

MATH 3A/6A LEC 12

Last class we proved the following asymptotic result:

$$\frac{s(\theta; X_1, \dots, X_n)}{\sqrt{I_n(\theta)}} \xrightarrow{d} N(0,1) \text{ by CLT}$$

If we are testing $H_a: \theta \neq \theta_0 \Rightarrow H_0: \theta = \theta_0$

$$\Rightarrow Z|H_0 = \frac{s(\theta_0; X_1, \dots, X_n)}{\sqrt{I_n(\theta_0)}}$$

which gives us an approximate test.

So what is the usefulness of this then? The most useful is when it's difficult to derive a $\hat{\theta}$! When is this the case?

Consider DBP: $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Logistic}(\theta, 1) := \frac{e^{-(x-\theta)}}{(1+e^{-(x-\theta)})^2}$

MM gives us $\hat{\theta}_{MM} = \bar{X}$ always. From there, there's a CLT.

Can we find an alternative test? Let's get the MLE

$$L(\theta; X_1, \dots, X_n) = \prod_{i=1}^n \frac{e^{-(X_i - \theta)}}{(1 + e^{-(X_i - \theta)})^2} = \frac{e^{-\sum_{i=1}^n (X_i - \theta)}}{\prod_{i=1}^n (1 + e^{-(X_i - \theta)})^2} = \frac{e^{-n\bar{X} + n\theta}}{\prod_{i=1}^n (1 + e^{-(X_i - \theta)})^2}$$

$$\ell(\theta; X_1, \dots, X_n) = -n\bar{X} + n\theta - 2 \sum_{i=1}^n \ln(1 + e^{\theta - X_i})$$

$$\ell'(\theta; X_1, \dots, X_n) = n - 2 \sum_{i=1}^n \frac{e^{\theta - X_i}}{1 + e^{\theta - X_i}} \stackrel{!}{=} 0 \quad \text{Good Luck!}$$

MLE not available in closed form!

$$\begin{aligned} \ell''(\theta; X_1, \dots, X_n) &= -2 \sum \frac{d}{d\theta} \left[\frac{e^{\theta - X_i}}{1 + e^{\theta - X_i}} \right] = -2 \sum \frac{(1 + e^{\theta - X_i})(e^{\theta - X_i}) - (e^{\theta - X_i})^2}{(1 + e^{\theta - X_i})^2} \\ &= -2 \sum \frac{e^{\theta - X_i}}{(1 + e^{\theta - X_i})^2} \end{aligned}$$

$$I_1(\theta) = E[-\ell''(\theta; X_1, \dots, X_n)] = 2n E \left[\frac{e^{-(X - \theta)}}{(1 + e^{-(X - \theta)})^2} \right] = \int_{\mathbb{R}} \frac{e^{-(x - \theta)}}{(1 + e^{-(x - \theta)})^2} \frac{e^{-(x - \theta)}}{(1 + e^{-(x - \theta)})^2} dx$$

$$= \int_{\mathbb{R}} \frac{(e^{-(x - \theta)})^2}{(1 + e^{-(x - \theta)})^4} dx$$

$$= \int_{\mathbb{R}} \left(\frac{1}{1+e^{-x-\theta}} \right)^2 \left(\frac{e^{-x-\theta}}{(1+e^{-x-\theta})^2} \right)^2$$

$$\text{let } u = \frac{1}{1+e^{-x-\theta}}, \quad 1-u = 1 - \frac{1}{1+e^{-x-\theta}} = \frac{e^{-x-\theta}}{1+e^{-x-\theta}}$$

$$\frac{du}{dx} = (1+e^{-x-\theta})^{-2} e^{-x-\theta} = \frac{1}{1+e^{-x-\theta}} \cdot \frac{e^{-x-\theta}}{1+e^{-x-\theta}} = u(1-u) \Rightarrow dx = \frac{1}{u(1-u)} du$$

$$x = -\infty \Rightarrow u = 0, \quad x = \infty \Rightarrow u = 1$$

$$\begin{aligned} &= \int_0^1 u^2(1-u)^2 \frac{1}{u(1-u)} du = \int_0^1 u(1-u) du = \int_0^1 (u - u^2) du = \left[\frac{u^2}{2} - \frac{u^3}{3} \right]_0^1 \\ &= \frac{1}{2} - \frac{1}{3} = \frac{1}{6} \end{aligned}$$

$$\Rightarrow J_n(\theta) = 2n \left(\frac{1}{6} \right) = \frac{n}{3}$$

$$\Rightarrow \text{To test } H_0: \theta = \theta_0, \text{ we ask}$$

$$\Rightarrow \hat{\theta} = \frac{n-2 \sum \frac{e^{\theta_0} e^{-x_i}}{1+e^{\theta_0} e^{-x_i}}}{\sqrt{\frac{n}{3}}} \quad ? \in (-2, 2)$$

e.g. $x = \langle 1.85, 4.18, 2.63, 3.91, 4.23, 4.24, 3.17, 3.69, 3.13, 1.04 \rangle, \quad n=10$
 $H_0: \theta=0$

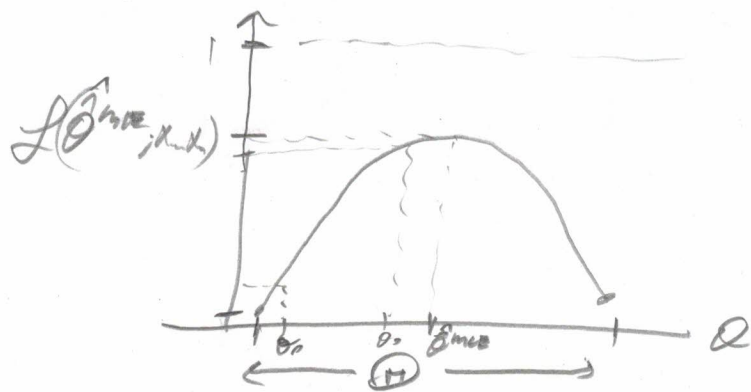
$$\Rightarrow \hat{\theta} = 4.77 \Rightarrow \text{Reject } H_0$$

Again, no estimate of θ is necessary...

Let's explore another strategy to create a test for $H_0: \theta = \theta_0$.
Consider the following test statistic, the likelihood ratio (LR):

$$\hat{LR} = \frac{L(\hat{\theta}_{MLE}; X_1, \dots, X_n)}{L(\theta_0; X_1, \dots, X_n)} = \prod_{i=1}^n \frac{L(\hat{\theta}_{MLE}; X_i)}{L(\theta_0; X_i)}$$

Note this ratio at a maximum is 1 since $L(\hat{\theta}_{MLE}; X_1, \dots, X_n)$ is the maximum the likelihood could ever become (by def)



Note: the denominator can never be zero since that would mean $\theta_0 \notin (H) \Rightarrow \hat{LR} \in [1, \infty)$

When indicates a departure from H_0 ? If the ratio is large i.e. $L(\hat{\theta}_{MLE}; X_1, \dots, X_n) \gg L(\theta_0; X_1, \dots, X_n)$

this means the data estimates θ far from $\theta_0 \Rightarrow$ Reject H_0 !

The last thing we need to have a working test is the distr. of the test statistic. Consider instead:

$$\hat{\Lambda} := 2 \ln(\hat{LR}) = 2 \ln \left(\frac{\ell(\hat{\theta}_{MLE}; X_n, Y_n)}{\ell(\theta_0; X_n, Y_n)} \right) = 2 \left(\ell(\hat{\theta}_{MLE}; X_n, Y_n) - \ell(\theta_0; X_n, Y_n) \right)$$

"Capece Lambda"

$\hat{\Lambda}$ and \hat{LR} are 1:1. If $\hat{LR} \uparrow \Leftrightarrow \hat{\Lambda} \uparrow$

So we reject if $\hat{\Lambda}$ is large. We now prove the asymptotic distr of $\hat{\Lambda}$ (see p. 489 of C & B)

Just like when proving the core MLE thm, we consider the 2nd order Taylor series for the log likelihood:

$$\ell(\theta_0; X_n, Y_n) \approx \underset{\substack{\uparrow \\ \text{drop this term going forward}}}{\ell(\hat{\theta}_{MLE}; X_n, Y_n)} + (\theta_0 - \hat{\theta}_{MLE}) \underbrace{\ell'(\hat{\theta}_{MLE}; X_n, Y_n)}_{=0} + \frac{1}{2} (\theta_0 - \hat{\theta}_{MLE})^2 \ell''(\hat{\theta}_{MLE}; X_n, Y_n)$$

$$\Rightarrow \ell(\theta_0; X_n, Y_n) = \ell(\hat{\theta}_{MLE}; X_n, Y_n) + \frac{1}{2} (\theta_0 - \hat{\theta}_{MLE})^2 \ell''(\hat{\theta}_{MLE}; X_n, Y_n)$$

$$\Rightarrow \ell(\hat{\theta}_{MLE}; X_n, Y_n) - \ell(\theta_0; X_n, Y_n) = -\frac{1}{2} (\theta_0 - \hat{\theta}_{MLE})^2 \ell''(\hat{\theta}_{MLE}; X_n, Y_n)$$

multi by 2

$$\begin{aligned} \Rightarrow \hat{\Lambda} &= -(\theta_0 - \hat{\theta}_{MLE})^2 \ell''(\hat{\theta}_{MLE}; X_n, Y_n) \cdot \frac{\ell''(\theta_0; X_n, Y_n)}{\ell''(\hat{\theta}_{MLE}; X_n, Y_n)} \\ &= -(\theta_0 - \hat{\theta}_{MLE})^2 \ell''(\theta_0; X_n, Y_n) \frac{\ell''(\hat{\theta}_{MLE}; X_n, Y_n)}{\ell''(\theta_0; X_n, Y_n)} \end{aligned}$$

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$$= \frac{(\theta_0 - \hat{\theta}_{MLE})^2}{1} A_1 = \frac{(\theta_0 - \hat{\theta}_{MLE})^2}{\sum - \ell''(\theta; x_i) \cdot \frac{1}{n}} \cdot \frac{1}{I(\theta)} A_1$$

$$= \frac{(\theta_0 - \hat{\theta}_{MLE})^2}{\frac{1}{n} I(\theta)} \cdot \frac{\frac{1}{n} \sum - \ell''(\theta; x_i)}{I(\theta)} A_1$$

A_2

$$= \underbrace{\left(\frac{\theta_0 - \hat{\theta}_{MLE}}{\sqrt{\frac{I(\theta)^{-1}}{n}}} \right)^2}_{B} A_1 A_2$$

Facts $B \xrightarrow{d} N(0,1)$ by core MLE thm

$\Rightarrow B^2 \xrightarrow{d} \chi^2$ by CMT which we have proved but it's true...

$$A_1 = \frac{\ell''(\hat{\theta}_{MLE}; x_1, \dots, x_n)}{\ell''(\theta; x_1, \dots, x_n)} \xrightarrow{p} 1 \text{ by CMT and } \hat{\theta}_{MLE} \xrightarrow{p} \theta$$

$$A_2 \xrightarrow{p} 1 \text{ by CMT and } \frac{1}{n} \sum - \ell''(\theta; x_i) \xrightarrow{p} E[-\ell''(\theta; x_i)] = I(\theta)$$

$\Rightarrow A_1 A_2 \xrightarrow{p} 1$ by Slutsky's (A)

$$\Rightarrow \hat{\Lambda} \xrightarrow{d} \chi^2_1 \text{ by Slutsky's (A)}$$

\Rightarrow we have a test of LR test (LRT)

Eg. If $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bern}(\theta)$, $\theta_{true} = \bar{X}$

By Wald test AND score test, the test statistic was $Z/H_0 = \frac{\hat{\theta}_{true} - \theta_0}{\sqrt{\frac{\theta_0(1-\theta_0)}{n}}}$

By the LRT,

$$\hat{L}R = \prod_{i=1}^n \frac{L(\bar{X}; X_1, \dots, X_n)}{L(\theta_0; X_1, \dots, X_n)} = \prod_{i=1}^n \frac{\bar{X}^{X_i} (1-\bar{X})^{1-X_i}}{\theta_0^{X_i} (1-\theta_0)^{1-X_i}} = \left(\frac{\bar{X}}{\theta_0}\right)^{\sum X_i} \left(\frac{1-\bar{X}}{1-\theta_0}\right)^{n-\sum X_i}$$

$$\hat{\Lambda} = 2 \ln(\hat{L}R) = 2 \left(\sum X_i \ln\left(\frac{\bar{X}}{\theta_0}\right) + (n - \sum X_i) \ln\left(\frac{1-\bar{X}}{1-\theta_0}\right) \right) \quad \text{which is not the score test statistic!}$$

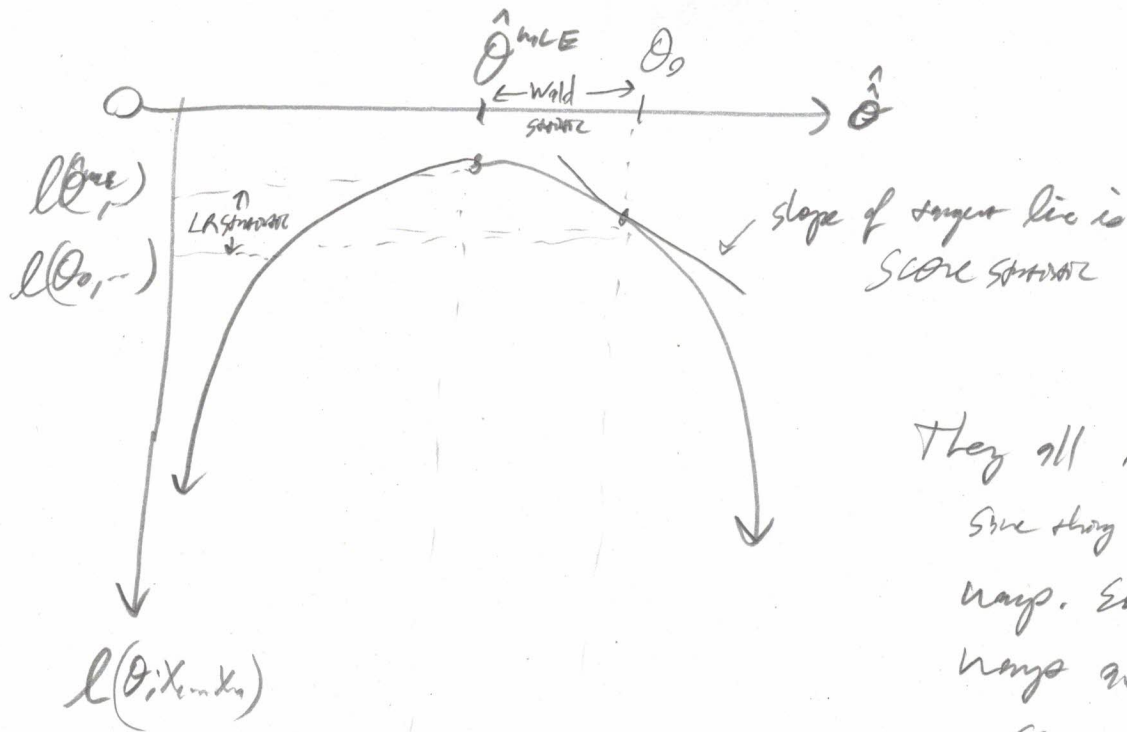
Calculate $\hat{\Lambda}$. The RET is always 1-sided because the difference in

$$\log\text{-lik is always } \geq 0, \quad F_{\chi^2_1}(C) = .95 \Rightarrow C \approx 3.84 \Rightarrow \text{RET} = [0, 3.84]$$

Flip a coin $n=100$ times, $\sum X_i = 61$. Test $H_0: \theta = .5$ at $\alpha = 5\%$.

$$\hat{\Lambda} = 2 \left(61 \ln\left(\frac{.61}{.5}\right) + 39 \ln\left(\frac{.39}{.5}\right) \right) = 9.88 \notin \text{RET} \Rightarrow \text{Reject } H_0!$$

Visualizing the Wald, Score and LR tests... for $H_0: \theta = \theta_0$ [8]



They all measure the same thing in ^{different} ways. Sometimes these ways are exactly equivalent, sometimes not. Sometimes the way is more convenient. Sometimes one has higher power. All assumptions.

