

PLSC 503 – Spring 2025

MLE: Testing and Inference + An Introduction to Models for Binary Responses

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- “The Trinity”
- An example
- Practical advice

1. Pick some $\mathbf{H}_A : \Theta = \Theta_A$
2. Estimate $\hat{\Theta}$
3. Determine distribution of $\hat{\Theta}$ under \mathbf{H}_A
4. Use (2) and (3) $\rightarrow \hat{\mathbf{S}} \sim h(\Theta, \hat{\Theta})$ (*test statistic*)
5. Assess $\Pr(\hat{\mathbf{S}}|\mathbf{H}_A)$

Single Coefficients: Significance Testing

Consistency / Efficiency / Normality:

$$\hat{\Theta}_{MLE} \overset{a}{\sim} \mathbf{N}[\Theta, \mathbf{I}(\hat{\Theta}_{MLE})]$$

Means that

$$\frac{\hat{\theta}_k - \theta_k}{\sqrt{\hat{\sigma}_k^2}} \sim N(0, 1)$$

So:

- Choose θ_A
- Estimate $\hat{\theta}_k, \hat{\sigma}_k^2$
- Compare $z_k = \frac{\hat{\theta}_k - \theta_A}{\sqrt{\hat{\sigma}_k^2}}$ to a z-table
- (Or, just look at your output...)

Single Coefficients: Confidence Intervals

To create a single confidence interval:

- Choose $\alpha \in (0, 1)$ = desired level of “significance”
- The $(1 - \alpha) \times 100$ -percent confidence intervals for $\hat{\theta}_k$ are:

$$\hat{\theta}_k \pm \left(z_{\alpha} \sqrt{\hat{\sigma}_k^2} \right)$$

- (Or just look at your output...)

More General Tests: “The Trinity”

Three tests:

- Likelihood-Ratio (“LR”)
- Wald
- Lagrangian Multiplier (or “score”)

Traits:

- Wald, LM \xrightarrow{a} LR
- For the linear model, Wald \geq LR \geq LM

Generally:

$$\mathbf{R}\Theta = \mathbf{r}$$

For one parameter:

$$\theta_2 = -2 \iff (0 \ 1 \ 0) \begin{pmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{pmatrix} = -2$$

For $>$ one parameter:

$$\Theta_A : \theta_2 = 1, \theta_1 = 2\theta_3$$

$$\begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & -2 \end{pmatrix} \begin{pmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$r = \text{rows}(\mathbf{R}) \in [0, K]$$

Likelihood Ratio Test

We know that:

$$L(\hat{\Theta}) \geq L(\Theta_A), \text{ but}$$

By how much?

Odds of one thing vs. another:

$$\frac{\Pr(\text{Something})}{\Pr(\text{Something Else})}$$

Implies:

$$\frac{L(\Theta_A)}{L(\hat{\Theta})} (\leq 1)$$

Suggests:

$$\ln L(\Theta_A) - \ln L(\hat{\Theta}) (\leq 0)$$

$$-2[\ln L(\Theta_A) - \ln L(\hat{\Theta})] \stackrel{a}{\sim} \chi_r^2$$

Traits:

- Intuition: Difference in $\ln L$ under constraint(s)
- Asymptotic
- Unreliable if $r > 100$ (or so)
- Easy to compute, but
- Requires that we have *both* $\ln L(\Theta_A)$ and $\ln L(\hat{\Theta})$

Idea: If Θ_A , then

$$\mathbf{R}\Theta = \mathbf{r}$$

So:

$$\mathbf{R}\Theta - \mathbf{r} = \mathbf{0}$$

But...

- We have only $\hat{\Theta}$ (from sample data)
- Possible that $\mathbf{R}\hat{\Theta} - \mathbf{r} = \mathbf{0}$ *due to chance* (sampling variability).
- Solution: Account for *variability* in $\hat{\Theta}$.

Wald Tests (continued)

Test statistic:

$$\mathbf{W} = (\mathbf{R}\hat{\boldsymbol{\Theta}} - \mathbf{r})' \left[\mathbf{R} \text{Var}(\hat{\boldsymbol{\Theta}}) \mathbf{R}' \right]^{-1} (\mathbf{R}\hat{\boldsymbol{\Theta}} - \mathbf{r})$$

Distribution:

$$\mathbf{W} \stackrel{a}{\sim} \chi_r^2$$

Traits:

- (+) Easy, fast
- (+) No need for $\ln L(\boldsymbol{\Theta}_{\mathbf{A}})$
- (-) Uses $\text{Var}(\hat{\boldsymbol{\Theta}})$, not $\text{Var}(\boldsymbol{\Theta}_{\mathbf{A}})$ (potentially poor coverage)
- (-) Can yield nonsensical results

Lagrange Multiplier (LM) Tests

Idea: If Θ_A , then

$$\left. \frac{\partial \ln L}{\partial \theta} \right|_{\Theta_A} \approx \mathbf{0}$$

Consider a new problem:

$$\max_{\Theta} [L(\Theta) - \lambda(\Theta - \Theta_A)]$$

Yields:

$$\tilde{\Theta} = \Theta_A$$

$$\tilde{\lambda} = \mathbf{g}(\tilde{\Theta})$$

Suggests

$$LM = \mathbf{g}(\tilde{\Theta})' \mathbf{I}(\tilde{\Theta})^{-1} \mathbf{g}(\tilde{\Theta})$$

$$LM \stackrel{a}{\sim} \chi_r^2$$

Traits:

(+) No need for $\hat{\Theta}$!

(-) No information on $\hat{\Theta}$...

Tests, Conceptually (C. Franklin remix)

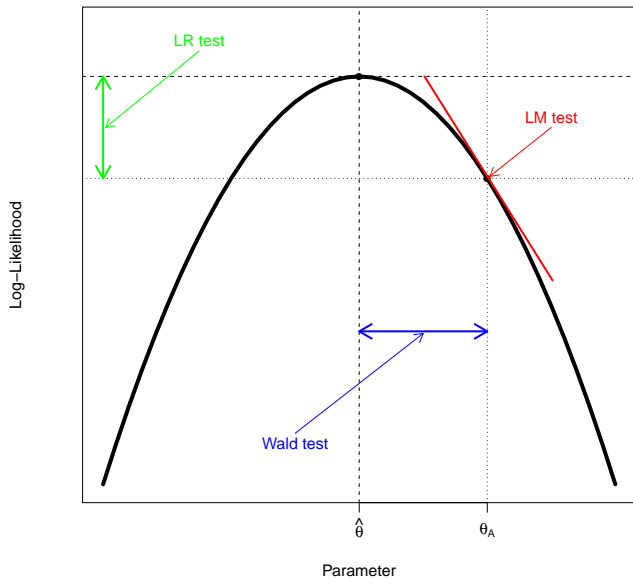
Three tests, compared:

- The LR asks, “**Did** the likelihood change much under the **null** hypotheses versus the alternative?”
- The Wald test asks, “Are the estimated parameters very far away from what they **would** be under the **null** hypothesis?”
- The LM test asks, “If I had a **less restrictive** likelihood function, **would** its derivative be close to zero here at the restricted ML estimate?”

h.t. Buse (1982):

- LR test \approx manic mountaineer
- Wald test \approx tired mountaineer
- LM test \approx lazy mountaineer

Tests, Conceptually (adapted from Fox 1997, p. 570)



- All are asymptotically identical...
- Require different estimates, but similar information
- Generally, preference goes $LR > Wald > LM$

Tests in R:

- Wald tests: `waldtest` (in `lmtest`), `wald.test` (in `aod`), etc.
- LR tests: `lrtest` (in `lmtest`), `RLRsim`, many others
- LMs “by-hand” (straightforward...)

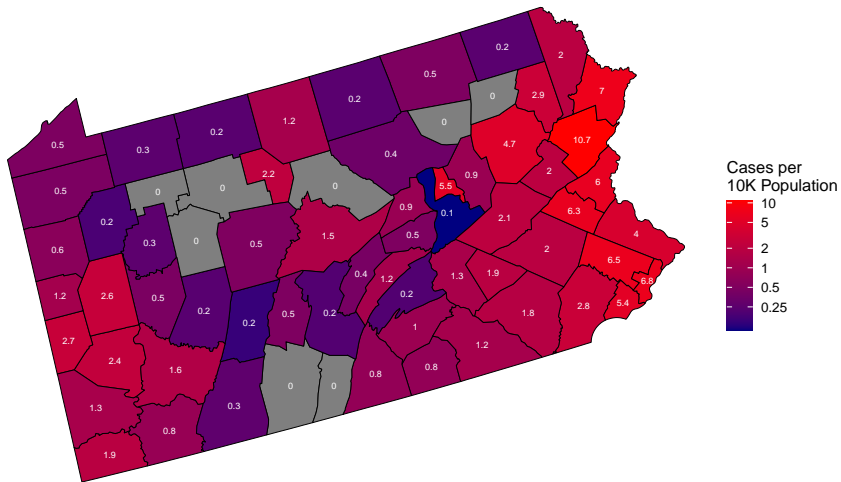
Example: Historical COVID-19 in Pennsylvania

Some (historical) data:

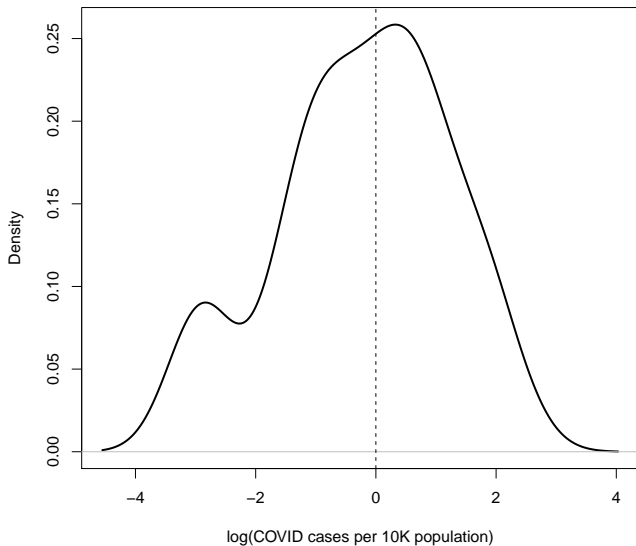
- COVID-19 cases, 67 counties, as of 3/30/2020
- Source: <https://github.com/nytimes/covid-19-data>
- (Badly) Skewed \rightarrow logged
- We're guessing $\sim N(\mu, \sigma^2)$...

PA COVID-19 Cases (per 10,000 population) by County, through March 30, 2020

Source: <https://github.com/nytimes/covid-19-data>



PA COVID-19 Cases per 10K Population, 3/30/2020 (logged)



```
> library(readr)
> library(maxLik)
> library(aod)
> library(lmtest)

# Get COVID data:

> COVID<-read_csv("https://raw.githubusercontent.com/PrisonRodeo/
  PLSC503-2025-git/master/Data/COVID-PA.csv")

# log-lik function:

> COVIDll <- function(param) {
+   mu <- param[1]
+   sigma <- param[2]
+   ll <- -0.5*log(sigma^2) - (0.5*((x-mu)^2/sigma^2))
+   ll
+ }

> x<-log(COVID$CasesPer10K+0.055)
```

```
> hats <- maxLik(COVID11, start=c(0,1))
> summary(hats)
-----
Maximum Likelihood estimation
Newton-Raphson maximisation, 5 iterations
Return code 2: successive function values
  within tolerance limit
Log-Likelihood: -56.4
2 free parameters
Estimates:
      Estimate Std. error t value Pr(> t)
[1,]   -0.217     0.172   -1.26   0.21
[2,]    1.407     0.122   11.58 <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
-----
```

≡ Mean-Only Linear Model

```
> COVIDLM<-lm(x~1)
> summary(COVIDLM)
```

Call:

```
lm(formula = x ~ 1)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.684	-0.972	0.163	0.969	2.595

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.217	0.173	-1.25	0.22

Residual standard error: 1.42 on 66 degrees of freedom

```
> hats$estimate  
[1] -0.217  1.407
```

```
> hats$gradient  
[1] 0.00000000422 0.00000223621
```

```
> hats$hessian  
      [,1] [,2]  
[1,] -33.8  0.0  
[2,]  0.0 -67.7
```


More moving parts...

```
> -(solve(hats$hessian))  
      [,1] [,2]  
[1,] 0.0296 0.0000  
[2,] 0.0000 0.0148
```

```
> sqrt(-(solve(hats$hessian)))  
      [,1] [,2]  
[1,] 0.172 0.000  
[2,] 0.000 0.122
```

Restricted model: fix $\mu = 0$:

```
> COVID11Alt <- function(param) {  
+   sigma <- param[1]  
+   ll <- -0.5*log(sigma^2) - (0.5*((x-0)^2/sigma^2))  
+   ll  
+ }
```

```
> hatsF <- maxLik(COVID11, start=c(0,1))  
> hatsR <- maxLik(COVID11Alt, start=c(1))
```

Log-likelihoods:

```
> hatsF$maximum  
[1] -56.4
```

```
> hatsR$maximum  
[1] -57.2
```

Testing:

```
> -2*(hatsR$maximum-hatsF$maximum)  
[1] 1.57
```

```
> pchisq(-2*(hatsR$maximum-hatsF$maximum),df=1,lower.tail=FALSE)  
[1] 0.21
```

LR tests (continued)

```
> library(lmtest) # install as necessary
```

```
> lrtest(hatsF,hatsR)
```

Likelihood ratio test

Model 1: hatsF

Model 2: hatsR

	#Df	LogLik	Df	Chisq	Pr(>Chisq)
1	2	-56.4			
2	1	-57.2	-1	1.57	0.21

```
> # Compare to Wald:
```

```
>
```

```
> wald.test(Sigma=vcov(hats),b=coef(hats),Terms=1:1,H0=0)
```

Wald test:

Chi-squared test:

X2 = 1.6, df = 1, P(> X2) = 0.21

Test $\mu = \sigma = 2$:

```
> aod::wald.test(Sigma=vcov(hats),b=coef(hats),Terms=1:2,H0=c(2,2),verbose=TRUE)
```

Wald test:

Coefficients:

```
[1] -0.22  1.41
```

Var-cov matrix of the coefficients:

```
      [,1] [,2]
[1,] 0.030 0.000
[2,] 0.000 0.015
```

Test-design matrix:

```
      [,1] [,2]
L1      1    0
L2      0    1
```

Positions of tested coefficients in the vector of coefficients: 1, 2

H0: -0.2166 = 2; 1.4073 = 2

Chi-squared test:

X2 = 190.0, df = 2, P(> X2) = 0.0

Test $\mu = 0, \sigma = 2$:

```
> aod::wald.test(Sigma=vcov(hats),b=coef(hats),Terms=1:2,H0=c(0,2))
```

Wald test:

Chi-squared test:

X2 = 25.4, df = 2, P(> X2) = 0.0000031

Test $\mu = -0.2, \sigma = 1.5$:

```
> aod::wald.test(Sigma=vcov(hats),b=coef(hats),Terms=1:2,H0=c(-0.2,1.5))
```

Wald test:

Chi-squared test:

X2 = 0.59, df = 2, P(> X2) = 0.74

Nonsensical Wald Test

Test : $\sigma = 0$:

```
> aod::wald.test(Sigma=vcov(hats),b=coef(hats),Terms=2:2,H0=0)
```

Wald test:

Chi-squared test:

X2 = 134.0, df = 1, P(> X2) = 0.0

Attempt the Same Nonsensical LR Test...

Test : $\sigma = 0$:

```
> hatsDumb <- maxLik(COVID11, start=c(mu=0,sigma=0),  
+                    fixed="sigma")
```

```
> summary(hatsDumb)
```

```
-----  
Maximum Likelihood estimation  
Newton-Raphson maximisation, 0 iterations  
Return code 100: Initial value out of range.  
-----
```

```
> lrtest(hatsF,hatsDumb)
```

```
Error in attr(11, "df") <- sum(activePar(object)) :  
  attempt to set an attribute on NULL
```


Binary Response Models

Linear Probability Model (LPM)

$$E(Y) = \mathbf{X}\beta$$

$$Y \in \{0, 1\}$$

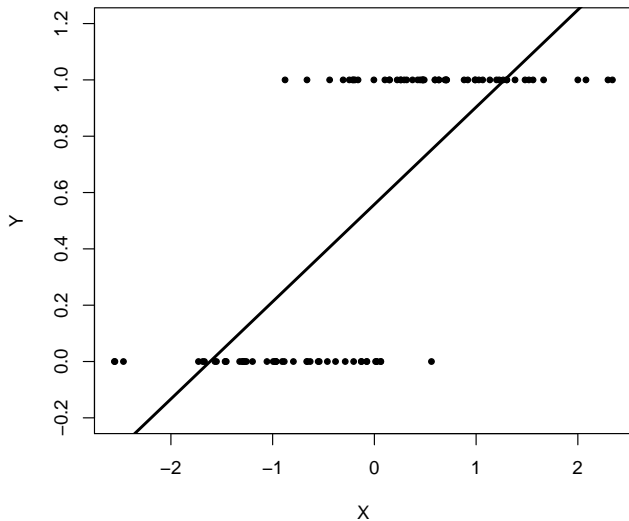
$$\begin{aligned} E(Y) &= 1[\Pr(Y = 1)] + 0[\Pr(Y = 0)] \\ &= \Pr(Y = 1) \end{aligned}$$

So:

$$\Pr(Y_i = 1) = \mathbf{X}_i\beta$$

or:

$$Y_i = \mathbf{X}_i\beta + u_i$$



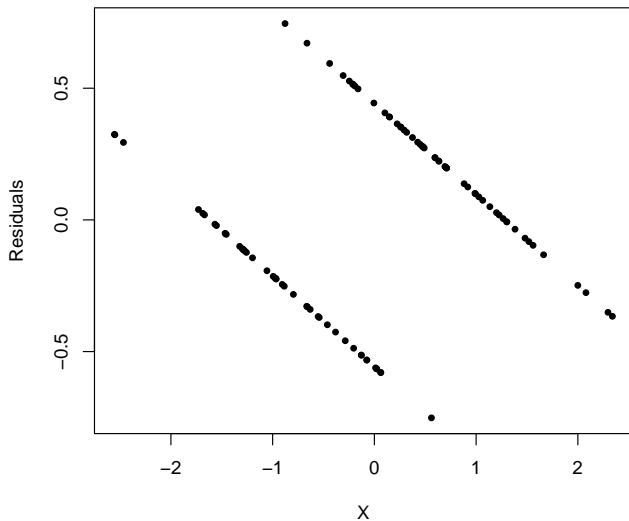
Variance:

$$\begin{aligned}\text{Var}(Y) &= E(Y)[1 - E(Y)] \\ &= \mathbf{X}_i\beta(1 - \mathbf{X}_i\beta)\end{aligned}$$

Residuals:

$$\hat{u}_i \in \{1 - \mathbf{X}_i\hat{\beta}, -\mathbf{X}_i\hat{\beta}\}$$

LPM Residuals



Concerns:

- Predictions $\notin [0, 1]$
- Functional form $\rightarrow \frac{\partial E(Y)}{\partial X} = \beta$ (reasonable?)

When *can* you use an LPM?

- When $\overline{Pr(Y_i = 1)} \approx 0.5$, and
- linearity seems reasonable, and
- you're a lazy economist at a fancy place.

See: Chen, Kaicheng, Robert S. Martin, and Jeffrey M. Wooldridge. 2023. “Another Look at the Linear Probability Model and Nonlinear Index Models.” Working paper: Michigan State University.

Start with:

$$Y_i^* = \mathbf{X}_i\beta + u_i$$

And:

$$Y_i = 0 \text{ if } Y_i^* < 0$$

$$Y_i = 1 \text{ if } Y_i^* \geq 0$$

So:

$$\begin{aligned}\Pr(Y_i = 1) &= \Pr(Y_i^* \geq 0) \\ &= \Pr(\mathbf{X}_i\beta + u_i \geq 0) \\ &= \Pr(u_i \geq -\mathbf{X}_i\beta) \\ &= \Pr(u_i \leq \mathbf{X}_i\beta) \\ &= \int_{-\infty}^{\mathbf{X}_i\beta} f(u) du\end{aligned}$$

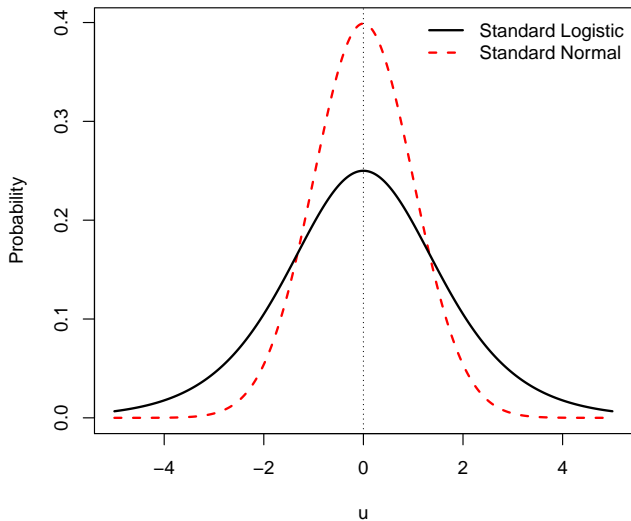
“Standard logistic” PDF:

$$\Pr(u) \equiv \lambda(u) = \frac{\exp(u)}{[1 + \exp(u)]^2}$$

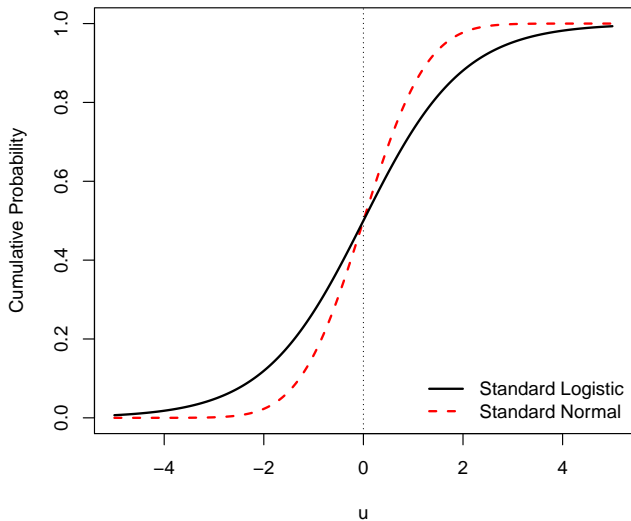
CDF:

$$\begin{aligned}\Lambda(u) &= \int \lambda(u) du \\ &= \frac{\exp(u)}{1 + \exp(u)} \\ &= \frac{1}{1 + \exp(-u)}\end{aligned}$$

Standard Normal and Logistic PDFs



Standard Normal and Logistic CDFs



For the standard logistic:

- $\lambda(u) = 1 - \lambda(-u)$
- $\Lambda(u) = 1 - \Lambda(-u)$
- $\text{Var}(u) = \frac{\pi^2}{3} \approx 3.29$

$$\begin{aligned}\Pr(Y_i = 1) &= \Pr(Y_i^* > 0) \\ &= \Pr(u_i \leq \mathbf{X}_i\boldsymbol{\beta}) \\ &= \Lambda(\mathbf{X}_i\boldsymbol{\beta}) \\ &= \frac{\exp(\mathbf{X}_i\boldsymbol{\beta})}{1 + \exp(\mathbf{X}_i\boldsymbol{\beta})}\end{aligned}$$

$$\text{(equivalently)} = \frac{1}{1 + \exp(-\mathbf{X}_i\boldsymbol{\beta})}$$

$$L_i = \left(\frac{\exp(\mathbf{X}_i\beta)}{1 + \exp(\mathbf{X}_i\beta)} \right)^{Y_i} \left[1 - \left(\frac{\exp(\mathbf{X}_i\beta)}{1 + \exp(\mathbf{X}_i\beta)} \right) \right]^{1-Y_i}$$

$$L = \prod_{i=1}^N \left(\frac{\exp(\mathbf{X}_i\beta)}{1 + \exp(\mathbf{X}_i\beta)} \right)^{Y_i} \left[1 - \left(\frac{\exp(\mathbf{X}_i\beta)}{1 + \exp(\mathbf{X}_i\beta)} \right) \right]^{1-Y_i}$$

$$\begin{aligned} \ln L &= \sum_{i=1}^N Y_i \ln \left(\frac{\exp(\mathbf{X}_i\beta)}{1 + \exp(\mathbf{X}_i\beta)} \right) + \\ &\quad (1 - Y_i) \ln \left[1 - \left(\frac{\exp(\mathbf{X}_i\beta)}{1 + \exp(\mathbf{X}_i\beta)} \right) \right] \end{aligned}$$

Digression I: Logit as an Odds Model

$$\text{Odds}(Z) \equiv \Omega(Z) = \frac{\Pr(Z)}{1 - \Pr(Z)}.$$

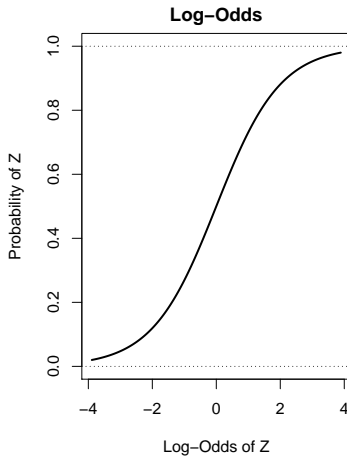
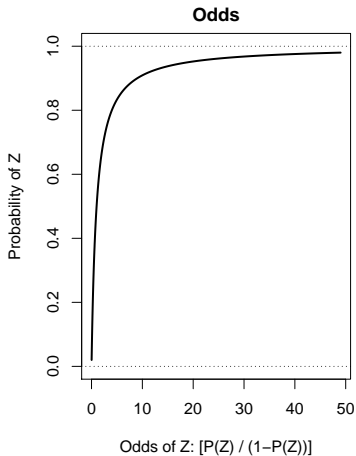
$$\ln[\Omega(Z)] = \ln \left[\frac{\Pr(Z)}{1 - \Pr(Z)} \right]$$

$$\ln[\Omega(Z_i)] = \mathbf{X}_i\beta$$

$$\begin{aligned}\Omega(Z_i) &= \frac{\Pr(Z)}{1 - \Pr(Z)} \\ &= \exp(\mathbf{X}_i\beta)\end{aligned}$$

$$\Pr(Z_i) = \frac{\exp(\mathbf{X}_i\beta)}{1 + \exp(\mathbf{X}_i\beta)}$$

Visualizing Log-Odds



Standard Normal PDF:

$$\Pr(u) \equiv \phi(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right)$$

Standard Normal CDF:

$$\Phi(u) = \int_{-\infty}^u \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right) du$$

$$\begin{aligned}\Pr(Y_i = 1) &= \Phi(\mathbf{X}_i\boldsymbol{\beta}) \\ &= \int_{-\infty}^{\mathbf{X}_i\boldsymbol{\beta}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(\mathbf{X}_i\boldsymbol{\beta})^2}{2}\right) d\mathbf{X}_i\boldsymbol{\beta}\end{aligned}$$

$$L = \prod_{i=1}^N [\Phi(\mathbf{X}_i\boldsymbol{\beta})]^{Y_i} [1 - \Phi(\mathbf{X}_i\boldsymbol{\beta})]^{(1-Y_i)}$$

$$\ln L = \sum_{i=1}^N Y_i \ln \Phi(\mathbf{X}_i\boldsymbol{\beta}) + (1 - Y_i) \ln [1 - \Phi(\mathbf{X}_i\boldsymbol{\beta})]$$

Digression II: The Random Utility Model

$$Y \in \{SQ, A\}$$

$$\begin{aligned} Y_i &= A && \text{if } E[U_i(A)] \geq E[U_i(SQ)] \\ &= SQ && \text{if } E[U_i(A)] < E[U_i(SQ)] \end{aligned}$$

$$E[U_i(A)] = \mathbf{X}_{iA}\boldsymbol{\beta} + u_{iA}$$

So:

$$\begin{aligned} \Pr(Y = A) &= \Pr\{E[U_i(A)] \geq E[U_i(SQ)]\} \\ &= \Pr\{(\mathbf{X}_{iA}\boldsymbol{\beta} + u_{iA}) \geq E[U_i(SQ)]\} \end{aligned}$$

Digression II: The Random Utility Model

Normalize:

$$E[U_i(SQ)] = 0$$

Then:

$$\begin{aligned}\Pr(Y = A) &= \Pr\{(\mathbf{X}_{iA}\boldsymbol{\beta} + u_{iA}) \geq 0\} \\ &= \Pr\{u_{iA} \geq -\mathbf{X}_{iA}\boldsymbol{\beta}\} \\ &= F(\mathbf{X}_{iA}\boldsymbol{\beta})\end{aligned}$$

Another Model: Complementary Log-Log

Uses:

$$\Pr(Y_i = 1) = 1 - \exp[-\exp(\mathbf{X}_i\beta)]$$

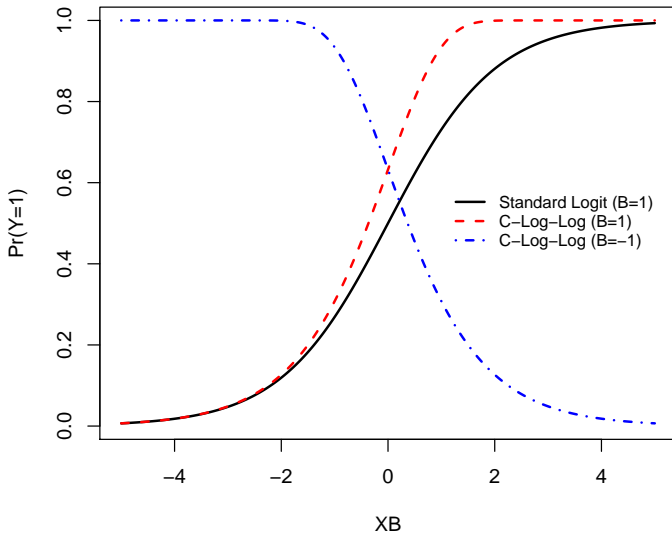
or

$$\ln\{-\ln[1 - \Pr(Y_i = 1)]\} = \mathbf{X}_i\beta$$

Likelihood is:

$$\begin{aligned} \ln L = & \sum_{i=1}^N Y_i \ln\{1 - \exp[-\exp(\mathbf{X}_i\beta)]\} + \\ & (1 - Y_i) \ln\{1 - \{1 - \exp[-\exp(\mathbf{X}_i\beta)]\}\} \end{aligned}$$

Logit and C-log-log CDFs



All require that:

- “Threshold” = $Y^* > 0$
- $E(u_i | \mathbf{X}, \beta) = 0$
- $\text{Var}(u_i) = \frac{\pi^2}{3}$ or 1.0.

In general:

- The Universe: $\text{Logit} > \text{Probit}$
- The (Social Science) Universe: Meh...
- $\hat{\beta}_{\text{Logit}} \approx 1.8 \times \hat{\beta}_{\text{Probit}}$
- Four reasons to prefer / use logit

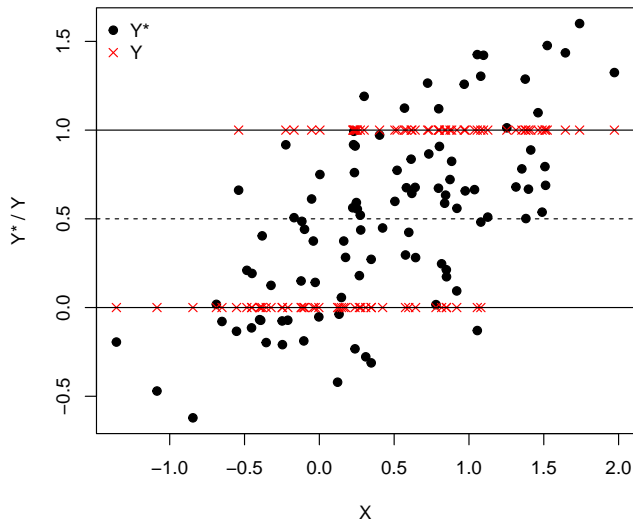
A Toy Example

```
> set.seed(7222009)
> ystar<-rnorm(100,0.5,0.5)
> y<-ifelse(ystar>0.5,1,0)
> x<-ystar+(0.5*rnorm(100))
> data<-data.frame(ystar,y,x)
```

```
> head(data)
```

	ystar	y	x
1	0.17977	0	0.2677
2	0.79428	1	1.5079
3	0.82408	1	0.8842
4	0.24658	0	0.8172
5	0.50966	1	1.1255
6	-0.07852	0	-0.6506

A Toy Example



Toy Example: Probit

```
> myprobit<-glm(y~x,family=binomial(link="probit"), data=data)
> summary(myprobit)
```

Call:

```
glm(formula = y ~ x, family = binomial(link = "probit"), data = data)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.963	-0.777	0.304	0.776	2.165

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.519	0.183	-2.83	0.0047 **
x	1.458	0.272	5.35	0.000000087 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 137.989 on 99 degrees of freedom
Residual deviance: 98.979 on 98 degrees of freedom
AIC: 103

Number of Fisher Scoring iterations: 5

Toy Example: Logit

```
> mylogit<-glm(y~x,family=binomial(link="logit"), data=data)
> summary(mylogit)
```

Call:

```
glm(formula = y ~ x, family = binomial(link = "logit"), data = data)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.959	-0.769	0.340	0.766	2.135

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.861	0.318	-2.71	0.0067 **
x	2.428	0.500	4.86	0.0000012 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 137.99 on 99 degrees of freedom
Residual deviance: 99.38 on 98 degrees of freedom
AIC: 103.4

Number of Fisher Scoring iterations: 4

Toy Example: C-Log-Log

```
> mycloglog<-glm(y~x,family=binomial(link="cloglog"), data=data)
> summary(mycloglog)
```

Call:

```
glm(formula = y ~ x, family = binomial(link = "cloglog"), data = data)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.001	-0.783	0.187	0.812	1.995

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-1.048	0.250	-4.20	0.00002710 ***
x	1.613	0.309	5.22	0.00000018 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 137.989 on 99 degrees of freedom
Residual deviance: 99.044 on 98 degrees of freedom
AIC: 103

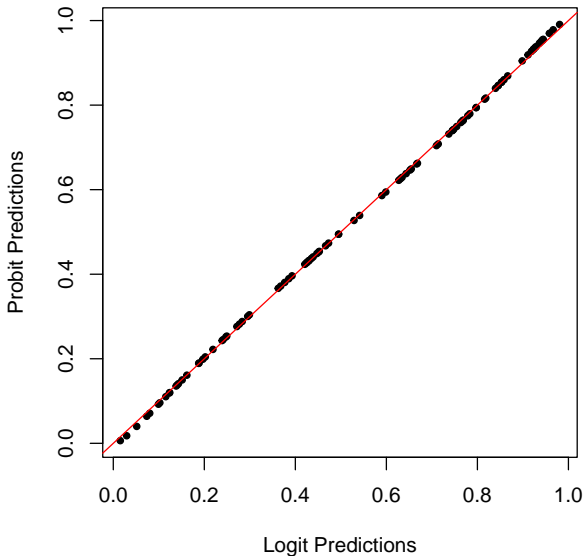
Number of Fisher Scoring iterations: 6

Toy Example (continued)

Note:

- z_s , P_s , $\ln L_s$ (via “residual deviance”) nearly identical
- Residuals, too
- $\hat{\beta}_{\text{Logit}}$ is $\frac{2.428}{1.458} = 1.54 \times \hat{\beta}_{\text{Probit}}$

Toy Example: Predicted Probabilities



Note: C-Log-Log Isn't "Reversible"

Suppose we generate a new dependent variable:

$$Y_{i\text{New}} = 1 - Y_i$$

What happens to our estimates?

	$\hat{\beta}_0$			$\hat{\beta}_1$		
	Y		Y_{New}	Y		Y_{New}
Probit	-0.52	\leftrightarrow	0.52	1.46	\leftrightarrow	-1.46
Logit	-0.86	\leftrightarrow	0.86	2.43	\leftrightarrow	-2.43
C-Log-Log	-1.05	\leftrightarrow	0.11	1.61	\leftrightarrow	-1.66