

Wald tests and likelihood ratio tests

- HW 2 due tomorrow
- HW 3 released later today, due next Friday
- Challenge 4: Deriving VIFs, released later today

Wald tests for multiple parameters

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 WBC_i + \beta_2 PLT_i$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_{(1)} \\ \beta_{(2)} \end{bmatrix}$$

$$\beta_{(1)} = \beta_0$$

$$\beta_{(2)} = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}$$

$$H_0: \beta_1 = \beta_2 = 0$$

$$H_A: \text{at least one of } \beta_1, \beta_2 \neq 0$$

$$\hat{\beta} \sim N\left(\begin{bmatrix} \beta_{(1)} \\ \beta_{(2)} \end{bmatrix}, \mathcal{I}^{-1}(\beta)\right)$$

$$\beta_{(2)} = \beta_{(2)}^0 \leftarrow \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\beta_{(2)} \neq \beta_{(2)}^0$$

$$\mathcal{I}^{-1}(\beta) = \begin{bmatrix} \mathcal{I}^{11} & \mathcal{I}^{12} \\ \mathcal{I}^{21} & \mathcal{I}^{22} \end{bmatrix}$$

$$\hat{\beta}_{(2)} \approx N(\beta_{(2)}, \mathcal{I}^{22})$$

$$\text{If } H_0 \text{ is true, then } \beta_{(2)} = \beta_{(2)}^0 \\ \Rightarrow \hat{\beta}_{(2)} \approx N(\beta_{(2)}^0, \mathcal{I}^{22})$$

$$\Rightarrow (\mathcal{I}^{22})^{-\frac{1}{2}} (\hat{\beta}_{(2)} - \beta_{(2)}^0) \\ \approx N(0, I)$$

$$(\hat{\Sigma}^{22})^{-\frac{1}{2}} (\hat{\beta}_{(2)} - \beta_{(2)}^0) \approx N(0, I)$$

$$W = (\hat{\beta}_{(2)} - \beta_{(2)}^0)^T \underbrace{(\hat{\Sigma}^{22})^{-1}}_{\text{positive semi-definite matrix}} (\hat{\beta}_{(2)} - \beta_{(2)}^0) \quad W \in \mathbb{R}$$

positive semi-definite matrix

def: A is PSD iff $x^T A x \geq 0 \quad \forall x$

$$\Rightarrow W \geq 0$$

$$H_0: \beta_{(2)} = \beta_{(2)}^0$$

$$H_A: \beta_{(2)} \neq \beta_{(2)}^0$$

if H_0 is true, do we

expect W to be large or small?

we expect $\hat{\beta}_{(2)} \approx \beta_{(2)} = \beta_{(2)}^0$ if H_0 is true $\Rightarrow W$ should be small

Large values of W are evidence against H_0

Fact: if $Z \sim N(0, I)$ then $Z^2 \sim \chi_1^2$. $\sum_{i=1}^q Z_i^2 \sim \chi_q^2$

$$W = (\hat{\beta}_{(2)} - \beta_{(2)}^0)^T (\mathcal{X}^{22})^{-1} (\hat{\beta}_{(2)} - \beta_{(2)}^0) \approx \chi^2_2 \quad \beta_{(2)} = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}$$

In general: $\beta = \begin{bmatrix} \beta_{(1)} \\ \beta_{(2)} \end{bmatrix}, \quad \beta_{(2)} \in \mathbb{R}^q, \quad \mathcal{X}^{22} \in \mathbb{R}^{q \times q}$

Then $W = (\hat{\beta}_{(2)} - \beta_{(2)}^0)^T (\mathcal{X}^{22})^{-1} (\hat{\beta}_{(2)} - \beta_{(2)}^0)$

$$\approx \chi^2_q \quad \text{under } H_0$$

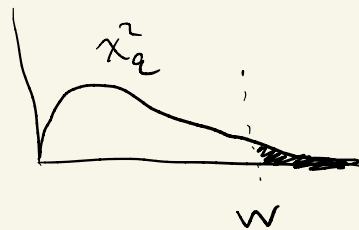
↑

parameters we test!

↑ $W \Rightarrow$ stronger evidence against H_0

p-value: $P(\chi^2_q > W)$

$\text{pchisq}(w, \text{df} = q, \text{lower.tail} = F)$



Class activity

https://sta712-f22.github.io/class_activities/ca_lecture_11.html

- + Wald tests for the dengue data

Likelihood ratio tests

```
m1 <- glm(Dengue ~ WBC + PLT, data = dengue,  
          family = binomial)  
summary(m1)
```

```
...  
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept)  2.6415063  0.1213233   21.77  <2e-16 ***  
## WBC         -0.2892904  0.0134349  -21.53  <2e-16 ***  
## PLT         -0.0065615  0.0005932  -11.06  <2e-16 ***  
## ---  
##      Null deviance: 6955.8  on 5719  degrees of freedom  
## Residual deviance: 5399.7  on 5717  degrees of freedom  
## AIC: 5405.7  
...
```

What information replaces R^2 and R^2_{adj} in the GLM output?

Deviance

Definition: The *deviance* of a fitted model with parameter estimates $\hat{\beta}$ is given by

$$2\ell(\text{saturated model}) - 2\ell(\hat{\beta})$$

Comparing deviances

```
m1 <- glm(Dengue ~ WBC + PLT, data = dengue,  
          family = binomial)  
summary(m1)
```

...

```
##      Null deviance: 6955.8    on 5719  degrees of freedom
```

```
## Residual deviance: 5399.7    on 5717  degrees of freedom
```

```
## AIC: 5405.7
```

...

Comparing deviances

Full model: $\log\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \beta_1 WBC_i + \beta_2 PLT_i$

Reduced model: $\log\left(\frac{p_i}{1 - p_i}\right) = \beta_0$

$$G = 2\ell(\hat{\beta}) - 2\ell(\hat{\beta}^0)$$

Why is G always ≥ 0 ?

Comparing deviances

Full model: $\log\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \beta_1 WBC_i + \beta_2 PLT_i$

Reduced model: $\log\left(\frac{p_i}{1 - p_i}\right) = \beta_0$

$$G = 2\ell(\hat{\beta}) - 2\ell(\hat{\beta}^0) = 1556.1$$

If the reduced model is correct, how unusual is $G = 1556.1$?

Likelihood ratio test