Statistics 305/605: Introduction to Biostatistical Methods for Health Sciences

Chapter 20, part 2: Inference in Logistic Regression

Jinko Graham

2018-12-03

Inference in Logistic Regression

- In logistic regression, the log-odds of the outcome is modeled by the straight-line relationship $\alpha + \beta_1 X_1$.
- The intercept α is not typically of interest; instead we focus on β_1 because it summarizes the effect of X_1 on Y.
- It turns out that the sampling distribution of $\hat{\beta}_1$ is approximately normal with mean β_1 and SD that depends on α and β_1.
- Let $SE(\hat{\beta}_1)$ denote the SE of $\hat{\beta}_1$, obtained by inserting parameter estimates $\hat{\alpha}$ and $\hat{\beta}_1$ into the SD formula for $\hat{\beta}_1$.
- For large samples, the pivotal quantity has an approximate standard-normal distribution; i.e.,

$$\frac{\hat{\beta}_1 - \beta_1}{SE(\hat{\beta}_1)} \sim N(0, 1)$$

- Hypothesis tests and CIs follow in the usual way.

Dataset

- We'll be working with the `bpd` dataframe of low-birthweight babies from the neonatal ICU of a large hospital:

```
head(bpd)
```

```
##   bpd birthwt gestage toxemia steroid
## 1   1     850      27       0       0
## 2   0    1500      33       0       0
## 3   1    1360      32       0       0
## 4   0     960      35       1       0
## 5   0    1560      33       0       0
## 6   0    1120      29       0       1
```

- The `bpd` dataframe has a variable `bpd` indicating whether the baby had bronchopulmonary dysplasia.
  - This condition results from damage to the lungs caused by a respirator and long-term use of oxygen.
  - Most infants recover, but some may have long-term breathing difficulty.

Logistic Regression of BPD on Birth Weight

```
bfit <- glm(bpd~birthwt,data=bpd,family=binomial())
summary(bfit)$coefficients
```

```
##                Estimate   Std. Error   z value     Pr(>|z|)
## (Intercept)  4.03429128 0.6957120604  5.798795 6.679332e-09
## birthwt     -0.00422914 0.0006407678 -6.600112 4.108460e-11
```

- β_1 is the increase in the log-odds of BPD associated with a one-gram increase in birthweight.
- If $\beta_1 = 0$, then the log-odds of BPD don't change with birthweight and so BPD and birthweight are not associated.
- To assess whether BPD is associated with birthweight, we test the hypotheses that $H_0 : \beta_1 = 0$ *vs.* $H_a : \beta_1 \neq 0$
- The estimate of β_1 is $\hat{\beta}_1 = -0.0042$ with SE 0.00064.
- The test statistic is

$$\frac{\hat{\beta}_1 - 0}{SE(\hat{\beta}_1)} = \frac{-0.0042 - 0}{0.00064} = -6.6,$$

which gives a tiny *p*value. Strong statistical evidence that BPD is associated with birth weight.

Approximate 95% CIs

- We will obtain 95% CI's for the following:
  - β_1, the increase in the log-odds of BPD associated with a one-gram increase in birthweight, and
  - e^{β_1}, the factor by which the odds of BPD changes with a one-gram increase in birthweight (an OR)
- An approximate 95% CI for β_1 is

$$\hat{\beta}_1 \pm z^* \times SE(\hat{\beta}_1) = \hat{\beta}_1 \pm 1.96 \times SE(\hat{\beta}_1);$$

  i.e., estimate $\pm$ margin of error.
- For the BPD data, the 95% CI for β_1 is

$$-0.0042 \pm 1.96 \times 0.00064 = (-0.0055, -0.0029)$$

- The 95% CI for e^{β_1} is obtained by exponentiating and so is

$$(e^{-0.0055}, e^{-0.0029}) = (.995, .997)$$

But CIs from R are obtained differently

- The `confint()` function in R, when applied to a `glm()`-fitted object (such as `bfit`), gets the CIs for logistic-regression coefficients differently.
- Its CIs are based on inverting hypothesis tests directly[1]:
  - E.G., 95% CI is set of all β_1 values, b, retained in testing $H_0 : \beta_1 = b$ *vs.* $H_a : \beta_1 \neq b$ at 5% level, with data at hand.
  - Recall: Similar approach used by `mantelhaen.test()` to get CI (see Ch16 notes, pg 23).

```
confint(bfit) # CIs for alpha and beta1
```

```
##                    2.5 %       97.5 %
## (Intercept)  2.727548536  5.466632033
## birthwt     -0.005565106 -0.003040923
```

```
exp(confint(bfit)["birthwt",]) # CI for OR parameter e^{beta1}
```

```
##     2.5 %    97.5 %
## 0.9944504 0.9969637
```

[1] Note to self: but inverting likelihood-ratio not Wald tests

Comparing CI methods

- In this example, the CI for e^{β_1} from applying `confint()` to the `glm()`-fitted object is (0.994,0.997), which is very similar to the CI of (0.995,0.997) for the pivotal-quantity method.
- Know how to extract what is needed from the coefficients summary below to calculate a CI for the logistic-regression coefficients using the pivotal-quantity method.

```
summary(bfit)$coefficients
```

```
##                Estimate   Std. Error   z value     Pr(>|z|)
## (Intercept)  4.03429128 0.6957120604  5.798795 6.679332e-09
## birthwt     -0.00422914 0.0006407678 -6.600112 4.108460e-11
```

- Need the coefficient estimate, its SE and the critical value z^*.
- The critical value will be provided; for 95% CIs it is 1.96.

Interpreting the CI

- Also, know how to interpret the CI from `confint()`.
  - e.g., the `birthwt` row of `confint(bfit)` gives us the 95% CI for β_1, the slope coefficient for `birthwt`.

```
confint(bfit)["birthwt",]
```

```
##        2.5 %       97.5 %
## -0.005565106 -0.003040923
```

- To get the 95% CI for the OR, e^{β_1}, exponentiate the above CI for β_1:

```
exp(confint(bfit)["birthwt",])
```

```
##     2.5 %    97.5 %
## 0.9944504 0.9969637
```

- Interpretation: "With 95% confidence, an increase in birthweight of 1 gram is associated with an estimated change in the odds of BPD by a factor of between 0.994 and 0.997."

Example with Binary Explanatory Variable

- The bpd dataframe also has a column for the toxemia status of the baby's mother (1 if she was toxic and 0 if not)

```
head(bpd, n=3)
```

```
##   bpd birthwt gestage toxemia steroid
## 1   1     850      27       0       0
## 2   0    1500      33       0       0
## 3   1    1360      32       0       0
```

- Logistic regression of BPD on the binary variable toxemia:

```
bfit2 <- glm(bpd~toxemia,data=bpd,family=binomial)
summary(bfit2)$coefficients
```

```
##               Estimate Std. Error   z value     Pr(>|z|)
## (Intercept) -0.5717863  0.1494999 -3.824660 0.0001309529
## toxemia     -0.7719484  0.4821774 -1.600964 0.1093849689
```

CI for the Toxemia Effect

- Recall: For a binary exposure, X_1, e^{β_1} is the odds-ratio (OR) for exposed *vs.* unexposed groups.
- In this example, e^{β_1} is the ratio of the odds of BPD given toxemia divided by the odds of BPD given no toxemia

```
confint(bfit2)["toxemia",] #CI for beta1, the log-OR
```

```
##      2.5 %     97.5 %
## -1.8057010  0.1162591
```

```
exp(confint(bfit2)["toxemia",]) # CI for OR
```

```
##     2.5 %    97.5 %
## 0.1643592 1.1232868
```

- An approximate 95% CI for this OR is $(0.164, 1.12)$: