

# Inference: Likelihood ratio vs. Wald approaches

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# Introduction: The Wald approach

- Thus far, all our inferences have been based on the result:

$$\hat{\beta} \sim N(\beta, \phi(\mathbf{X}^T \mathbf{W} \mathbf{X})^{-1})$$

- This approach has the great advantage of simplicity: all you need to know is  $\hat{\beta}$  and  $\widehat{\text{Var}}(\hat{\beta})$  and you may construct by hand all the tests and confidence intervals you need for any element of  $\beta$  or any linear combination of the elements of  $\beta$  (these are called “Wald tests”, “Wald confidence intervals”, etc.)
- Recall, however, that the result on the previous slide is based on an approximation to the likelihood at the MLE, and this approximation may be poor at  $\beta$  values far from  $\hat{\beta}$

# Likelihood ratios

- A competing approach is based on likelihood ratios
- We consider the univariate case first, comparing the likelihood at an arbitrary value  $\theta$  with that of the MLE  $\hat{\theta}$ :

$$\lambda = \frac{L(\theta)}{L(\hat{\theta})}$$

- **Theorem:** As  $n \rightarrow \infty$  with iid data, subject to the usual regularity conditions,

$$-2 \log \lambda \xrightarrow{d} \chi_1^2$$

# Likelihood ratios for regression

- This result can be extended to multivariate and non-iid cases as well; consider two models:

$$\text{Full: } \boldsymbol{\beta} = (\boldsymbol{\beta}^{(1)}, \boldsymbol{\beta}^{(2)})$$

$$\text{Reduced: } \boldsymbol{\beta} = (\boldsymbol{\beta}_0^{(1)}, \boldsymbol{\beta}^{(2)})$$

where  $\boldsymbol{\beta}_0^{(1)}$  is a specified vector of constants

- Letting  $\lambda$  denote the likelihood ratio comparing the reduced model to the full model, we have

$$-2 \log \lambda \sim \chi_q^2,$$

where  $q$  is the length of  $\boldsymbol{\beta}^{(1)}$  (typically, the number of parameters assumed to be zero)

# Likelihood ratio tests and confidence intervals

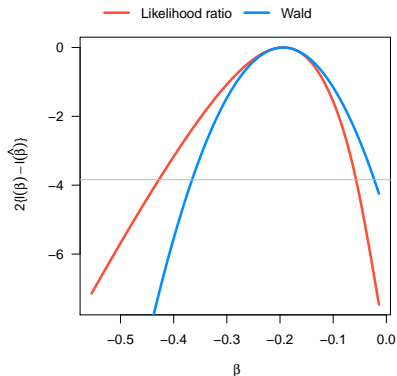
- This result allows us to carry out hypothesis tests by calculating  $p = \Pr(\chi_q^2 \geq 2 \log(\lambda))$
- It also allows us to construct  $(1 - \alpha)$  confidence intervals by inverting the above test – *i.e.*, finding the set of parameter values  $\beta_0^{(1)}$  such that

$$-2 \log \frac{L(\hat{\beta} | \beta^{(1)} = \beta_0^{(1)})}{L(\hat{\beta})} \leq \chi_{1-\alpha, q}^2,$$

where  $\chi_{1-\alpha, q}^2$  is the  $(1 - \alpha)$  quantile of the  $\chi^2$  distribution with  $q$  degrees of freedom

# Wald vs. Likelihood ratio

Estimating the effect of age upon survival for females in the Donner party:



95% confidence intervals:

Wald:  $(-0.365, -0.023)$

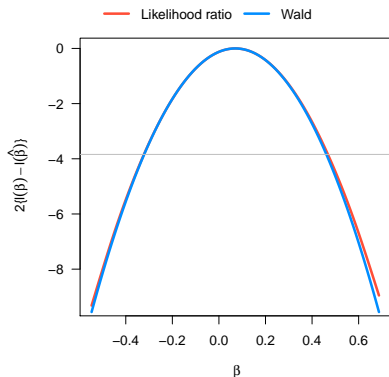
LR:  $(-0.428, -0.057)$

## Remarks

- As you can see, the Wald approach is incapable of capturing asymmetry in the likelihood function, and must therefore always produce symmetric confidence intervals about the MLE
- The likelihood ratio is not subject to this restriction (the downside, of course, is that we must refit a new model at all the different values for  $\beta$ )
- This impacts hypothesis testing as well: for testing the interaction term, the Wald test gives  $p = 0.087$  while the LRT gives  $p = 0.048$

# Wald vs. Likelihood ratio

For the donner data,  $n = 45$  and  $p = 3$ ; when  $n$  is larger, the agreement is much better (here,  $n = 100$ ,  $p = 2$ ):



95% confidence intervals:

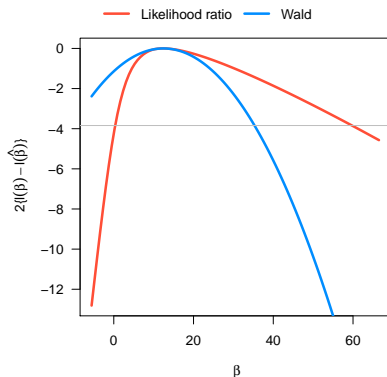
Wald:  $(-0.321, 0.461)$

LR:  $(-0.322, 0.468)$



# Wald vs. Likelihood ratio

When  $n$  is smaller, the agreement is even worse (here,  $n = 6$ ,  $p = 2$ ):



95% confidence intervals:

Wald:  $(-10.4, 35.3)$

LR:  $(0.336, 59.7)$

# Likelihood ratio vs. Wald: Summary

- The Wald approach enjoys popularity due to its simplicity (likelihood ratio confidence intervals are obviously difficult to construct by hand)
- The two approaches often agree quite well
- However, there are also situations where the two disagree dramatically
- Tests and confidence intervals based on likelihood ratios are more accurate, and should be trusted over the Wald approach