Simple logistic regression

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Applied STAtistics group at AAU

Department of Mathematical Sciences

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Introduction



Outline of session:

- ▶ Data
- ► Model
- ► Inference

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Data



Wisconsin Breast Cancer Database covers 683 observations of 10 variables in relation to examining tumors in the breast.

- ▶ Nine clinical variables with a score between 0 and 10.
- ► The binary variable Class with levels benign/malignant.

We will use 4 of the predictors, where 2 have been discretized.

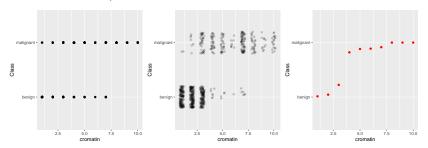
id	nuclei	cromatin	Size.low	Size.medium	Shape.low	Class
1 2	1 10	3	TRUE FALSE	FALSE TRUE	TRUE FALSE	benign benign
25 26	7 1	3 2	TRUE TRUE	FALSE FALSE	FALSE TRUE	 malignant benign
682 683	4 5	10 10	FALSE FALSE	FALSE FALSE	FALSE FALSE	malignant malignant

Plot of data



Three different plots of the same data, where from left to right:

- ► many points are plotted on top of each other
- points are plotted as semi-transparent and "jittered"
- ► fractions are plotted instead of "0"s and "1"s.



Binary response



- ► We consider a binary response *y* with outcome 1 or 0, e.g. malignant or beneign.
- ► Furthermore, we are given an explanatory variable *x*, which is numeric, e.g. score.
- ► We shall study models for

$$P(y = 1 \mid x)$$

- e.g. the probability that a tumor with score x is malignant.
- ► We shall see methods for determining whether or not score actually influences the probability, i.e. is *y* independent of *x*?

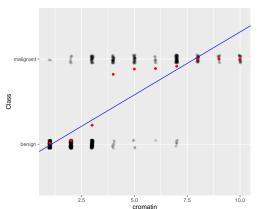
A linear model



► The simple linear model is often inappropriate.

$$P(y = 1 | x) = \alpha + \beta x$$

▶ If β is positive and x sufficiently large, then the probability exceeds 1.



Logistic model



Instead we consider the odds that the tumor is malignant

$$Odds(y = 1 | x) = \frac{P(y = 1 | x)}{P(y = 0 | x)} = \frac{P(y = 1 | x)}{1 - P(y = 1 | x)}$$

which can have any positive value.

The logistic model is defined as:

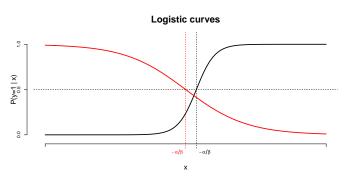
$$logit(P(y=1|x)) = log(Odds(y=1|x)) = \alpha + \beta x$$

The function $logit(p) = log(\frac{p}{1-p})$ - i.e. \log of odds - is termed the logistic transformation.

Remark that log odds can be any number, where zero corresponds to $P(y=1\,|\,x)=0.5$. Solving $\alpha+\beta x=0$ shows that for the score $x_0=-\alpha/\beta$ the tumor has fifty-fifty chance of being malignant.

Simple logistic regression





Examples of logistic curves. The black curve has a positive β -value (=10), whereas the red has a negative β (=-3). Note that:

- \blacktriangleright Increasing the absolute value of β yields a steeper curve.
- ▶ When $P(y = 1 \mid x) = \frac{1}{2}$ then logit is zero, i.e. $\alpha + \beta x = 0$.

Odds-ratio



Interpretation of β :

What happens to odds, if we increase x by 1?

Consider the so-called odds-ratio:

$$\frac{\mathtt{Odds}(y=1\,|\,x+1)}{\mathtt{Odds}(y=1\,|\,x)} = \frac{\exp(\alpha+\beta(x+1))}{\exp(\alpha+\beta x)} = \exp(\beta)$$

where we see, that $\exp(\beta)$ equals the odds for score x+1 relative to odds for score x.

This means that when x increases by 1, then the relative change in odds is given by $100(\exp(\beta) - 1)\%$.

Inference



► For the cancer data the estimates are

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-5.28	0.3919	-13.47	2.201e-41
cromatin	1.365	0.1173	11.64	2.624e-31

- ▶ With $\hat{\alpha} = -5.28$ and $\hat{\beta} = 1.37$ we see that a score of $-\hat{\alpha}/\hat{\beta} = 3.87$ corresponds to fifty/fifty risk of malignant tumor.
- ► Since $\exp(\hat{\beta}) = 3.92$, increasing the score by 1 increases the risk of malignant tumor by 292%.
- ▶ Null hypothesis of no relation between score and class of tumor is

$$H_0: \beta = 0$$

with the alternative $\beta \neq 0$.

 $ightharpoonup \hat{\beta}$ is 11.6 standard errors away from zero, so H_0 is clearly rejected with a p-value of practically zero.

Confidence interval for odds ratio



	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-5.28	0.3919	-13.47	2.201e-41
cromatin	1.365	0.1173	11.64	2.624e-31

From the summary:

- Standard error on $\hat{\beta}$ is 0.12 and hence a 95% confidence interval for log-odds ratio is $\hat{\beta} \pm 1.96 \times 0.12 = (1.14, 1.6)$.
- Corresponding interval for odds ratio: $(\exp(1.14), \exp(1.6)) = (3.11, 4.93),$

i.e. the relative increase in odds is - with confidence 95% - between 211% and 393%.

Plot of model predictions against actual data



