Lecture 28: Logistic Regression

Chapter 8.4

Binary Outcome Variables

Outcome Variable

Logit Transformation

Odds

Outcome Variable

Figure 8.13 from page 388

Simple Logistic Regression Example p.388

So say we fit a logistic regression with:

- Y_i is `spam`: binary variable of whether message was classified as spam (1 if spam)
- x_i is `to_multiple`: binary variable indicating if more than one recipient listed

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.1161	0.0562	-37.67	0.0000
`to_multiple`	-1.8092	0.2969	-6.09	0.0000

Inverse Logit Transformation

Fitted Probabilities

Fitted Model Using Backwards Regression

The following model was selected in the text using backwards selection using $\alpha = 0.05$.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.8057	0.0880	-9.15	0.0000
to_multiple?	-2.7514	0.3074	-8.95	0.0000
word winner used?	1.7251	0.3245	5.32	0.0000
special formatting?	-1.5857	0.1201	-13.20	0.0000
'RE:' in subject?	-3.0977	0.3651	-8.48	0.0000
attachment?	0.2127	0.0572	3.72	0.0002
word password used?	-0.7478	0.2956	-2.53	0.0114

Fitted Model Using Backwards Regression

The following variables increase the probability that the email is spam, since $b > 0$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.8057	0.0880	-9.15	0.0000
word winner used?	1.7251	0.3245	5.32	0.0000
attachment?	0.2127	0.0572	3.72	0.0002

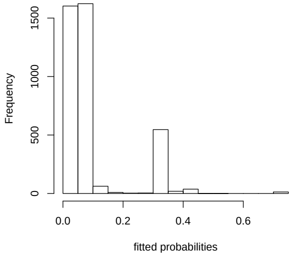
Fitted Model Using Backwards Regression

The following variables decrease the probability that the email is spam, since $b < 0$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.8057	0.0880	-9.15	0.0000
to_multiple?	-2.7514	0.3074	-8.95	0.0000
special formatting?	-1.5857	0.1201	-13.20	0.0000
'RE:' in subject?	-3.0977	0.3651	-8.48	0.0000
word password used?	-0.7478	0.2956	-2.53	0.0114

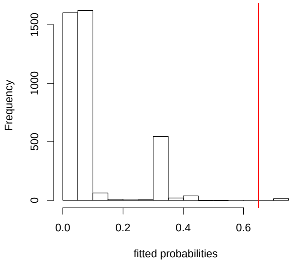
Fitted Probabilities

These are all 3921 fitted probabilities $\widehat{p}$:



Using Cutoffs to Classify Emails as Spam

Say we use a cutoff of 65% to classify an email spam or not:



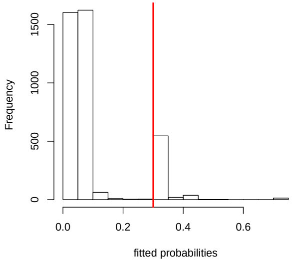
Using Cutoffs to Classify Emails as Spam

Using a cutoff of 65%:

		Classification: Not Spam $\widehat{p}_i < .65$	Spam $\widehat{p}_i \geq .65$
Truth	Not Spam: $Y_i = 0$	3351	3
	Spam: $Y_i = 1$	357	10

Using Cutoffs to Classify Emails as Spam

Now say we use a cutoff of 30% to classify an email spam or not:



Using Cutoffs to Classify Emails as Spam

Using a cutoff of 30%:

		Classification	
		Not Spam $\widehat{p}_i < .30$	Spam $\widehat{p}_i \geq .30$
Truth	Not Spam: $Y_i = 0$	3138	416
	Spam: $Y_i = 1$	166	201

Using Cutoffs to Classify Emails as Spam

Conditions for Logistic Regression