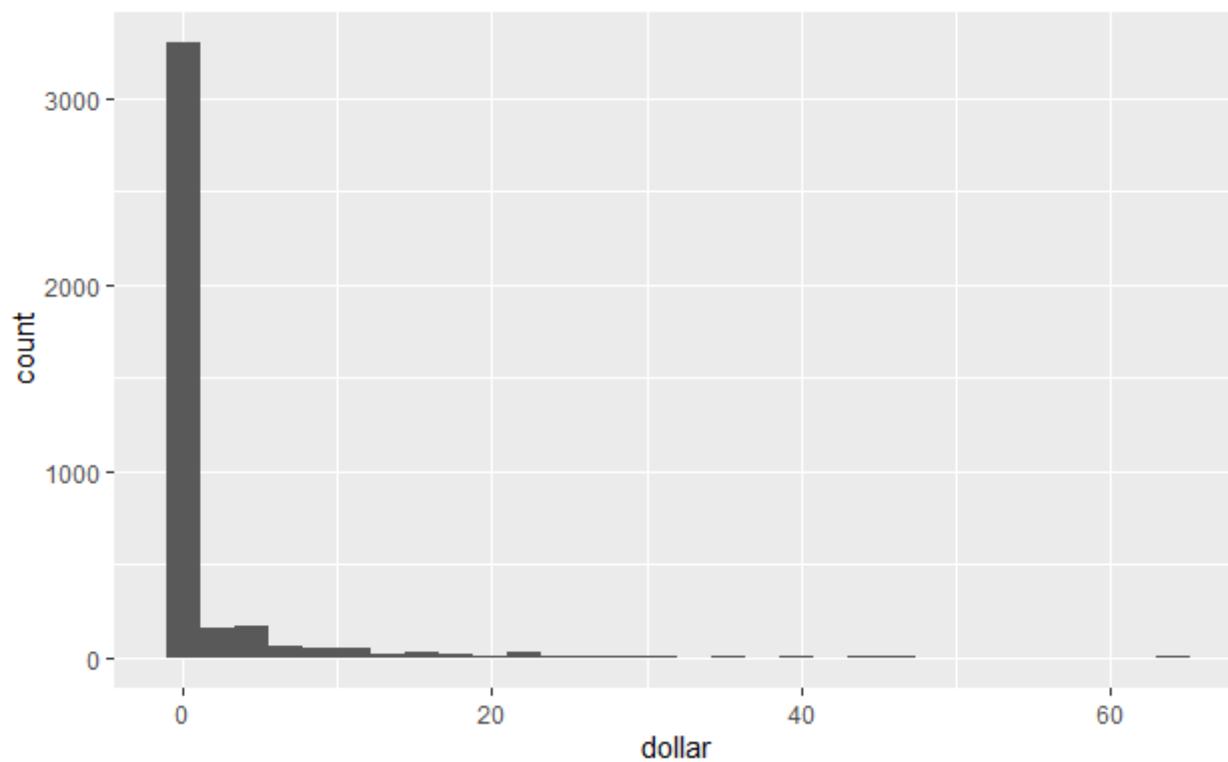
## dollar

Variable que recoge las veces que aparece el simbolo dolar.

Hide

```
summary(email$dollar)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.000	0.000	0.000	1.467	0.000	64.000

[Hide](#)

```
ctable(email$dollar, email$spam)
```

## Cross-Tabulation, Row Proportions

dollar \* spam

Data Frame: email

	spam	0	1	Total
dollar				
0	2886 ( 90.9%)	289 ( 9.1%)	3175 (100.0%)	
1	97 ( 80.8%)	23 ( 19.2%)	120 (100.0%)	
2	122 ( 80.8%)	29 ( 19.2%)	151 (100.0%)	
3	4 ( 40.0%)	6 ( 60.0%)	10 (100.0%)	
4	139 ( 95.2%)	7 ( 4.8%)	146 (100.0%)	
5	15 ( 75.0%)	5 ( 25.0%)	20 (100.0%)	
6	43 ( 97.7%)	1 ( 2.3%)	44 (100.0%)	
7	9 ( 75.0%)	3 ( 25.0%)	12 (100.0%)	
8	34 ( 97.1%)	1 ( 2.9%)	35 (100.0%)	
9	10 (100.0%)	0 ( 0.0%)	10 (100.0%)	
10	22 (100.0%)	0 ( 0.0%)	22 (100.0%)	
11	10 (100.0%)	0 ( 0.0%)	10 (100.0%)	
12	20 (100.0%)	0 ( 0.0%)	20 (100.0%)	
13	7 (100.0%)	0 ( 0.0%)	7 (100.0%)	
14	14 (100.0%)	0 ( 0.0%)	14 (100.0%)	
15	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
16	23 (100.0%)	0 ( 0.0%)	23 (100.0%)	
17	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
18	14 (100.0%)	0 ( 0.0%)	14 (100.0%)	
19	0 ( 0.0%)	1 (100.0%)	1 (100.0%)	
20	10 (100.0%)	0 ( 0.0%)	10 (100.0%)	
21	7 (100.0%)	0 ( 0.0%)	7 (100.0%)	
22	12 (100.0%)	0 ( 0.0%)	12 (100.0%)	
23	7 (100.0%)	0 ( 0.0%)	7 (100.0%)	
24	7 (100.0%)	0 ( 0.0%)	7 (100.0%)	
25	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
26	6 ( 85.7%)	1 ( 14.3%)	7 (100.0%)	
27	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
28	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
29	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
30	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
32	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
34	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
36	1 ( 50.0%)	1 ( 50.0%)	2 (100.0%)	
40	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
44	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
46	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
48	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
54	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
63	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
64	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	

Hide

```
ctable(email$dollar_binned, email$spam)
```

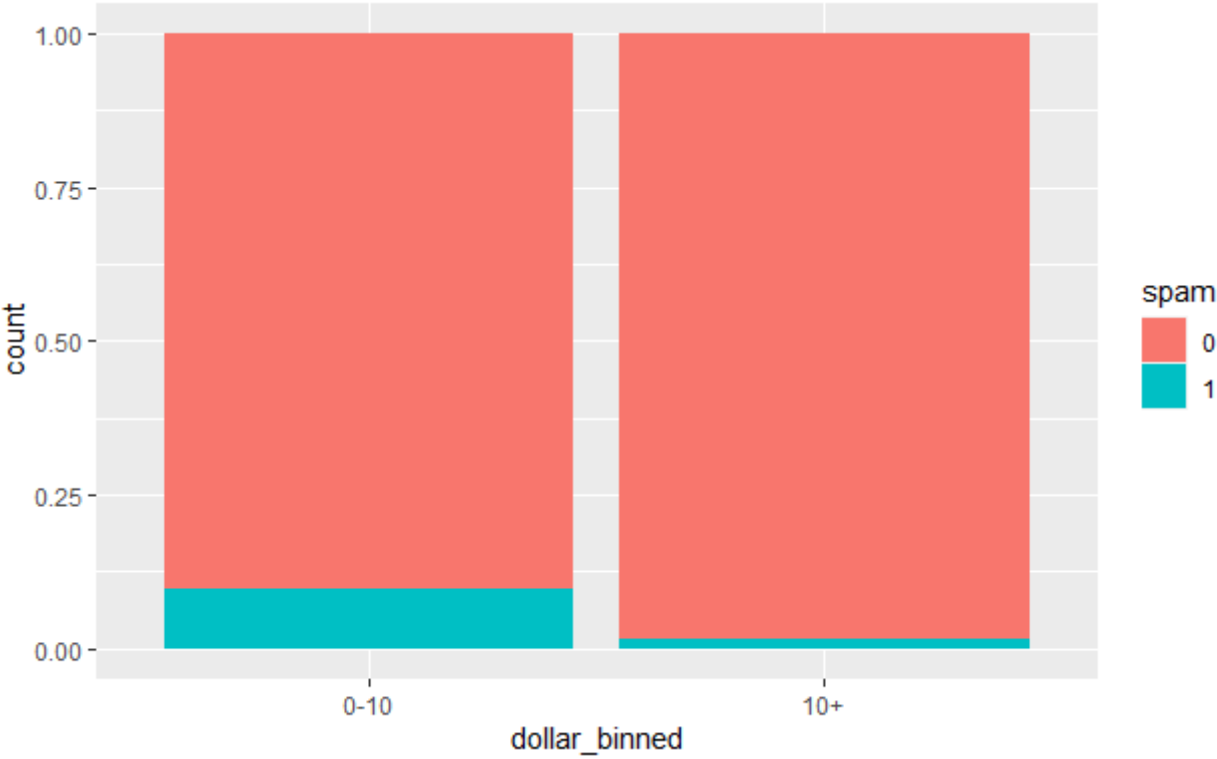


Cross-Tabulation, Row Proportions  
dollar\_binned \* spam  
Data Frame: email

	spam	0	1	Total
dollar_binned				
0-10	3359 (90.2%)	364 ( 9.8%)	3723 (100.0%)	
10+	195 (98.5%)	3 ( 1.5%)	198 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

Hide

```
ggplot(email, aes(dollar_binned, fill = spam)) + geom_bar(position = "fill")
```



# password

Cuántas veces se repite la palabra password dentro de una correo electronico

Hide

```
table(email$password)
```

0	1	2	3	4	5	6	8	11	13	18	22	28
3809	22	39	8	23	5	3	5	2	1	1	2	1

Hide

```
ctable(email$password, email$spam)
```

Cross-Tabulation, Row Proportions  
password \* spam  
Data Frame: email

	spam	0	1	Total
password				
0	3446 ( 90.5%)	363 ( 9.5%)	3809 (100.0%)	
1	20 ( 90.9%)	2 ( 9.1%)	22 (100.0%)	
2	37 ( 94.9%)	2 ( 5.1%)	39 (100.0%)	
3	8 (100.0%)	0 ( 0.0%)	8 (100.0%)	
4	23 (100.0%)	0 ( 0.0%)	23 (100.0%)	
5	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
6	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
8	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
11	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
13	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
18	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
22	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
28	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	

Vamos a convertir la variable password en binaria, 0 - ninguna / 1 - alguna vez

Hide

```
email <- email %>%
  mutate(password_binary = ifelse(password == 0,0,1))

ctable(email$password_binary, email$spam)
```

Cross-Tabulation, Row Proportions  
password\_binary \* spam  
Data Frame: email

	spam	0	1	Total
password_binary				
0	3446 (90.5%)	363 ( 9.5%)	3809 (100.0%)	
1	108 (96.4%)	4 ( 3.6%)	112 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

En un 9.5% de los casos en los que no aparece la palabra password se declara como spam y solo un 3.6% cuando aparece alguna vez la palabra password.

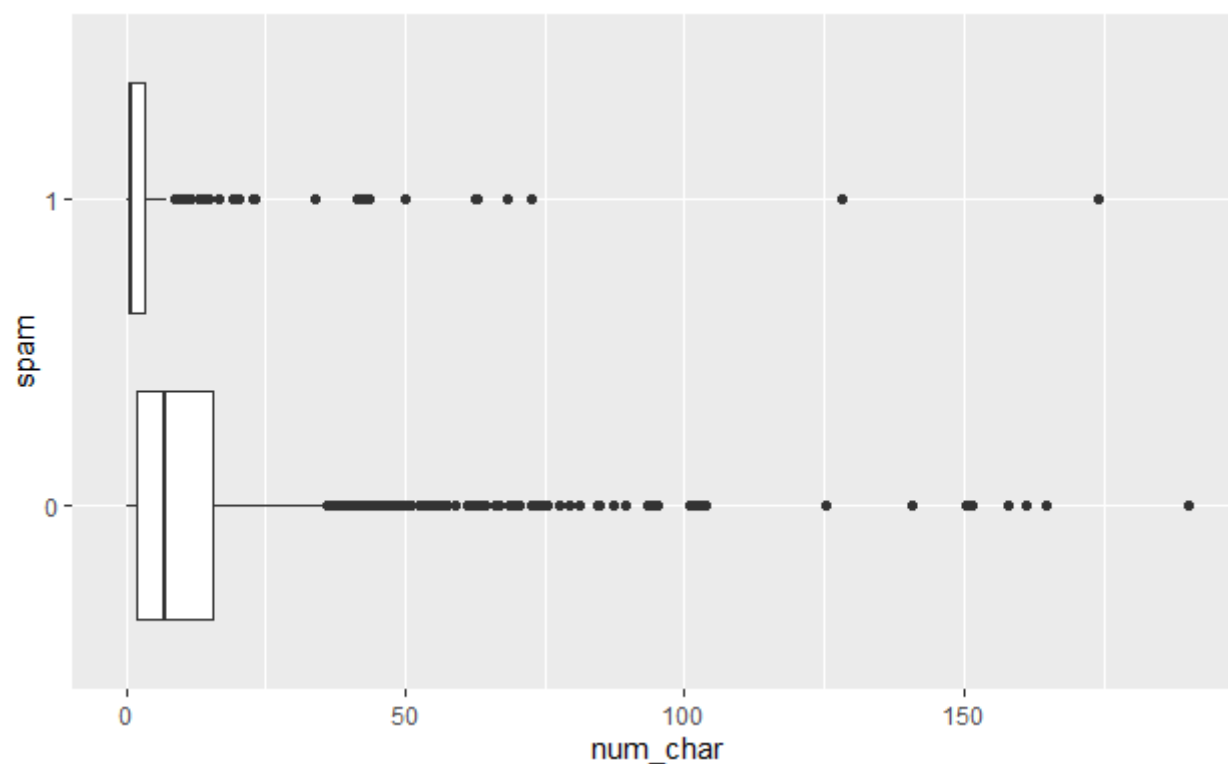
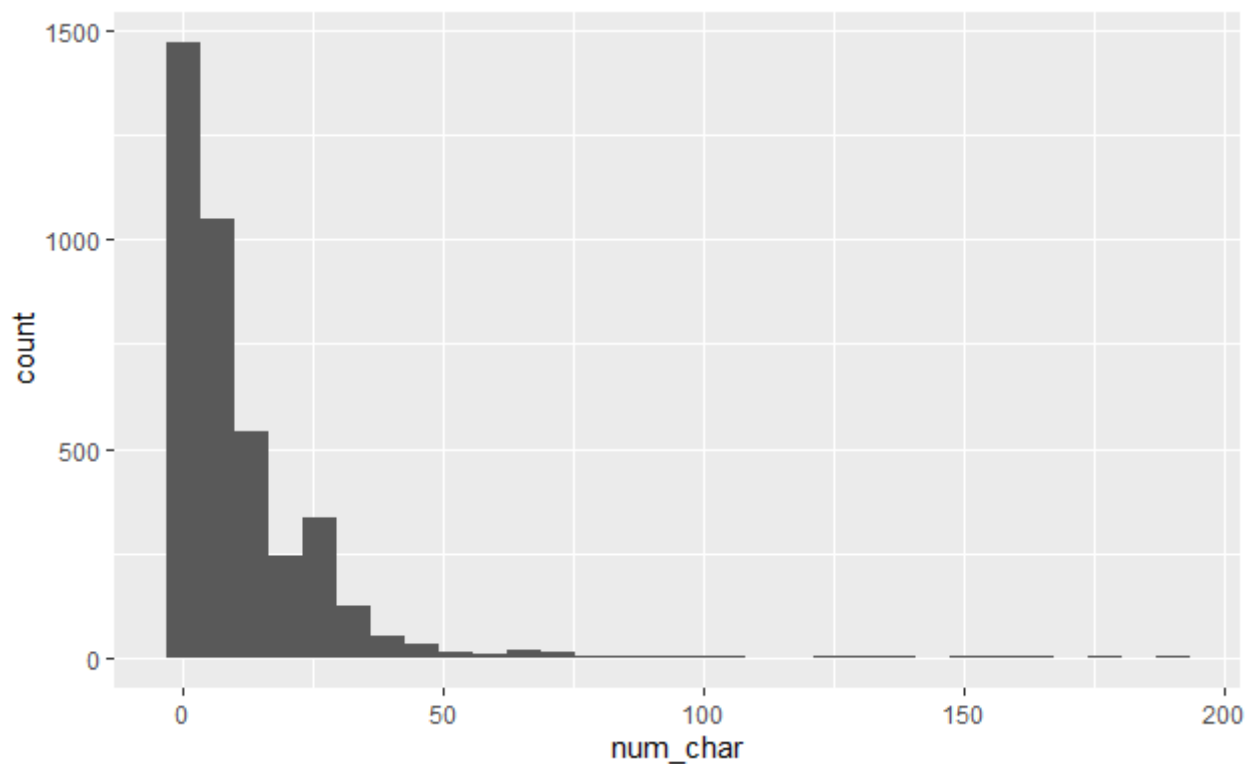
# num\_char

¿Son determinantes los caracteres a la hora de establecer un correo como spam?

Hide

```
summary(email$num_char)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.001	1.459	5.856	10.707	14.084	190.087



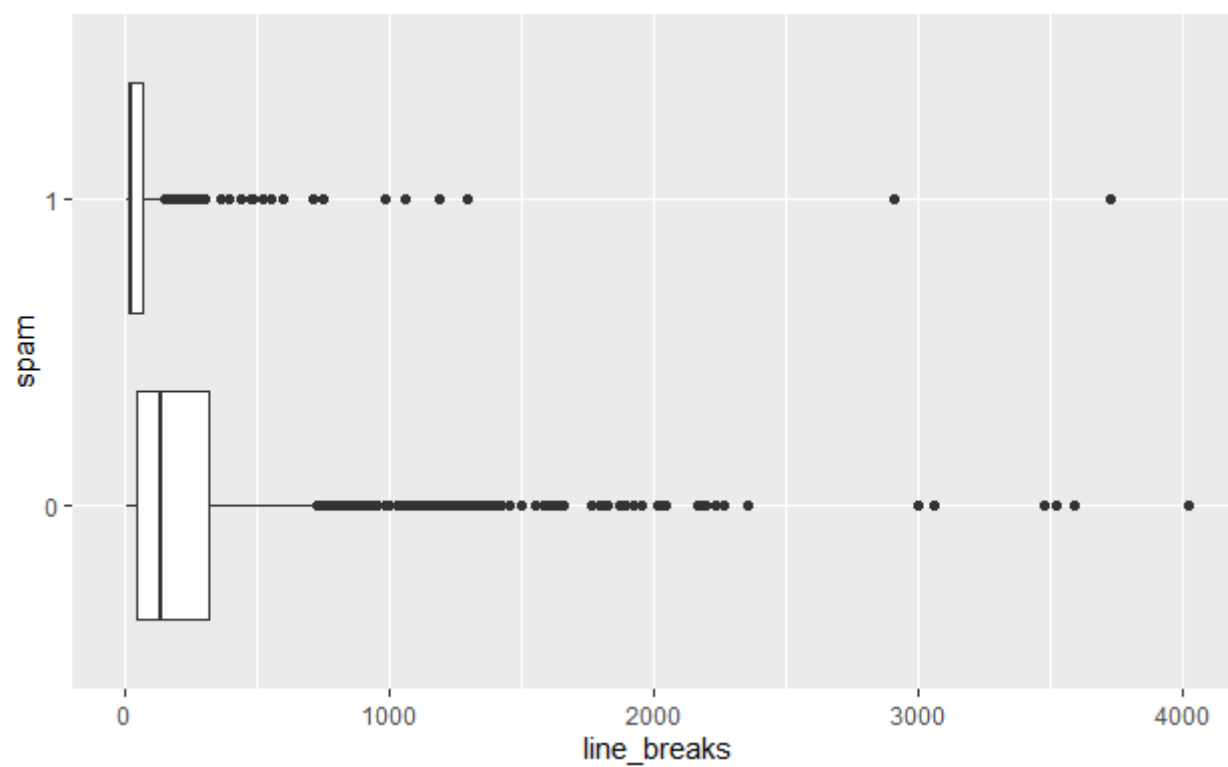
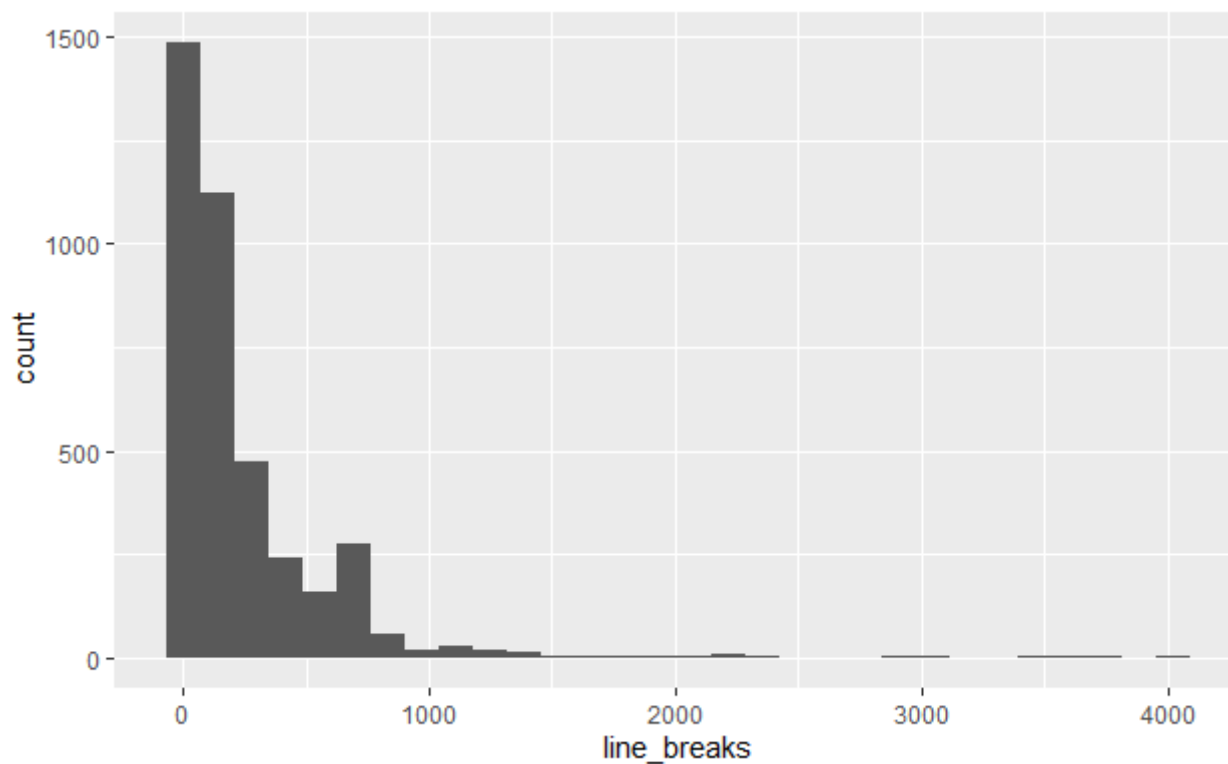
## line\_breaks - saltos de linea

¿ Los saltos de liena son determinantes a la hora de declarar un correo como spam?

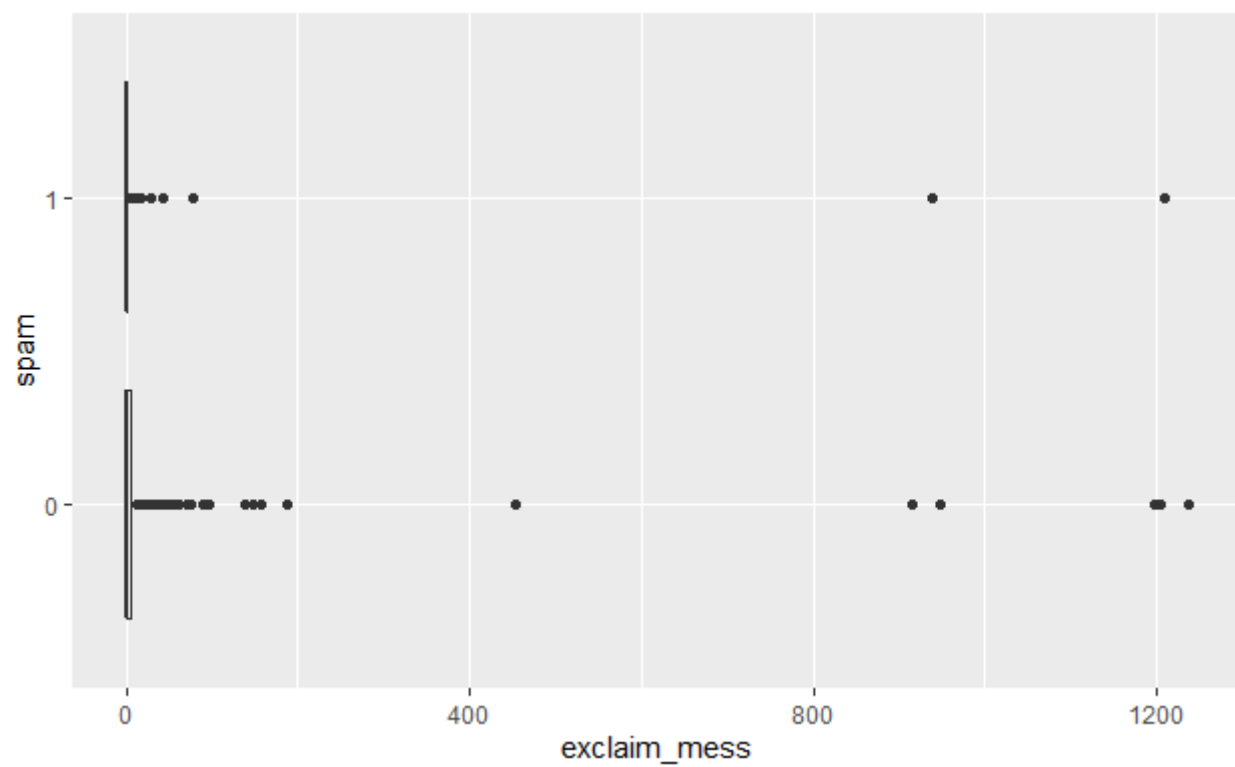
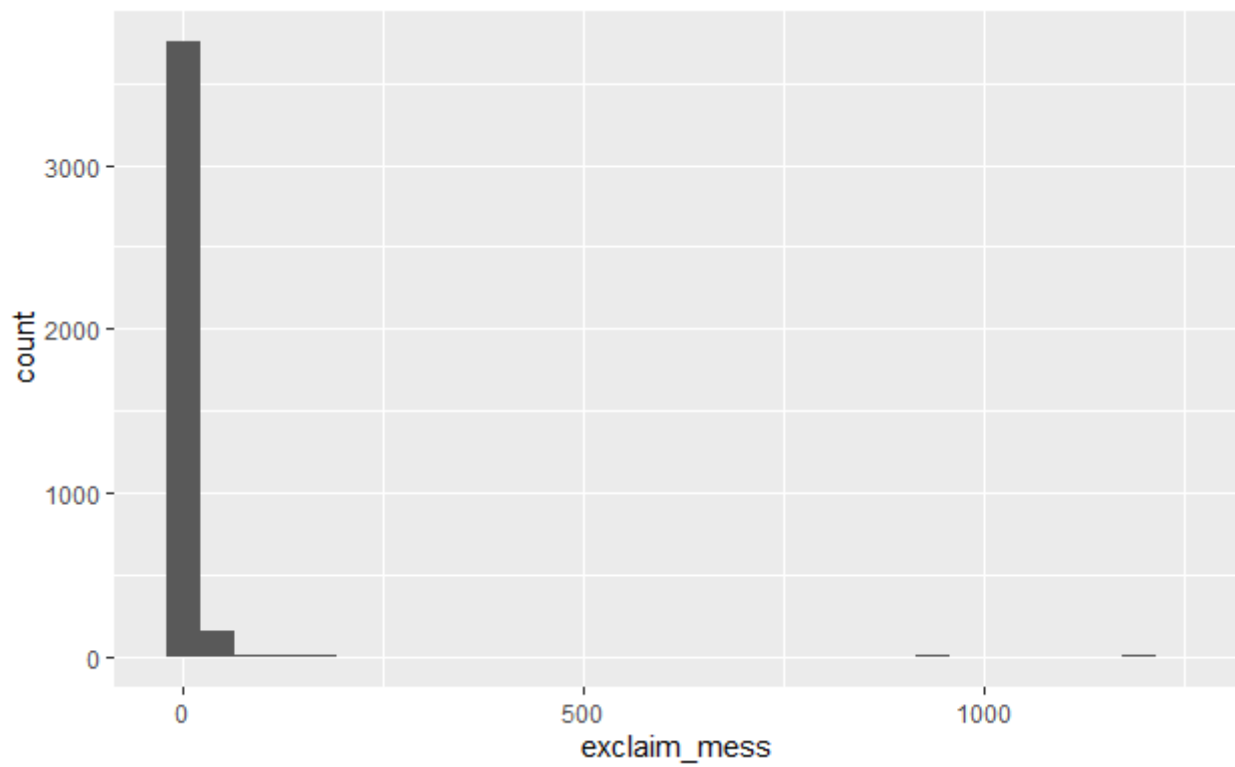
Hide

```
summary(email$line_breaks)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.0	34.0	119.0	230.7	298.0	4022.0



# exclaim\_mess

[Hide](#)

```
ctable(email$exclaim_mess, email$spam)
```

## Cross-Tabulation, Row Proportions

exclaim\_mess \* spam

Data Frame: email

	spam	0	1	Total
exclaim_mess				
0	1219 ( 84.9%)	216 ( 15.1%)	1435 (100.0%)	
1	650 ( 88.7%)	83 ( 11.3%)	733 (100.0%)	
2	482 ( 95.1%)	25 ( 4.9%)	507 (100.0%)	
3	116 ( 90.6%)	12 ( 9.4%)	128 (100.0%)	
4	185 ( 97.4%)	5 ( 2.6%)	190 (100.0%)	
5	112 ( 99.1%)	1 ( 0.9%)	113 (100.0%)	
6	112 ( 97.4%)	3 ( 2.6%)	115 (100.0%)	
7	49 ( 96.1%)	2 ( 3.9%)	51 (100.0%)	
8	91 ( 97.8%)	2 ( 2.2%)	93 (100.0%)	
9	40 ( 88.9%)	5 ( 11.1%)	45 (100.0%)	
10	83 ( 97.6%)	2 ( 2.4%)	85 (100.0%)	
11	17 (100.0%)	0 ( 0.0%)	17 (100.0%)	
12	53 ( 94.6%)	3 ( 5.4%)	56 (100.0%)	
13	20 (100.0%)	0 ( 0.0%)	20 (100.0%)	
14	42 ( 97.7%)	1 ( 2.3%)	43 (100.0%)	
15	11 (100.0%)	0 ( 0.0%)	11 (100.0%)	
16	28 ( 96.6%)	1 ( 3.4%)	29 (100.0%)	
17	11 ( 91.7%)	1 ( 8.3%)	12 (100.0%)	
18	26 (100.0%)	0 ( 0.0%)	26 (100.0%)	
19	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
20	29 (100.0%)	0 ( 0.0%)	29 (100.0%)	
21	9 (100.0%)	0 ( 0.0%)	9 (100.0%)	
22	15 (100.0%)	0 ( 0.0%)	15 (100.0%)	
23	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
24	11 (100.0%)	0 ( 0.0%)	11 (100.0%)	
25	6 (100.0%)	0 ( 0.0%)	6 (100.0%)	
26	11 (100.0%)	0 ( 0.0%)	11 (100.0%)	
27	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
28	5 ( 83.3%)	1 ( 16.7%)	6 (100.0%)	
29	8 (100.0%)	0 ( 0.0%)	8 (100.0%)	
30	13 (100.0%)	0 ( 0.0%)	13 (100.0%)	
31	12 (100.0%)	0 ( 0.0%)	12 (100.0%)	
32	13 (100.0%)	0 ( 0.0%)	13 (100.0%)	
33	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
34	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
35	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
36	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
38	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
39	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
40	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
41	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
42	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
43	2 ( 66.7%)	1 ( 33.3%)	3 (100.0%)	
44	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
45	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
46	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
47	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
48	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	

49	3 (100.0%)	0 ( 0.0%)	3 (100.0%)
52	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
54	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
55	4 (100.0%)	0 ( 0.0%)	4 (100.0%)
57	2 (100.0%)	0 ( 0.0%)	2 (100.0%)
58	2 (100.0%)	0 ( 0.0%)	2 (100.0%)
62	2 (100.0%)	0 ( 0.0%)	2 (100.0%)
71	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
75	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
78	0 ( 0.0%)	1 (100.0%)	1 (100.0%)
89	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
94	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
96	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
139	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
148	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
157	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
187	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
454	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
915	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
939	0 ( 0.0%)	1 (100.0%)	1 (100.0%)
947	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
1197	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
1203	2 (100.0%)	0 ( 0.0%)	2 (100.0%)
1209	0 ( 0.0%)	1 (100.0%)	1 (100.0%)
1236	1 (100.0%)	0 ( 0.0%)	1 (100.0%)
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)

-----

Vamos ahora a analizar las variables categoricas.

## to\_multiple

Vamos a ver primero, del total de correos analizados, cuantos se envian a multiples personas y cuantos no

[Hide](#)

```
freq(email$to_multiple, style = "rmarkdown")
```

```
### Frequencies
#### email$to_multiple
**Type:** Factor
```

		Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
**0**		3301	84.19	84.19	84.19	84.19
**1**		620	15.81	100.00	15.81	100.00
**\<NA\>**		0			0.00	100.00
**Total**		3921	100.00	100.00	100.00	100.00

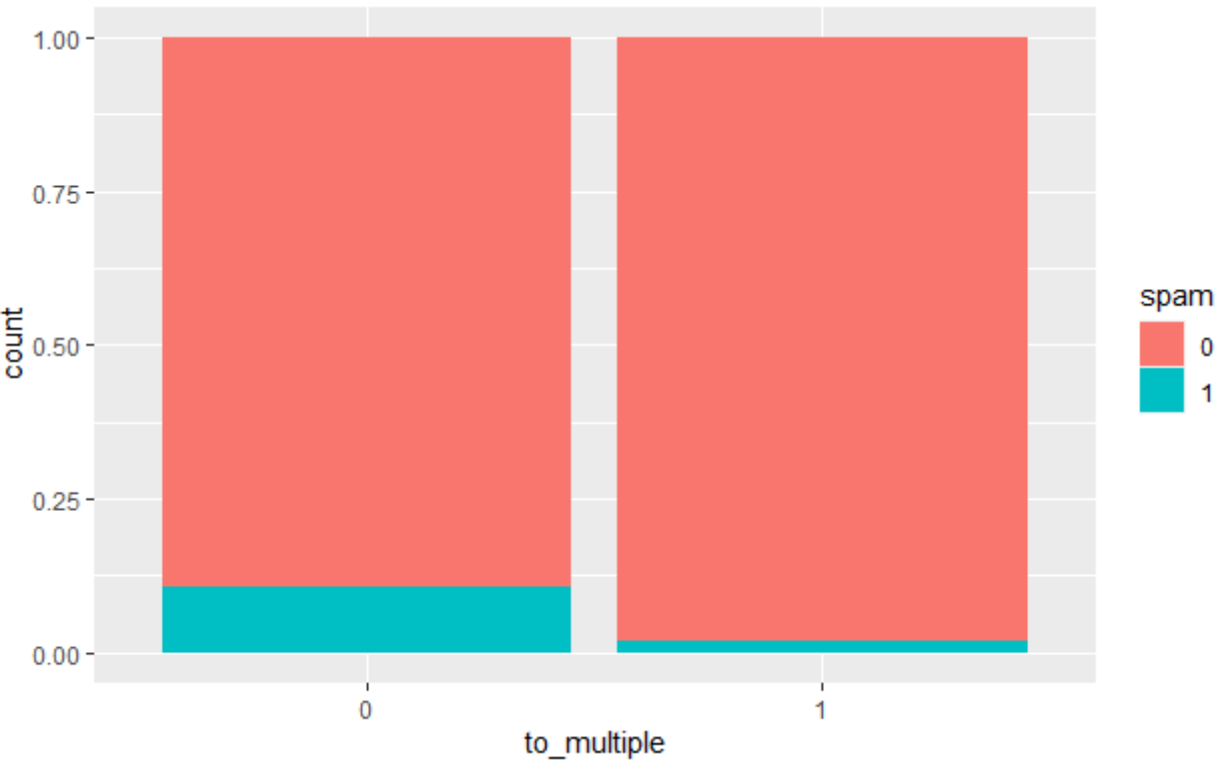
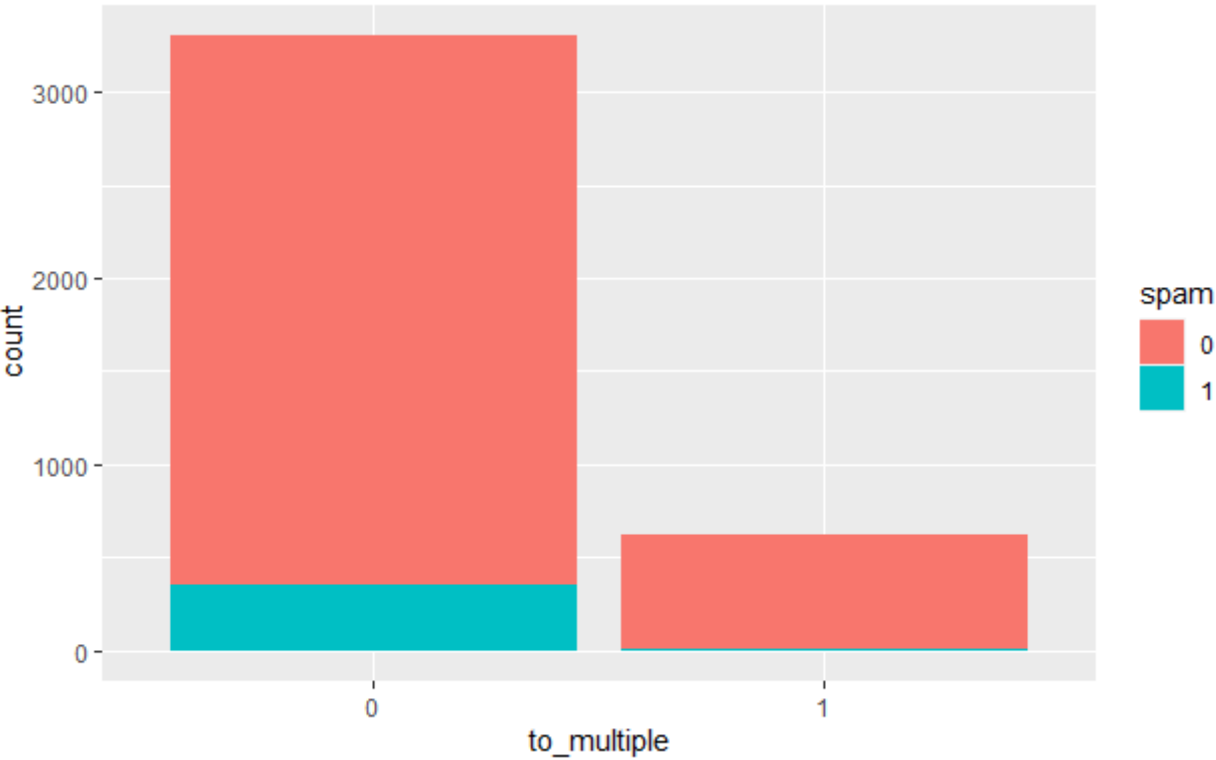
influye que el correo se envíe a multiples personas a la vez, para declararlo como spam ??

[Hide](#)

```
ctable(email$to_multiple, email$spam)
```

Cross-Tabulation, Row Proportions  
to\_multiple \* spam  
Data Frame: email

	spam	0	1	Total
to_multiple				
0	2946 (89.2%)	355 (10.8%)	3301 (100.0%)	
1	608 (98.1%)	12 ( 1.9%)	620 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	





# from

¿DE donde proviene el correo, cuantos correos tienen un origen y cuantos no??

Hide

```
freq(email$from, style = "rmarkdown")
```

### Frequencies  
#### email\$from  
\*\*Type:\*\* Factor

		Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
	**0**	3	0.077	0.077	0.077	0.077
	**1**	3918	99.923	100.000	99.923	100.000
	**\<NA\>**	0			0.000	100.000
	**Total**	3921	100.000	100.000	100.000	100.000

Hide

```
ctable(email$from, email$spam)
```

Cross-Tabulation, Row Proportions  
from \* spam  
Data Frame: email

	spam	0	1	Total
from				
0	0 ( 0.0%)	3 (100.0%)	3 (100.0%)	
1	3554 (90.7%)	364 ( 9.3%)	3918 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

# sent\_email

¿ del total de mails, cuantos son enviados y cuantos no?

Hide

```
freq(email$sent_email, style = "rmarkdown")
```

### Frequencies  
#### email\$sent\_email  
\*\*Type:\*\* Factor

		Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
	**0**	2831	72.20	72.20	72.20	72.20
	**1**	1090	27.80	100.00	27.80	100.00
	**\<NA\>**	0			0.00	100.00
	**Total**	3921	100.00	100.00	100.00	100.00

Hide

```
ctable(email$sent_email, email$spam)
```

Cross-Tabulation, Row Proportions  
sent\_email \* spam  
Data Frame: email

	spam	0	1	Total
sent_email				
0	2464 ( 87.0%)	367 (13.0%)	2831 (100.0%)	
1	1090 (100.0%)	0 ( 0.0%)	1090 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	

# image - imagen

Cuantos correos del total analizados tienen imagen y cuantos no

Hide

```
freq(email$image, style = "rmarkdown")
```

### Frequencies  
#### email\$image  
\*\*Type:\*\* Numeric

	&nbsp;	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
	**0**	3811	97.195	97.195	97.195	97.195
	**1**	76	1.938	99.133	1.938	99.133
	**2**	17	0.434	99.566	0.434	99.566
	**3**	11	0.281	99.847	0.281	99.847
	**4**	2	0.051	99.898	0.051	99.898
	**5**	2	0.051	99.949	0.051	99.949
	**9**	1	0.026	99.974	0.026	99.974
	**20**	1	0.026	100.000	0.026	100.000
	**\<NA\>**	0			0.000	100.000
	**Total**	3921	100.000	100.000	100.000	100.000

Influye el numero de imagenes a la hora de declarar un correo como spam??

Hide

```
ctable(email$image, email$spam)
```

```
Cross-Tabulation, Row Proportions
image * spam
Data Frame: email
```

	spam	0	1	Total
image				
0	3446 ( 90.4%)	365 ( 9.6%)	3811 (100.0%)	
1	74 ( 97.4%)	2 ( 2.6%)	76 (100.0%)	
2	17 (100.0%)	0 ( 0.0%)	17 (100.0%)	
3	11 (100.0%)	0 ( 0.0%)	11 (100.0%)	
4	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
5	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
9	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
20	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	

# WINNER

Cuántas veces aparece la palabra ganador y cuántas no ¿¿?

Hide

```
summary(email$winner)
```

```
no  yes
3857 64
```

Hide

```
freq(email$winner, style = "rmarkdown")
```

```
### Frequencies
#### email$winner
**Type:** Factor
```

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
**no**	3857	98.37	98.37	98.37	98.37
**yes**	64	1.63	100.00	1.63	100.00
**\<NA\>**	0			0.00	100.00
**Total**	3921	100.00	100.00	100.00	100.00

Influye la palabra winner a la hora de declarar un correo como spam

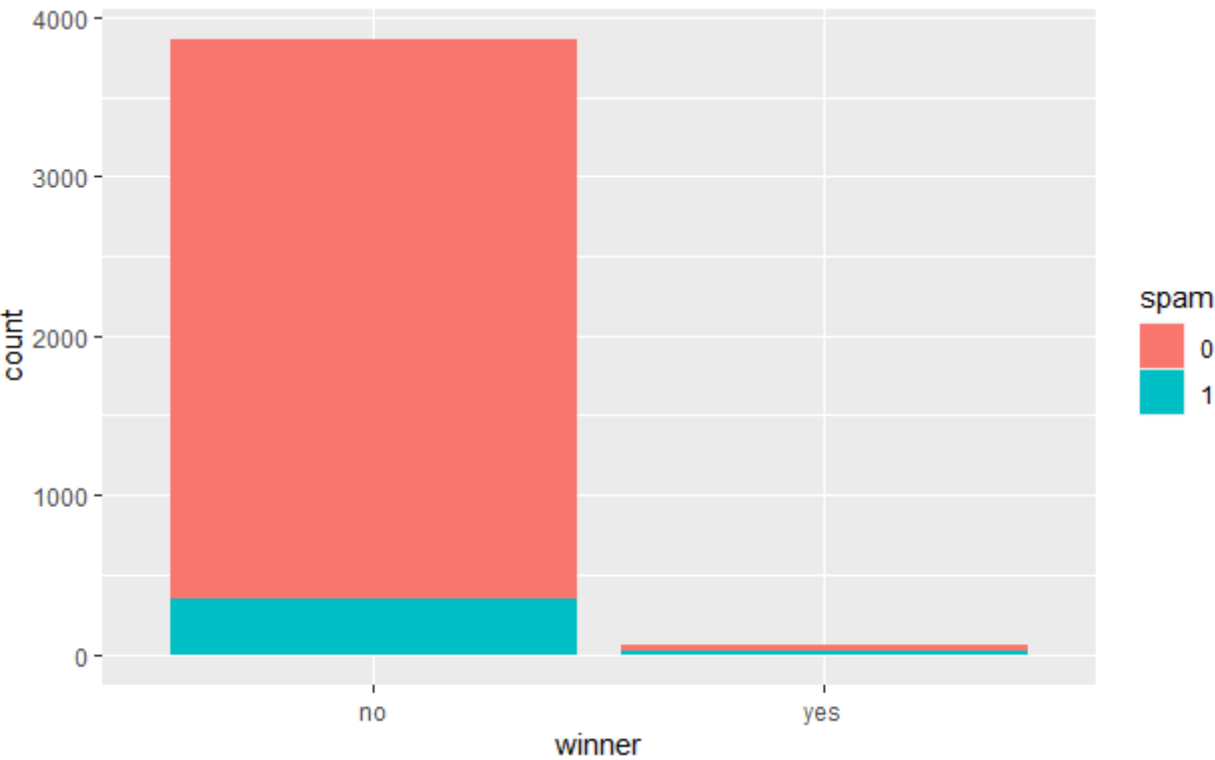
Hide

```
ctable(email$winner, email$spam)
```

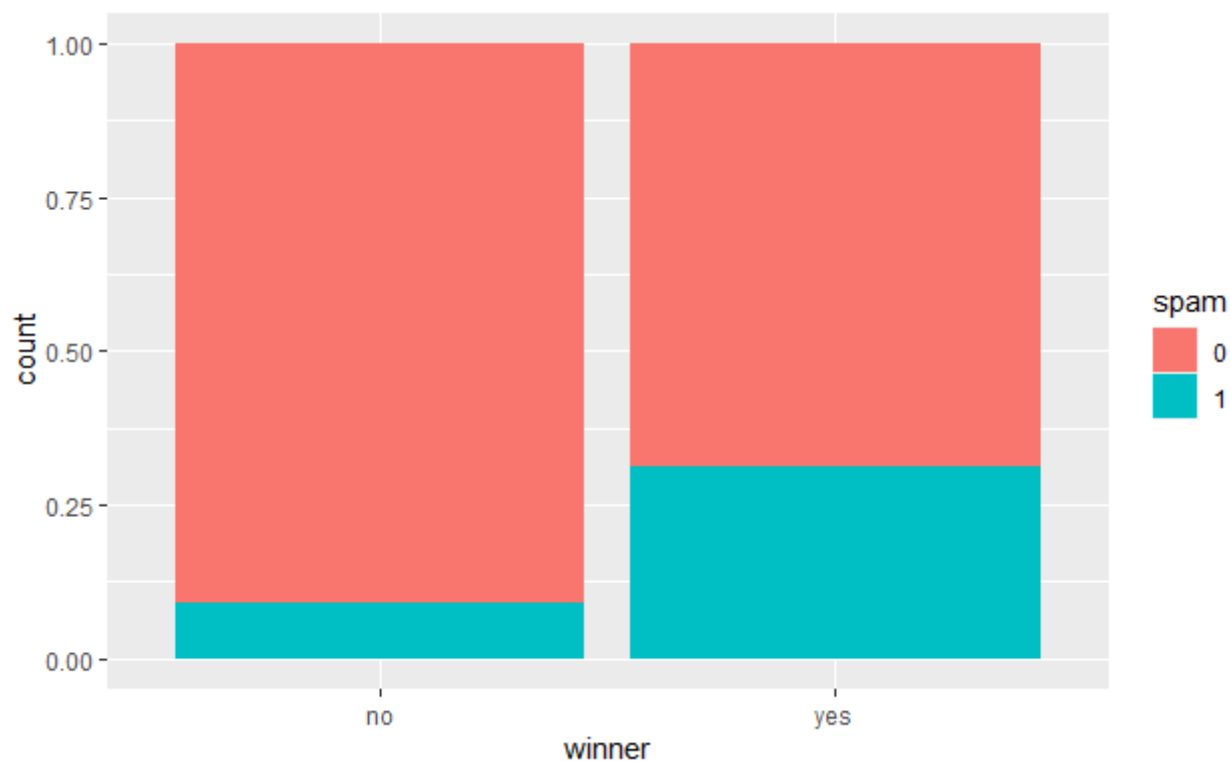
Cross-Tabulation, Row Proportions  
winner \* spam  
Data Frame: email

	spam	0	1	Total
winner				
no	3510 (91.0%)	347 ( 9.0%)	3857 (100.0%)	
yes	44 (68.8%)	20 (31.2%)	64 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

vamos a ver un grafico de esto en valores absolutos



vamos a ver un grafico en terminos relativos



## inherit - heredar

[Hide](#)

```
summary(email$inherit)
```

```

Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.000  0.000   0.000   0.038  0.000   9.000

```

[Hide](#)

```
table(email$inherit)
```

```

  0    1    2    6    9
3793 122    3    2    1

```

Vamos a ver el numero de veces que se repite la palabra heredar(inherit)

[Hide](#)

```
freq(email$inherit, style = "rmarkdown")
```

```
### Frequencies
#### email$inherit
**Type:** Numeric
```

	&nbsp;	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
	**0**	3793	96.736	96.736	96.736	96.736
	**1**	122	3.111	99.847	3.111	99.847
	**2**	3	0.077	99.923	0.077	99.923
	**6**	2	0.051	99.974	0.051	99.974
	**9**	1	0.026	100.000	0.026	100.000
	**\<NA\>**	0			0.000	100.000
	**Total**	3921	100.000	100.000	100.000	100.000

Hide

```
ctable(email$inherit, email$spam)
```

Cross-Tabulation, Row Proportions  
inherit \* spam  
Data Frame: email

	spam	0	1	Total
inherit				
0	3440 ( 90.7%)	353 ( 9.3%)	3793 (100.0%)	
1	109 ( 89.3%)	13 ( 10.7%)	122 (100.0%)	
2	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
6	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
9	0 ( 0.0%)	1 (100.0%)	1 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	

# viagra

Hide

```
unique(email$viagra)
```

```
[1] 0 8
```

Del total de correos analizados, cuantos contienen la palabra viagra y cuantos no

Hide

```
freq(email$viagra, style = "rmarkdown")
```

```
### Frequencies
#### email$viagra
**Type:** Numeric
```

	&nbsp;	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
	**0**	3920	99.974	99.974	99.974	99.974
	**8**	1	0.026	100.000	0.026	100.000
	**\<NA\>**	0			0.000	100.000
	**Total**	3921	100.000	100.000	100.000	100.000

# password

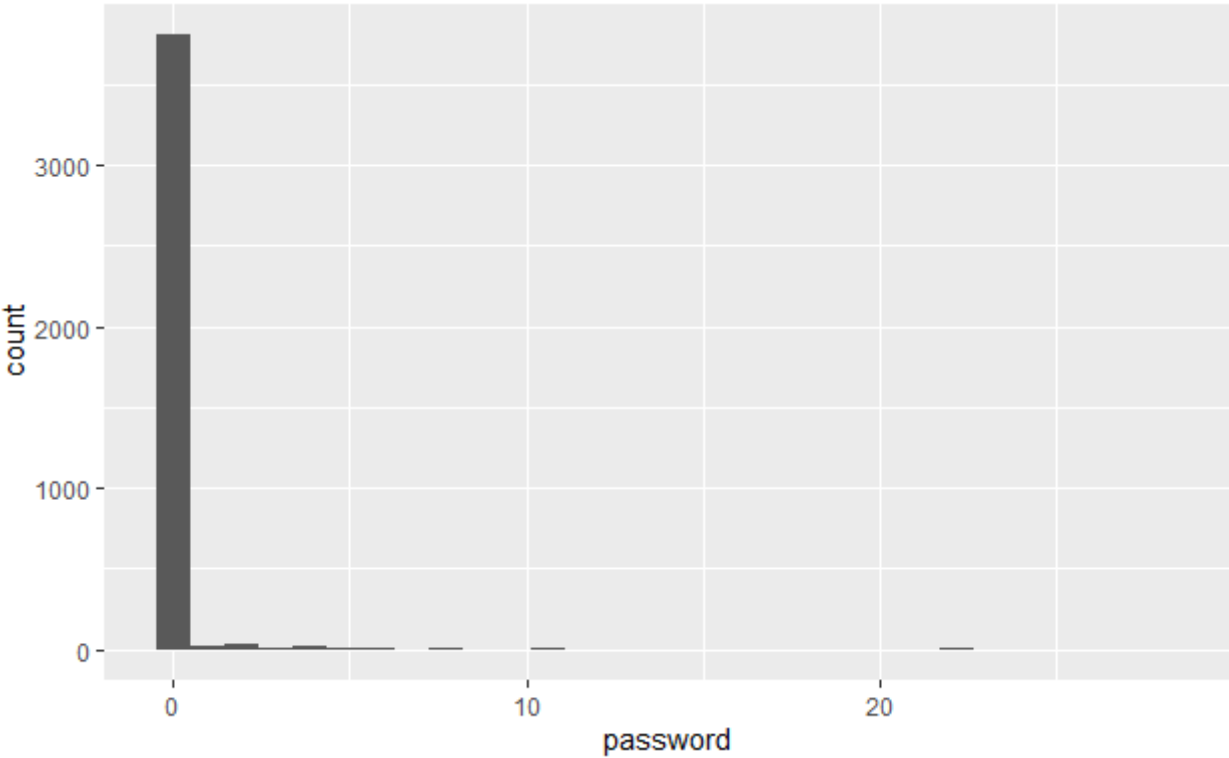
Cuántas veces aparece la palabra password repetida en estos correos

Hide

```
freq(email$password, style = "rmarkdown")
```

```
### Frequencies
#### email$password
**Type:** Numeric
```

	&nbsp;	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
	**0**	3809	97.144	97.144	97.144	97.144
	**1**	22	0.561	97.705	0.561	97.705
	**2**	39	0.995	98.699	0.995	98.699
	**3**	8	0.204	98.903	0.204	98.903
	**4**	23	0.587	99.490	0.587	99.490
	**5**	5	0.128	99.617	0.128	99.617
	**6**	3	0.077	99.694	0.077	99.694
	**8**	5	0.128	99.821	0.128	99.821
	**11**	2	0.051	99.872	0.051	99.872
	**13**	1	0.026	99.898	0.026	99.898
	**18**	1	0.026	99.923	0.026	99.923
	**22**	2	0.051	99.974	0.051	99.974
	**28**	1	0.026	100.000	0.026	100.000
	**\<NA\>**	0			0.000	100.000
	**Total**	3921	100.000	100.000	100.000	100.000



Influye la aparicion de la palabra password a la hora de determinar un correo como spam

Hide

```
ctable(email$password, email$spam)
```

Cross-Tabulation, Row Proportions

password \* spam

Data Frame: email

-----				
	spam	0	1	Total
password				
0	3446 ( 90.5%)	363 ( 9.5%)	3809 (100.0%)	
1	20 ( 90.9%)	2 ( 9.1%)	22 (100.0%)	
2	37 ( 94.9%)	2 ( 5.1%)	39 (100.0%)	
3	8 (100.0%)	0 ( 0.0%)	8 (100.0%)	
4	23 (100.0%)	0 ( 0.0%)	23 (100.0%)	
5	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
6	3 (100.0%)	0 ( 0.0%)	3 (100.0%)	
8	5 (100.0%)	0 ( 0.0%)	5 (100.0%)	
11	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
13	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
18	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
22	2 (100.0%)	0 ( 0.0%)	2 (100.0%)	
28	1 (100.0%)	0 ( 0.0%)	1 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	
-----				

Creamos una variable dependiente binaria

s...	to_multiple	fr...	cc	sent_email	time	im...	attach	dollar	win...
<fctr>	<fctr>	<fctr>	<int>	<fctr>	<S3: POSIXct>	<dbl>	<dbl>	<dbl>	<fctr>



s...	to_multiple	fr...	cc	sent_email	time	im...	attach	dollar	win...	
<fctr>	<fctr>	<fctr>	<int>	<fctr>	<S3: POSIXct>	<dbl>	<dbl>	<dbl>	<fctr>	
0	0	1	0	0	2012-01-01 07:16:41	0	0	0	no	
0	0	1	0	0	2012-01-01 08:03:59	0	0	0	no	
0	0	1	0	0	2012-01-01 17:00:32	0	0	4	no	
0	0	1	0	0	2012-01-01 10:09:49	0	0	0	no	
0	0	1	0	0	2012-01-01 11:00:01	0	0	0	no	
0	0	1	0	0	2012-01-01 11:04:46	0	0	0	no	

6 rows | 1-10 of 22 columns

Hide

```
ctable(email$password_binary, email$spam)
```

Cross-Tabulation, Row Proportions  
password\_binary \* spam  
Data Frame: email

	spam	0	1	Total
password_binary				
0	3446 (90.5%)	363 ( 9.5%)	3809 (100.0%)	
1	108 (96.4%)	4 ( 3.6%)	112 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

# format

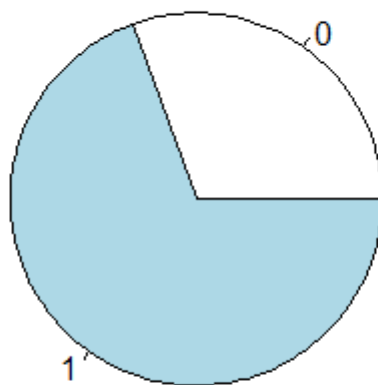
Cuantos correos tienen formato y cuantos no lo tienen

Hide

```
freq(email$format, style = "rmarkdown")
```

### Frequencies  
#### email\$format  
\*\*Type:\*\* Factor

		Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
	**0**	1195	30.48	30.48	30.48	30.48
	**1**	2726	69.52	100.00	69.52	100.00
	**\<NA\>**	0			0.00	100.00
	**Total**	3921	100.00	100.00	100.00	100.00



Influye que los correos tengan formato a la hora de declararlos como spam??

Hide

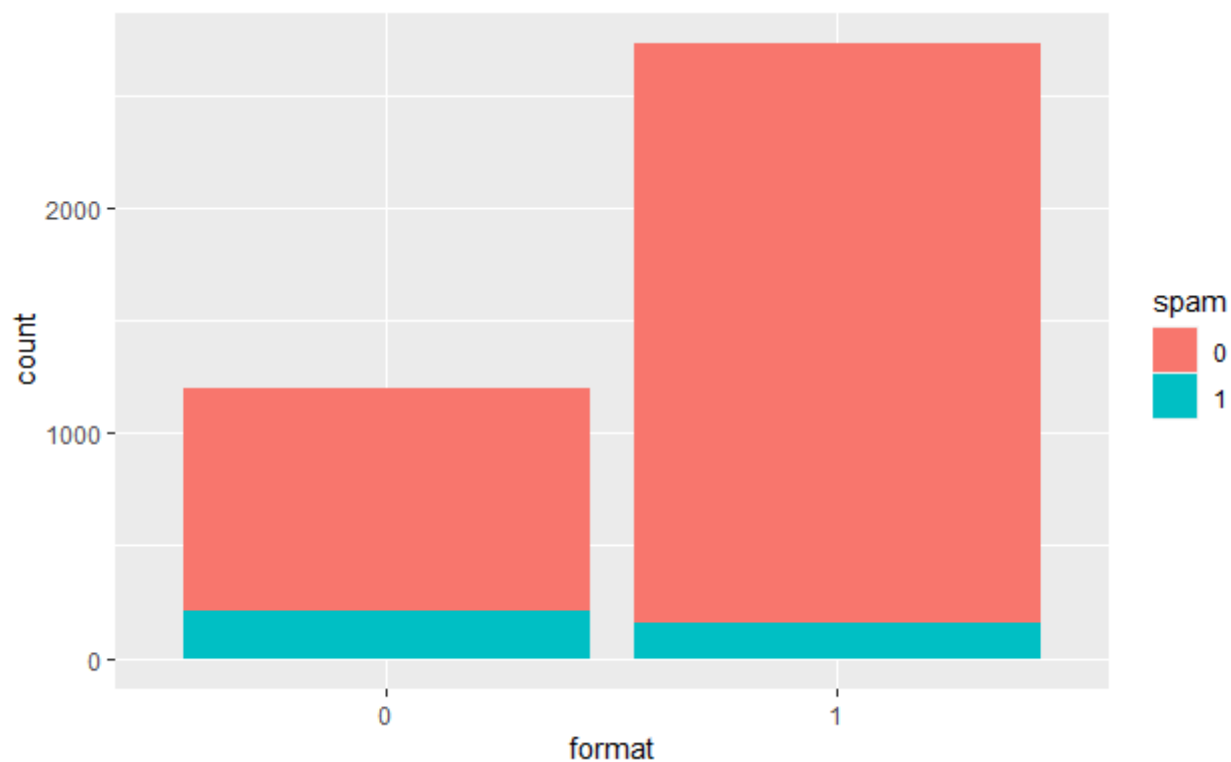
```
ctable(email$format, email$spam)
```

Cross-Tabulation, Row Proportions

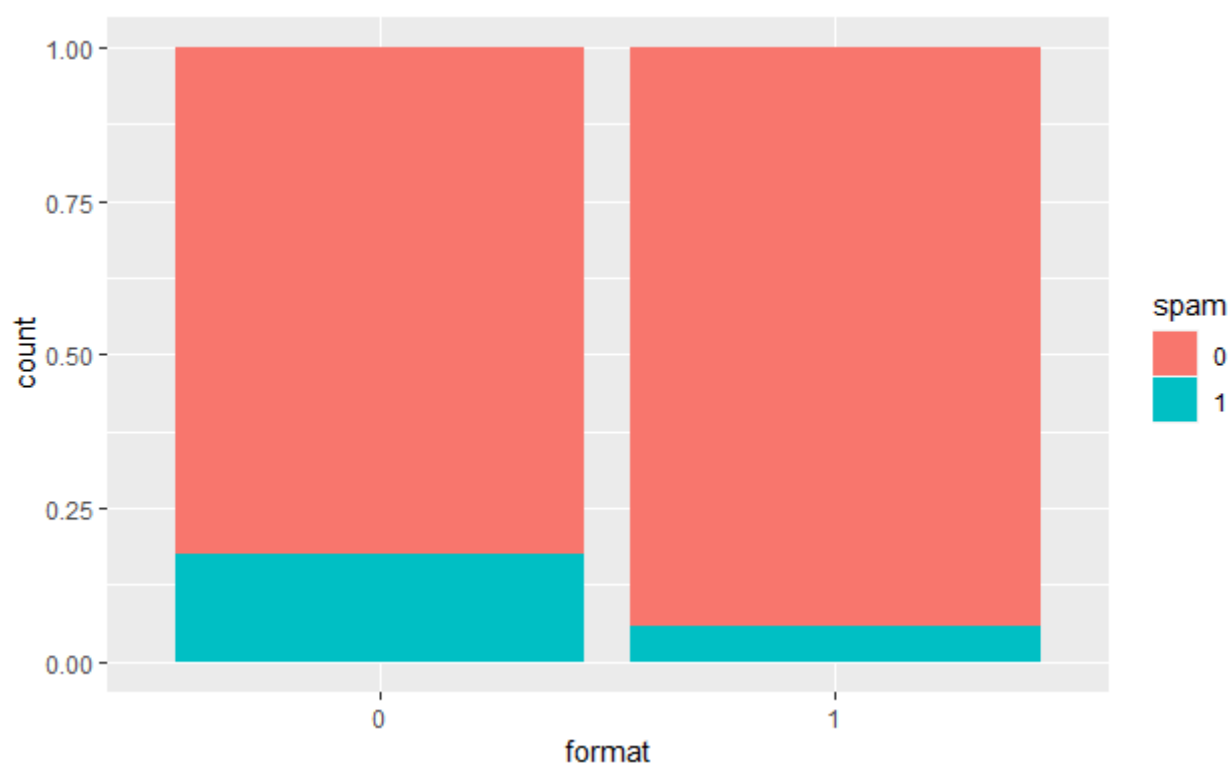
format \* spam

Data Frame: email

	spam	0	1	Total
format				
0	986 (82.5%)	209 (17.5%)	1195 (100.0%)	
1	2568 (94.2%)	158 ( 5.8%)	2726 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	



Vamos a ver el grafico en terminos relativos



## re\_subj

[Hide](#)

```
summary(email$re_subj)
```

```
  0    1  
2896 1025
```

Hide

```
unique(email$re_subj)
```

```
[1] 0 1
Levels: 0 1
```

Cuántas veces tenemos re\_subj y cuantos no en estos correos

Hide

```
ctable(email$re_subj, email$spam)
```

Cross-Tabulation, Row Proportions

re\_subj \* spam

Data Frame: email

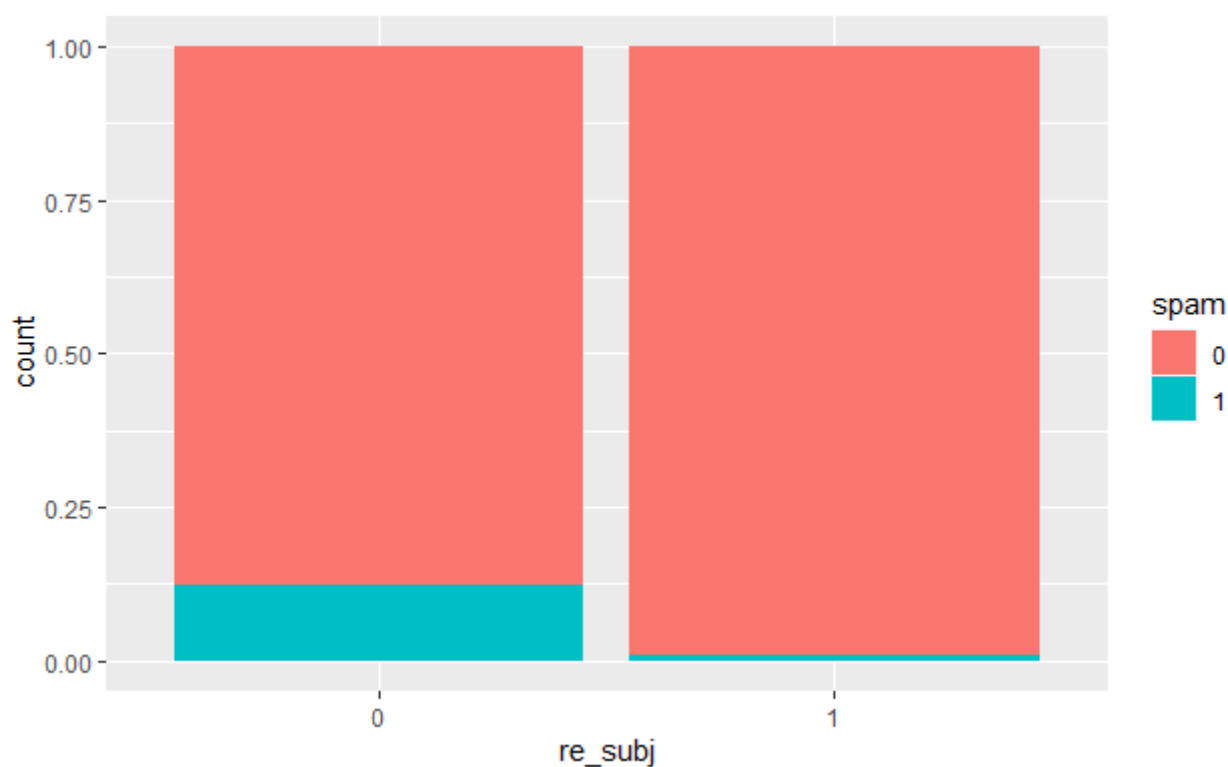
```
-----
```

	spam	0	1	Total
re_subj				
0	2537 (87.6%)	359 (12.4%)	2896 (100.0%)	
1	1017 (99.2%)	8 ( 0.8%)	1025 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

```
-----
```

Hide

```
ggplot(email, aes(re_subj, fill = spam)) + geom_bar(position = "fill")
```



Son declarados como spam mayoritariamente los correos que NO tiene r\_subj, en concreto un 12%.

## exclaim\_subj

Hide

```
ctable(email$exclaim_subj, email$spam)
```

Cross-Tabulation, Row Proportions

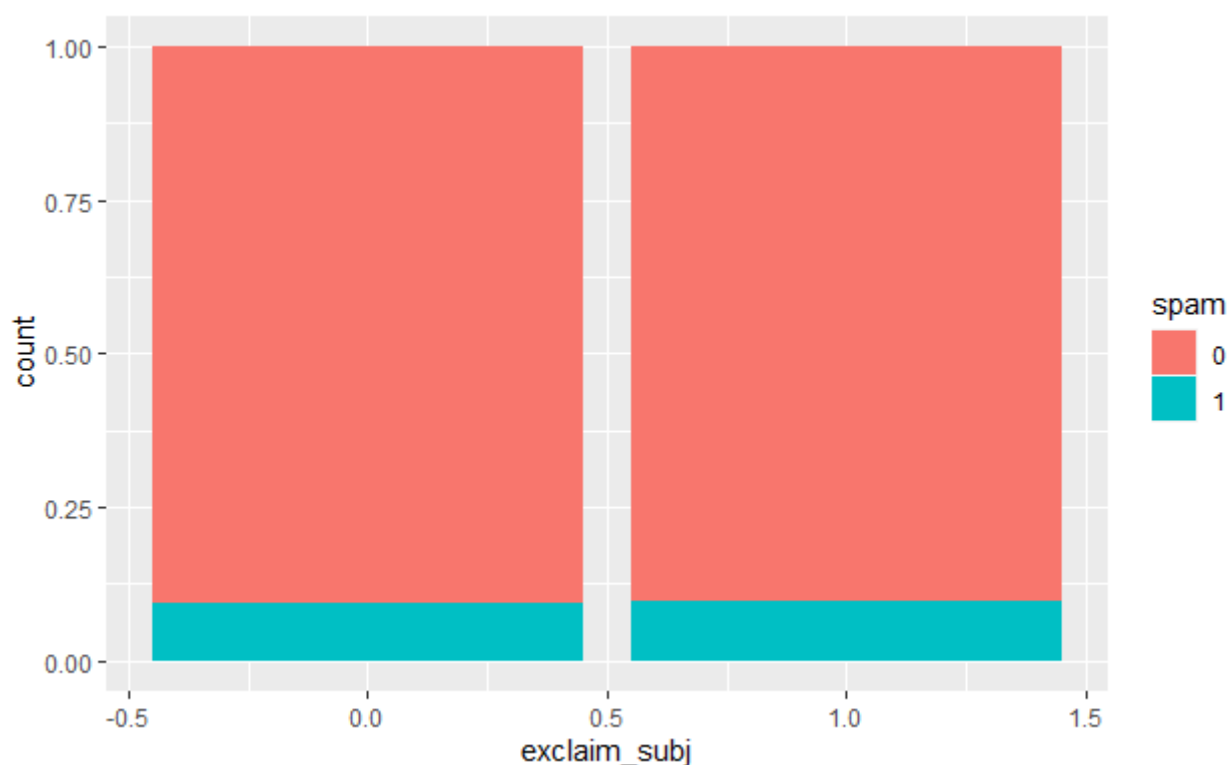
exclaim\_subj \* spam

Data Frame: email

	spam	0	1	Total
exclaim_subj				
0	3269 (90.7%)	337 ( 9.3%)	3606 (100.0%)	
1	285 (90.5%)	30 ( 9.5%)	315 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

Hide

```
ggplot(email, aes(exclaim_subj, fill = spam)) + geom_bar(position = "fill")
```



Parece que los correos exclaim y los que no lo tienen, son declarados como spam en la misma proporción (9.3 - 9.5), por lo que no parece que sea una variable determinante a la hora de diferenciar entre spam y no spam

## urgent\_subj

Hide

```
freq(email$urgent_subj, style = "rmarkdown")
```

```
### Frequencies
#### email$urgent_subj
**Type:** Factor
```

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
**0**	3914	99.82	99.82	99.82	99.82
**1**	7	0.18	100.00	0.18	100.00
**\<NA\>**	0			0.00	100.00
**Total**	3921	100.00	100.00	100.00	100.00

Hide

```
ctable(email$urgent_subj, email$spam)
```

Cross-Tabulation, Row Proportions

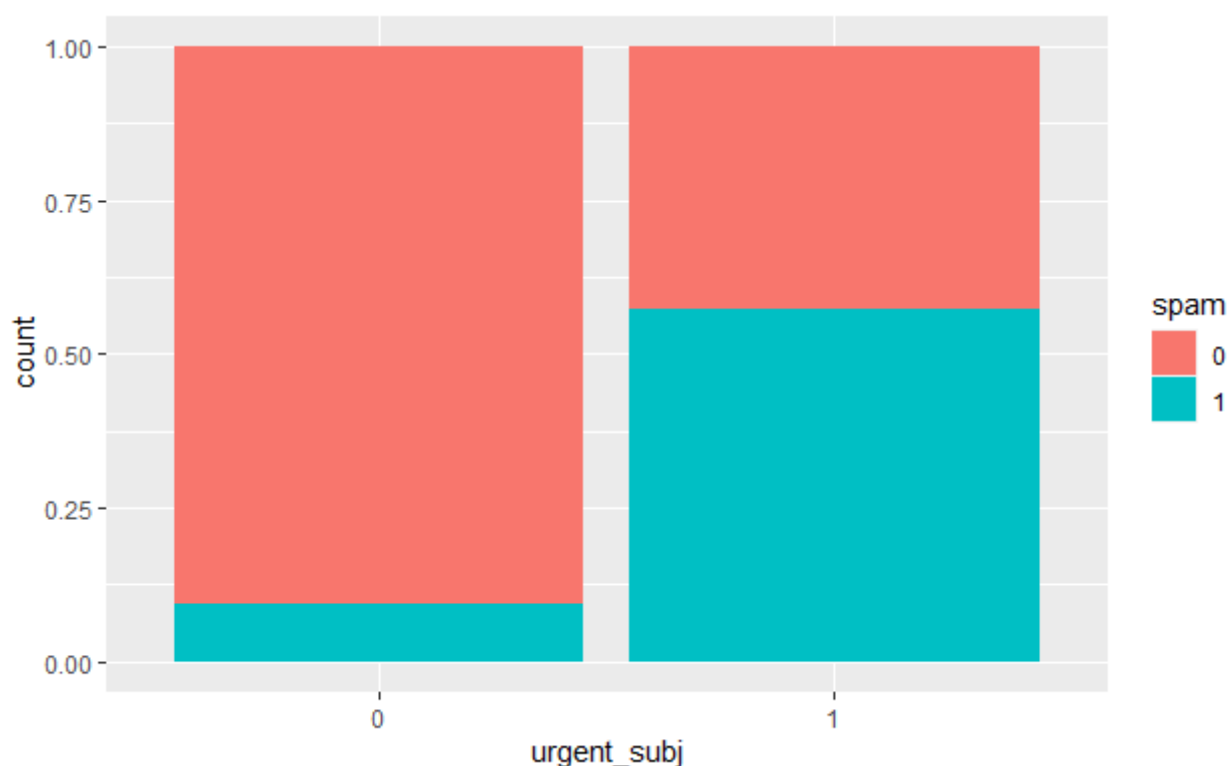
urgent\_subj \* spam

Data Frame: email

	spam	0	1	Total
urgent_subj				
0	3551 (90.7%)	363 ( 9.3%)	3914 (100.0%)	
1	3 (42.9%)	4 (57.1%)	7 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

Hide

```
ggplot(email, aes(urgent_subj, fill = spam)) + geom_bar(position = "fill")
```



Solo tenemos 7 correos que son urgent\_subj, lo que supone un 0.18%. Eso si el 57% de estos(4) son declarados spam, frente al 43%(3) que no lo son. El porcentaje de casos no urgent\_subj, no es muy representativo, pero vamos a mantener esta variable.

## time

De la variable time vamos a obtener los meses, por si hubiera algun mes en el que se declaren mas correos como spam.

Hide

```
class(email$time)
```

```
[1] "POSIXct" "POSIXt"
```

Hide

```
class(email$time)
```

```
[1] "Date"
```

Hide

```
email$mes <- format(as.Date(email$time), "%m")
```

```
# ya tenemos una nueva columna con los meses en los que se envian los correos
```

Vamos a ver en que meses se envian mas correos y si estos influyen a la hora de establecer un correo como spam

Hide

```
freq(email$mes, style = "rmarkdown")
```

```
### Frequencies
```

```
#### email$mes
```

```
**Type:** Character
```

	&nbsp;	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
**01**	1300	33.15	33.15	33.15	33.15	
**02**	1326	33.82	66.97	33.82	66.97	
**03**	1291	32.93	99.90	32.93	99.90	
**04**	4	0.10	100.00	0.10	100.00	
**\<NA\>**	0			0.00	100.00	
**Total**	3921	100.00	100.00	100.00	100.00	

Hide

```
ctable(email$mes, email$spam)
```

Cross-Tabulation, Row Proportions

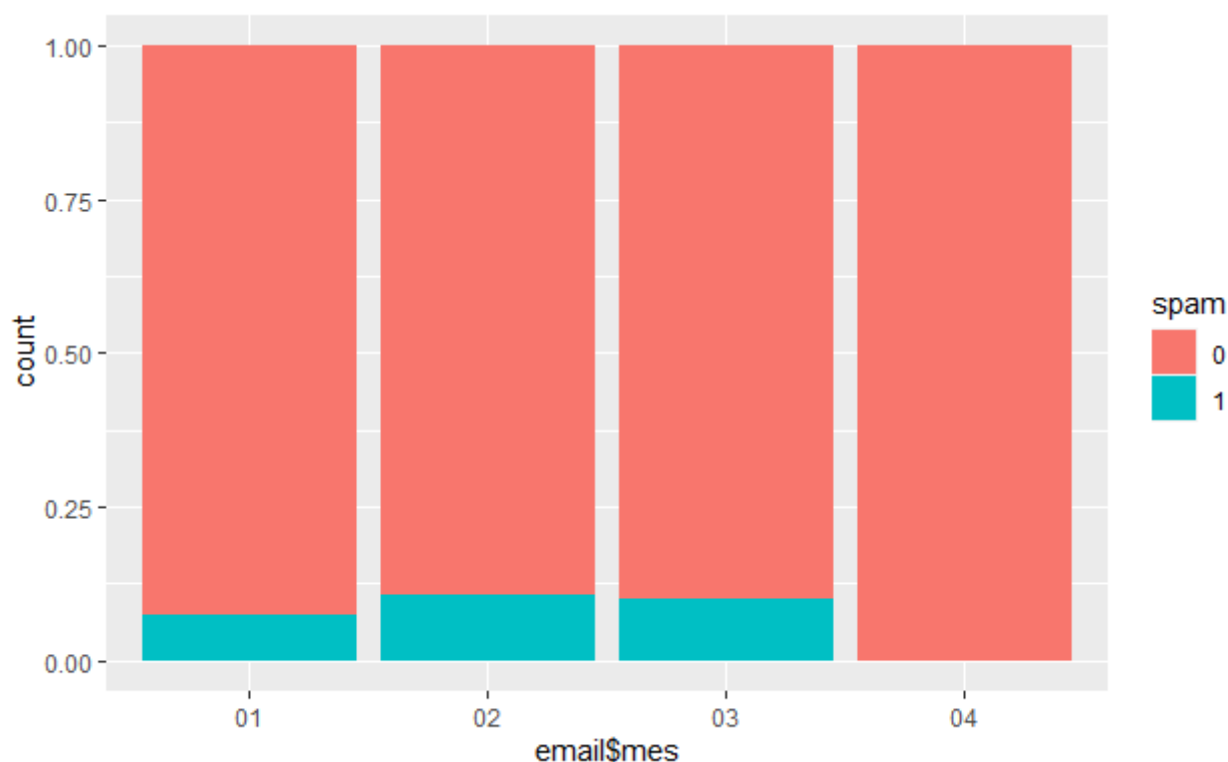
mes \* spam

Data Frame: email

	spam	0	1	Total
mes				
01	1206 ( 92.8%)	94 ( 7.2%)	1300 (100.0%)	
02	1183 ( 89.2%)	143 (10.8%)	1326 (100.0%)	
03	1161 ( 89.9%)	130 (10.1%)	1291 (100.0%)	
04	4 (100.0%)	0 ( 0.0%)	4 (100.0%)	
Total	3554 ( 90.6%)	367 ( 9.4%)	3921 (100.0%)	

Hide

```
ggplot(email, aes(email$mes, fill = spam)) + geom_bar(position = "fill")
```



En este conjunto de datos solo tenemos información de correos enviados de Enero - Abril en proporción de un 33% los tres primeros meses y de un 1% el mes de Abril.

Los mails declarados como spam se reparten entre los 3 primeros meses, de forma bastante homogénea, no parece muy significativa esta variable.

## number

¿Con qué frecuencia aparecen los números grandes, pequeños o no hay números, en estos correos?

Hide

```
library(summarytools)
```



```
Registered S3 method overwritten by 'pryr':
```

```
method      from
print.bytes Rcpp
```

Hide

```
summary(email$number)
```

```
none small  big
549  2827  545
```

Hide

```
freq(email$number, style= "rmarkdown")
```

```
### Frequencies
```

```
#### email$number
```

```
**Type:** Factor
```

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
<b>none</b>	549	14.00	14.00	14.00	14.00
<b>small</b>	2827	72.10	86.10	72.10	86.10
<b>big</b>	545	13.90	100.00	13.90	100.00
<b>&lt;NA&gt;</b>	0			0.00	100.00
<b>Total</b>	3921	100.00	100.00	100.00	100.00

Influye que haya numeros o su tamaño a la hora de catalogar el correo como spam??

Hide

```
library(ggplot2)
```

```
ctable(email$number, email$spam)
```

```
Cross-Tabulation, Row Proportions
```

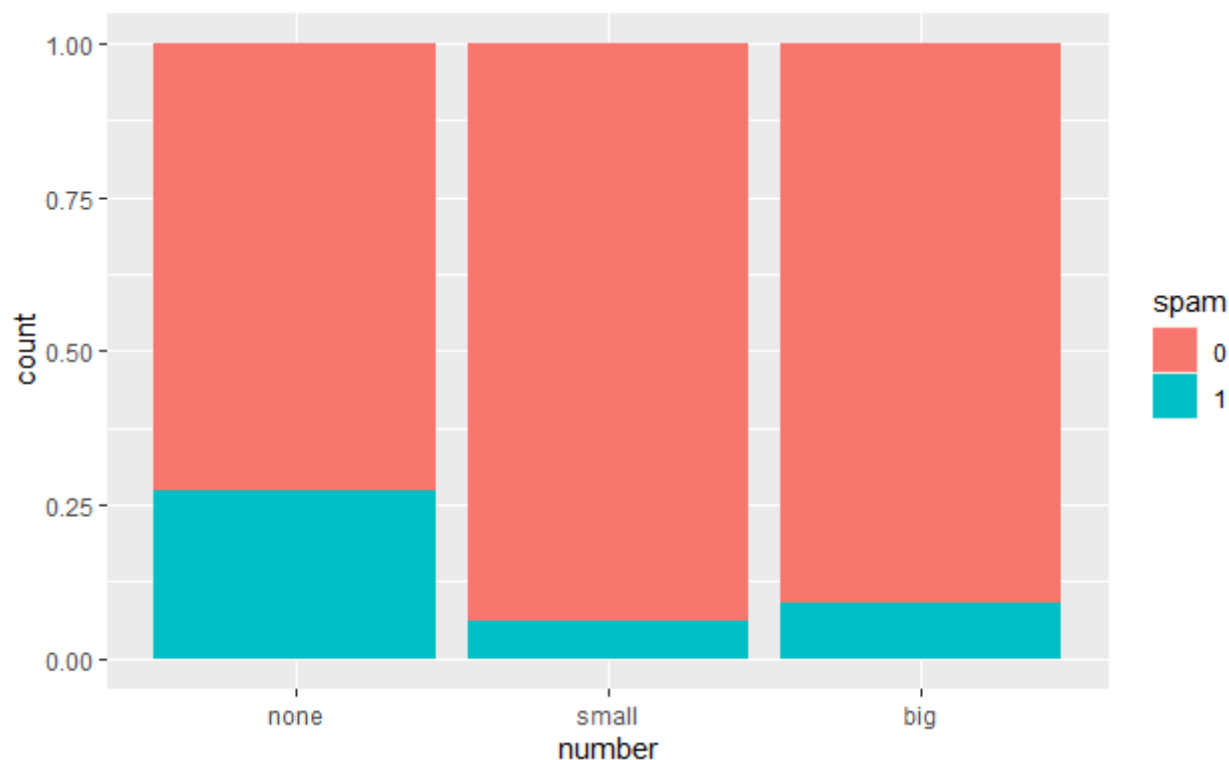
```
number * spam
```

```
Data Frame: email
```

	spam	0	1	Total
number				
none	400 (72.9%)	149 (27.1%)	549 (100.0%)	
small	2659 (94.1%)	168 ( 5.9%)	2827 (100.0%)	
big	495 (90.8%)	50 ( 9.2%)	545 (100.0%)	
Total	3554 (90.6%)	367 ( 9.4%)	3921 (100.0%)	

Hide

```
ggplot(email, aes(x = number, fill = spam)) + geom_bar(position = "fill")
```

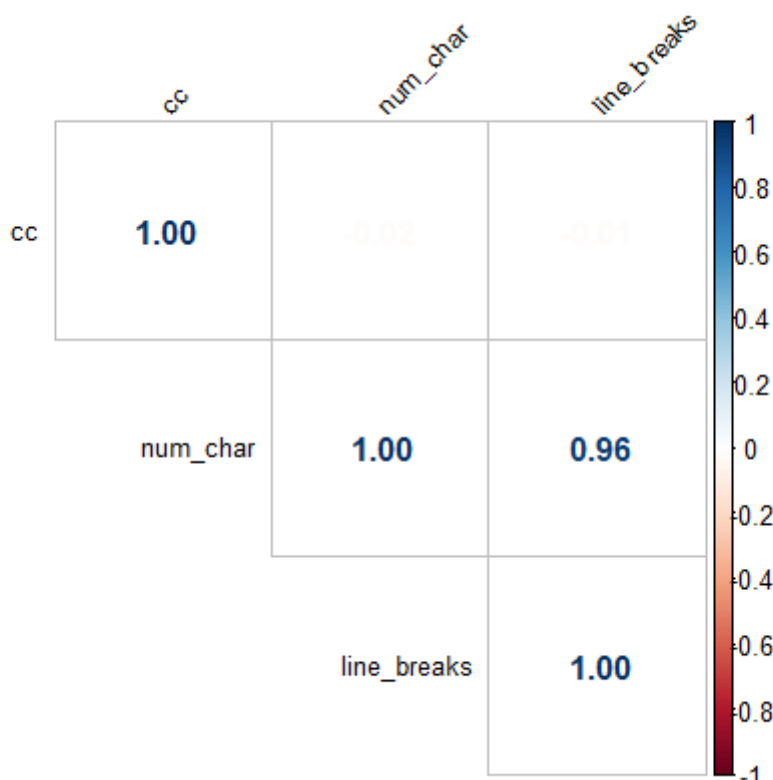


Podemos observar que cuando no hay numeros en los correos, la posibilidad de catalogar el correo como spam se dispara a un 27%, mientras que cuando los hay pequeños es de un 6% y grandes de un 9%

## Analisis bidimensional

Vamos a analizar si las variables cuantitativas estan correlacionadas entre ellas, de ser asi, habria que eliminarlas:

cc, num\_chart, line\_breaks



El numero de caracteres del correo y el de saltos de linea estan altamente correlacionados (0.96), vamos a mantenerlos de momento

# Conclusion.

1 - Variables a eliminar: time, exclaim\_subj, viagra,

2 - variables que nos quedamos: password\_binary, dollar\_binnes, attach\_binary, to\_multiple, from, cc, sent\_email, image, winner, inherit, num\_chart, line\_breaks, format, re\_subj urgent\_subj, exclaim\_mess, number

3 - Se han modificado 3 variables (password\_binary, dollar\_binnes, attach\_binary), dejandolas como binarias, aunque deberían haber sido mas...

## vamos a eliminar las variables que no correspondan:

[Hide](#)

```
email <- subset( email, select = -c(time, exclaim_subj, viagra,password, dollar, attach ) )  
  
head(email)
```

Vamos a convertir a las variables categoricas en variables factores ordenadas

[Hide](#)

```
email$password_binary = factor(email$password_binary= order = TRUE, levels = c(0, 1))
```

```
Error: inesperado '=' in "email$password_binary = factor(email$password_binary="
```

[Hide](#)

```
NA
```

## Aqui terminamos el analisis descriptivo de este dataset y tenemos que comenzar con el analisis predictivo.

[Hide](#)

```
modelo = glm(spam~ password_binary, dollar_binnes, attach_binary, data = email)
```

```
Error in glm(spam ~ password_binary, dollar_binnes, attach_binary, data = email) :  
objeto 'dollar_binnes' no encontrado
```