Logistic regression: Probabilities and odds ratios

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Introduction

- An important distinction between linear and logistic regression is that the regression coefficients in logistic regression are not terribly meaningful on their own

- In linear regression, a coefficient $\beta_j = 1$ means that if you change x_j by 1, the expected value of Y will go up by 1 (very interpretable)

- In logistic regression, a coefficient $\beta_j = 1$ means that if you change x_j by 1, the log of the odds that Y occurs will go up by 1 (much less interpretable)

Introduction (cont'd)

- When outcomes are categorical, it is much easier to think about the outcome in terms of probabilities and odds ratios
- These are the quantities that are usually reported and described in an analysis, rather than the regression coefficients themselves
- Today's lecture is about estimating, constructing confidence intervals, and carrying out hypothesis tests for these quantities

Estimating probabilities

- We have already talked about estimation of probabilities based on the fit of a logistic regression model:
  - (1) Given a vector of explanatory variables $\mathbf{x}$, calculate the linear predictor $\hat{\eta} = \mathbf{x}^T \widehat{\boldsymbol{\beta}}$
  - (2) Estimate the probability based on

$$\hat{\pi} = \frac{e^{\hat{\eta}}}{1 + e^{\hat{\eta}}}$$

- It should be noted that, since maximum likelihood estimates are invariant to transformation, $\hat{\pi}$ may also be considered the maximum likelihood estimate of π

Confidence intervals for probabilities

- Construction of confidence intervals proceeds similarly
- Using the fact that

$$\frac{\mathbf{x}^T\widehat{\boldsymbol{\beta}} - \mathbf{x}^T\boldsymbol{\beta}}{\widehat{\mathrm{SE}}} \ \dot\sim\ z,$$

where $\widehat{\mathrm{SE}} = \sqrt{\mathbf{x}^T(\mathbf{X}^T\mathbf{W}\mathbf{X})^{-1}\mathbf{x}}$

- We can then construct a confidence interval for η:

$$(L, U) = (\hat{\eta} - z_{\alpha/2}\widehat{\mathrm{SE}}, \hat{\eta} + z_{\alpha/2}\widehat{\mathrm{SE}})$$

- A $(1 - \alpha)$ confidence interval for π is therefore

$$\left(\frac{e^L}{1 + e^L}, \frac{e^U}{1 + e^U}\right)$$

Hypothesis testing

- In principle, one could carry out hypothesis tests of $H_0 : \pi = \pi_0$ based on this approach as well: calculate

$$\eta_0 = \log\left(\frac{\pi_0}{1 - \pi_0}\right)$$

  and then test $H_0 : \eta = \eta_0$ based on the fact that, under H_0,

$$\frac{\hat{\eta} - \eta_0}{\widehat{\text{SE}}} \dot\sim z$$

- In practice, however, it is quite rare to have a hypothesis about a specific type of subject that you are interested in testing

Limitations of estimating probabilities

- Probabilities have the advantage that they are particularly easy to interpret (everyone knows what a probability is)
- However, working with probabilities is inconvenient for logistic regression in many ways
- First of all, the model is not linear in probability
- Suppose $\beta_j = 1$ and x_j changes by 1; how does that affect the probability?
- Well, if we started out at 50%, it goes up to 73%; but if we start at 90%, it only goes up to 96%

Limitations of estimating probabilities (cont'd)

- Another way of putting this is that in order to calculate the change in probability as one explanatory variable changes, you have to specify all the explanatory variables

- This complicates (when lots of variables are present, greatly complicates) the most attractive feature of an additive model: the ability to describe what happens when you change one thing and leave the rest the same

Logistic regression and case-control studies

- This has particularly important consequences for case-control studies
- **Theorem:** In a case-control study, the maximum likelihood estimates $\widehat{\beta}_1, \ldots, \widehat{\beta}_{p-1}$ as well as their approximate sampling distributions are equivalent to that obtained from the logistic regression model, under the assumptions that
  - (a) The model is correct
  - (b) The selection of cases and controls is independent of the explanatory variables

Case-control assumptions

- The assumption that selection of cases and controls is independent of the explanatory variables is actually a pretty big assumption, often violated in actual case-control studies
- This is a major source of bias
- For example, case-control studies have found links between childhood leukemia and exposure to electromagnetic fields (EMF)

Electromagnetic field example

- However, subsequent investigations have indicated that this is due entirely to case-control bias
- Families with low socioeconomic status are more likely to live near electromagnetic fields
- Families with low socioeconomic status are also less likely to participate in studies as controls
- Socioeconomic status does not affect the participation of cases, however (cases are usually eager to participate)
- This results in a spurious association between EMF and leukemia

The intercept

- Another important thing to note from the preceding theorem is that it makes no claim about $\hat{\beta}_0$
- This is because the case-control sampling affects the likelihood with respect to β_0, as the sampling probabilities are absorbed into the intercept:

$$\beta_0^{\text{Case control}} = \beta_0^{\text{General population}} + \log\left(\frac{\tau_1}{\tau_0}\right),$$

where τ_1 and τ_0 are the selection probabilities for cases and controls, respectively

- In the usual situation where we intentionally oversample cases, this leads to overestimation of β_0
- Thus, it is not possible to estimate the β_0 that describes the general population (unless we know τ_1 and τ_0), and therefore not possible to estimate probabilities either

Odds ratios: introduction

- Given that the regression coefficients are difficult to interpret, but that estimation of probabilities has a number of drawbacks, how should we summarize and report our model?

- It turns out that odds ratios provide a readily interpretable and easily estimated compromise, without any of the drawbacks of estimating probabilities

Estimation of odds ratios

- Note that the odds of the event occurring for a subject with vector of explanatory variables $\mathbf{x}$ is

$$\frac{\pi}{1 - \pi} = \exp(\mathbf{x}^T \boldsymbol{\beta})$$

- Thus, the odds ratio for comparing two subjects, one with explanatory variables $\mathbf{x}_1$ and the other with $\mathbf{x}_2$, is

$$\frac{\pi_2/(1 - \pi_2)}{\pi_1/(1 - \pi_1)} = \frac{\exp(\mathbf{x}_2^T \boldsymbol{\beta})}{\exp(\mathbf{x}_1^T \boldsymbol{\beta})}$$
$$= \exp\{(\mathbf{x}_2 - \mathbf{x}_1)^T \boldsymbol{\beta}\})$$

Estimation of odds ratios (cont'd)

- In particular, consider the odds ratio for what happens when x_j changes by an amount δ_j, while the rest of the explanatory variables remain the same:

$$\text{OR} = \exp(\delta_j \beta_j)$$

- This is exactly what we need: all the other variables vanish and our estimate depends only on the β_j and the change in x_j

- We can therefore estimate this odds ratio, as well as carry out inference, based entirely on $\hat{\beta}_j$

- In particular, we don't even need to be able to estimate β_0, so we can apply these results to case-control studies

Estimation of odds ratios: example

- For example, what is the odds ratio for a member of the Donner party failing to survive the winter with a 10-year increase in age?

$$OR = \exp(10 \cdot 0.0325) = 1.4 \qquad \text{(Male)}$$
$$OR = \exp(10 \cdot 0.1941) = 7.0 \qquad \text{(Female)}$$

- Note that these odds ratios apply to any 10-year difference (50 vs. 40, 30 vs. 20, etc.) due to the linearity assumption

Confidence intervals for odds ratios

- As with probabilities, confidence intervals for odds ratios can be obtained by first obtaining confidence intervals in terms of $\widehat{\boldsymbol{\beta}}$ and then transforming

- The confidence intervals for the slope of the effect of age on the linear predictors are

$$(-0.0366, 0.1016) \qquad \text{(Male)}$$
$$(0.0227, 0.3654) \qquad \text{(Female)}$$

- The confidence intervals for the odds ratios of dying (again, with a change of 10 years in age) are:

$$e^{10 \cdot (L,U)} = (0.7, 2.8) \qquad \text{(Male)}$$
$$e^{10 \cdot (L,U)} = (1.3, 38.6) \qquad \text{(Female)}$$

Hypothesis tests

- Hypothesis tests of odds ratios (and for that matter, probabilities) are directly equivalent to tests of regression coefficients, since all the following are equivalent:
    - $\beta_j = 0$
    - Odds ratio $= 1$
    - Difference in probabilities $= 0$
    - Ratio of probabilities (relative risk) $= 1$

Hypothesis tests: Example

- For example, the test of $H_0 : \beta_{\texttt{Age|Male}} = 0$ yields

$$z = \frac{-0.03248}{0.03527} = -0.921,$$

and $p = 2\Phi^{-1}(-0.921) = 0.36$

- Meanwhile, the test of $H_0 : \beta_{\texttt{Age|Female}} = 0$ yields $p = .03$

- The tests are relatively low-powered because there are only 45 subjects; hence the relatively high p-values despite the large estimated effects

- This phenomenon was apparent from the wide confidence intervals as well

Confidence intervals: Wald vs. likelihood ratio

- This is not the only way (indeed, it isn't even the best way) to approach inference for GLMs

- The approach we have discussed today is known as the *Wald* approach, after the statistician Abraham Wald

- This approach, however, is based on an approximation to the likelihood at $\widehat{\beta}$; it does not necessarily provide accurate information about values of β far from $\widehat{\beta}$

- Next time, we will discuss an alternative approach to testing and constructing confidence intervals based on likelihood ratios and see that it suffers less from the approximation problem